U.S. Department Of Transportation

National Highway Traffic Safety Administration

Technical Support Document:

Final Rulemaking for Model Years 2024-2026 Light-Duty Vehicle Corporate Average Fuel Economy Standards

March 2022

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Table of Acronyms and Abbreviations

AAA	American Automobile Association
AALA	American Automotive Labeling Act
AC	Air conditioning
ADAS	Advanced driver assistance systems
ADEAC	Advanced cylinder deactivation
ADSL	Advanced diesel engine
ADVENG	Non-basic engine technologies
AEB	Automatic Emergency Braking
AEO	Annual Energy Outlook
AER	All-electric range
AERO	Aerodynamic drag technology
AERO10	Aero Drag Reduction, Level 2 (10% reduction)
AERO15	Aero Drag Reduction, Level 3 (15% reduction)
AERO20	Aero Drag Reduction, Level 4 (20% reduction)
AERO5	Aero Drag Reduction, Level 1 (5% reduction)
AFV	Alternative fuel vehicle
AGM	Absorbed-glass-mat
AHSS	Advanced high strength steel
AIC	Akaike Information Criterion
AKI	Anti-Knock Index
AL	Aluminum
AMTL	Advanced Mobility Technology Laboratory
APA	Administrative Procedure Act
AT	Automatic transmissions
AT10	10-speed automatic transmission
AT10L2	10-speed automatic transmission, Level 2
AT5	5-speed automatic transmission
AT6	6-speed automatic transmission
AT7	7-speed automatic transmission
AT8	8-speed automatic transmission
AT8L2	8-speed automatic transmission, Level 2
AT9	9-speed automatic transmission
ATK	Atkinson cycle engine
AWD	All-wheel drive
BEA	Bureau of Economic Analysis
BEV	Battery electric vehicle
BEV200	200-mile range BEV

BEV300	300-mile range BEV
BEV400	400-mile range BEV
BEV500	500-mile range BEV
BISG	Belt Integrated Starter Generator
BLIS	Blind Spot Information System
BLS	Bureau of Labor Statistics
BMEP	Brake mean effective pressure
BMU	Battery management unit
BNEF	Bloomberg New Energy Finance
BPT	Benefit-per-ton
BSD	Blind Spot Detection
BSFC	Brake-specific fuel consumption
BTU	British thermal unit
CAA	Clean Air Act
CAFE	Corporate Average Fuel Economy
CARB	California Air Resources Board
CARS	Car Allowance Rebate System
CBD	Center for Biological Diversity
CBI	Confidential business information
CEGR1	Advanced turbocharged downsized technology with exhaust gas recirculation
CFR	Code of Federal Regulations
CH_4	Methane
CIB	Crash Imminent Braking
CISG	Crank integrated starter generator
CNG	Compressed natural gas
CO	Carbon monoxide
CO_2	Carbon dioxide
CO_2e	Carbon dioxide equivalent
COV	Coefficient of Variation
COVID-19	Coronavirus disease of 2019
CPI	Consumer Price Index
CPM	Cost per mile
CUV	Crossover utility vehicle
CVT	Continuously variable transmission
CVTL2	Continuous variable transmission level 2HEG
CY	Calendar Year
DBS	Dynamic Brake Support
DC	Direct current
DCT	Dual clutch transmission

DD	Direct drive transmission
DEAC	Cylinder deactivation
DFS	Dynamic fleet share
DMC	Direct manufacturing costs
DOE	U.S. Department of Energy
DOHC	Dual overhead cam
DOT	U.S. Department of Transportation
DRI	Dynamic Research, Inc.
DSLI	Advanced diesel engine with improvements
DSLIAD	Advanced diesel engine with improvements and advanced cylinder deactivation
ECU	Engine control units
eCVT	Electronic continuously variable transmission
E.O.	Executive Order
EETT	Electrical and Electronics Technical Team
EFR	Engine fiction reduction
EGR	Exhaust gas recirculation
EHPS	Electro-hydraulic power steering
EIA	U.S. Energy Information Administration
EISA	Energy Independence and Security Act of 2007
ELEC	Electrification and hybridization
ELECACC	Electric accessory improvement technologies
EPA	U.S. Environmental Protection Agency
EPCA	Energy Policy and Conservation Act of 1975
EPS	Electric power steering
ESC	Electronic Stability Control
ETDS	Electric traction drive system
ETW	Equivalent test weight
EU	European Union
EV	Electric vehicle
FARS	Fatal Accident Reporting System
FCA	Fiat Chrysler Automobiles
FCEV	Fuel cell electric vehicle
FCIV	Fuel consumption improvement value
FCV	Fuel cell vehicle
FCW	Forward Collision Warning
FE	Fuel economy
Fed. Reg.	Federal Register
FFV	Flexible fuel vehicle
FHWA	Federal Highway Administration

Final SEIS	Final Supplemental Environmental Impact Statement
FMVSS	Federal Motor Vehicle Safety Standards
FR	Fatality Rate
FRIA	Final Regulatory Impact Analysis
FTP	Federal Test Procedure
FWD	Front-wheel drive
g/mi	grams per mile
GDP	Gross domestic product
GES	General Estimates System
gpm	Gallons per mile
GREET	Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation
GVWR	Gross vehicle weight rating
HCR	High compression ratio
HEG	High efficiency gearbox
HEV	Hybrid electric vehicle
HP	Horsepower
HWFET	Highway Fuel Economy Test
IACC	Improved accessories
IACMI	Institute for Advanced Composites Manufacturing Innovation
IAV	IAV Automotive Engineering, Inc.
ICCT	International Council on Clean Transportation
ICE	Internal combustion engine
ICM	Indirect Cost Multiplier
IMEP	Indicated Mean Effective Pressure
IQR	Inner quartile range
JLR	Jaguar Land Rover
KABCO	Scale used to represent injury severity in crash reporting
km	kilometer
km/h	kilometers per hour
kWh	Kilowatt hour
LBNL	Lawrence Berkeley National Laboratory
LCA	Lane Change Alert
LDB	Low Drag Brakes
LDV	Light duty passenger vehicle
LDW	Lane Departure Warning
LE	Learning effect
LEV	Low-emission vehicle
LFP	Lithium iron phosphate
LIDAR	Light Detection and Ranging

LKA	Lane Keep Assist
LS	Low sulfur
LT	Light truck
LTVs	Light trucks and vans
MAD	Minimum absolute deviation
MAIS	Maximum abbreviated injury scale
MCT	Multi-cycle test
MDHD	Medium-duty and heavy-duty
MDPCS	Minimum domestic passenger car standard
MIT	Massachusetts Institute of Technology
MOVES	Motor Vehicle Emission Simulator
MPG	Miles per gallon
MPGe	Miles-per-gallon equivalent
mph	Miles per hour
MR0	Baseline Mass Reduction Technology
MR1	Mass Reduction - 5.0% of Glider Weight
MR2	Mass Reduction - 7.5% of Glider Weight
MR3	Mass Reduction - 10.0% of Glider Weight
MR4	Mass Reduction - 15.0% of Glider Weight
MR5	Mass Reduction - 20.0% of Glider Weight
MR6	Mass Reduction - 28.2% of Glider Weight
MSRP	Manufacturer suggested retail price
MT	Manual transmissions
MY	Model Year
NA	Naturally Aspirated
NADA	National Automotive Dealers Association
NAS	National Academy of Sciences
NASEM	National Academies of Sciences, Engineering, and Medicine
NASS-CDS	National Automotive Sampling System Crashworthiness Data System
NBER	National Bureau of Economic Research
NCA	Lithium nickel cobalt aluminum oxide
NCAP	New Car Assessment Program
NCSA	National Center for Statistics and Analysis
NEMS	National Energy Modeling System
NEPA	National Environmental Policy Act
NESCCAF	Northeast States Center for a Clean Air Future
NHTS	National Household Transportation Survey
NHTSA	National Highway Traffic Safety Administration
NMC	Nickel manganese cobalt

NO_X	Nitrogen oxide
NPRM	Notice of proposed rulemaking
NRC	National Research Council
NVH	Noise-vibration-harshness
NVPP	National Vehicle Population Profile
OEM	Original equipment manufacturer
OHV	Over-head valve
OMB	Office of Management and Budget
ORNL	Oak Ridge National Laboratory
PADD	Petroleum Administration for Defense District
PAEB	Pedestrian Automatic Emergency Braking
PAN	Polyacrylonitrile
PC	Passenger car
PDO	Property damage-only
PFI	Port fuel injection
PHEV	Plug-in hybrid electric vehicle
PHEV20	PHEV with 20-mile range
PHEV20H	PHEV20 with high compression ratio engine
PHEV20T	PHEV20 with turbo engine
PHEV50	PHEV with 50-mile range
PHEV50H	PHEV50 with high compression ratio engine
PHEV50T	PHEV50 with turbo engine
PIC	NHTSA's CAFE Public Information Center
PM_{10}	Particulate matter 10 microns or less in diameter
$PM_{2.5}$	Particulate matter 2.5 microns or less in diameter
PRIA	Preliminary Regulatory Impact Analysis
PS	Power split
PV	Passenger vehicle
RADAR	Radio Detection and Ranging
RDPI	Real disposable personal income
RIM	Resin Infiltration Process
ROLL0	Baseline tire rolling resistance
ROLL10	Tire rolling resistance, 10% improvement
ROLL20	Tire rolling resistance, 20% improvement
RPE	Retail price equivalent
RRC	Rolling resistance coefficient
RTM	Resin transfer molding
RWD	Rear-wheel drive
s.f.	Square foot

SAE	Society of Automotive Engineers
SAX	Secondary axle disconnect
SC-CH_4	Social cost of methane
SC-GHG	Social cost of greenhouse gases
SC-N_2O	Social cost of nitrous oxide
scf	Standard cubic feet
SCO	Synthetic crude oil
Secretary	Secretary of Transportation
SGDI	Stoichiometric gasoline direct injection
SHEV	Strong hybrid electric vehicle
SHEVP2	Parallel strong hybrid electric vehicle
SHEVPS	Power split strong hybrid electric vehicle
SIR	Societal injury risk
SO_2	Sulfur dioxide
SOC	State of charge
SOHC	Single overhead cam
SPR	U.S. Strategic Petroleum Reserve
SS12V	12-volt stop start
SUV	Sport utility vehicle
SWRI	South-West Research Institute
TAR	Technical Assessment Report
TCU	Transmission control unit
TE	Tailpipe Emissions
TPMS	Tire Pressure Monitoring System
TRANS	Transmission technologies
TS&D	Transportation, Storage, and Distribution
TSD	Technical Support Document
TURBO1	Turbocharged engine
TURBO2	Advanced turbocharged engine
TURBOAD	Turbocharged engine with advanced cylinder deactivation
TURBOD	Turbocharged engine with cylinder deactivation
TWh	Terawatt-hour
TZEV	Transitional zero-emissions vehicle
U.S.	United States
U.S.C.	United States Code
UDDS	Urban Dynamometer Driving Schedule
UMTRI	University of Michigan Transportation Research Institute
US06	A high acceleration aggressive driving schedule also identified as Supplemental Federal Test Procedures

USITC	U.S. International Trade Commission
VCR	Variable compression ratio
VIN	Vehicle Identification Number
VMT	Vehicle miles traveled
VOC	Volatile organic compounds
VSL	Value of a statistical life
VTG	Variable turbo geometry engine
VTGE	Variable turbo geometry engine with eBooster
VTO	DOE Vehicle Technologies Office
VTTS Memo	DOT’s 2016 Value of Travel Time Savings memorandum
VVL	Variable Valve Lift
VVT	Variable Valve Timing
ZEV	Zero emissions vehicle

1 What is NHTSA analyzing, and why?

The National Highway Traffic Safety Administration (NHTSA) is establishing revised Corporate Average Fuel Economy (CAFE) standards for passenger cars and light trucks produced for model years (MYs) 2024-2026. On January 20, 2021, President Biden signed Executive Order (E.O.) 13990, Protecting Public Health and the Environment and Restoring Science to Tackle the Climate Crisis. E.O. 13990 directed the agency to review the 2020 final rule that previously established CAFE standards for MYs 2021-2026, and to consider whether to suspend, revise, or rescind that action by issuing a proposal by July 2021.[1] Because of President Biden's direction, NHTSA reexamined the 2020 final rule and proposed to revise the fuel economy standards set in 2020 so that they would instead have increased at a rate of 8 percent per year annually from MY 2024 through MY 2026 for both passenger cars and light trucks. In reviewing public comments on that proposal and considering the available information and analysis in light of NHTSA's statutory mandate to insulate our nation's economy against external factors associated with petroleum consumption, NHTSA is issuing final standards that increase in stringency for both passenger cars and light trucks at the rates of 8 percent, 8 percent, and 10 percent over MYs 2024, 2025, and 2026, respectively. NHTSA estimates that over the lives of vehicles produced prior to MY 2030, the final standards will save about 60 billion gallons of gasoline and increase electricity consumption by about 180 terawatt-hours (TWh).

Accounting for emissions from both vehicles and upstream energy sector processes (*e.g.*, petroleum refining and electricity generation), NHTSA estimates that the final standards will reduce greenhouse gas emissions by about 605 million metric tons of carbon dioxide (CO_2), about 730 thousand tons metric tons of methane (CH_4), and about 17 thousand tons of nitrous oxide (N_2O). For example, Figure 1-1 shows NHTSA's estimate of future CO_2 emissions under each alternative:

[1] 86 Fed. Reg. 7037 (Jan. 25, 2021).

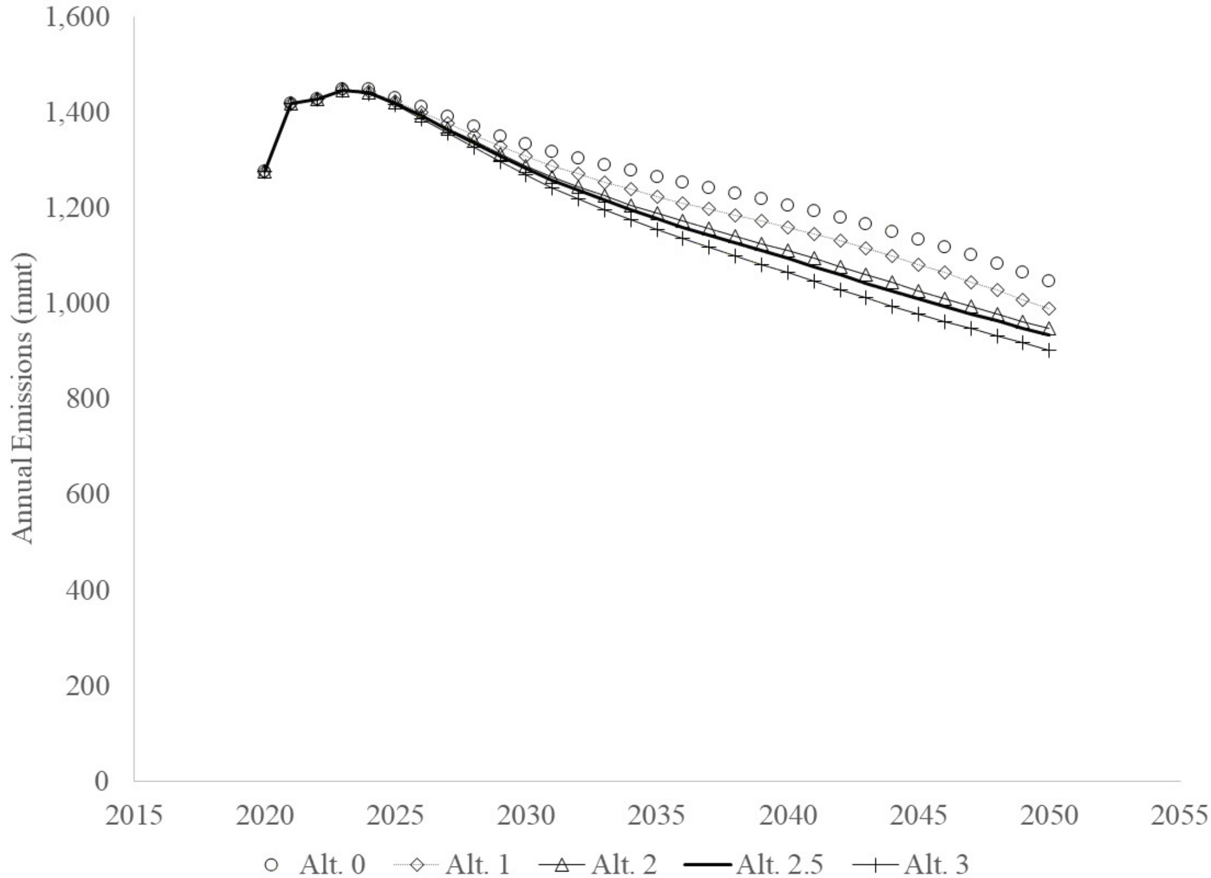

Figure 1-1 – Estimated Annual CO_2 Emissions Attributable to Light-Duty On-Road Fleet

Also accounting for vehicular and upstream emissions, NHTSA has estimated annual emissions of most criteria pollutants (i.e., pollutants for which the U.S. Environmental Protection Agency [EPA] has issued National Ambient Air Quality Standards). NHTSA estimates that under each regulatory alternative, annual emissions of carbon monoxide (CO), volatile organic compounds (VOC), nitrogen oxide (NO_X), and particulate matter 2.5 microns or less in diameter ($PM_{2.5}$) attributable to the light-duty on-road fleet will decline dramatically between 2020 and 2050, and that emissions in any given year could be very nearly the same under each regulatory alternative. For example, Figure 1-2 shows NHTSA's estimate of future NO_X emissions under each alternative.

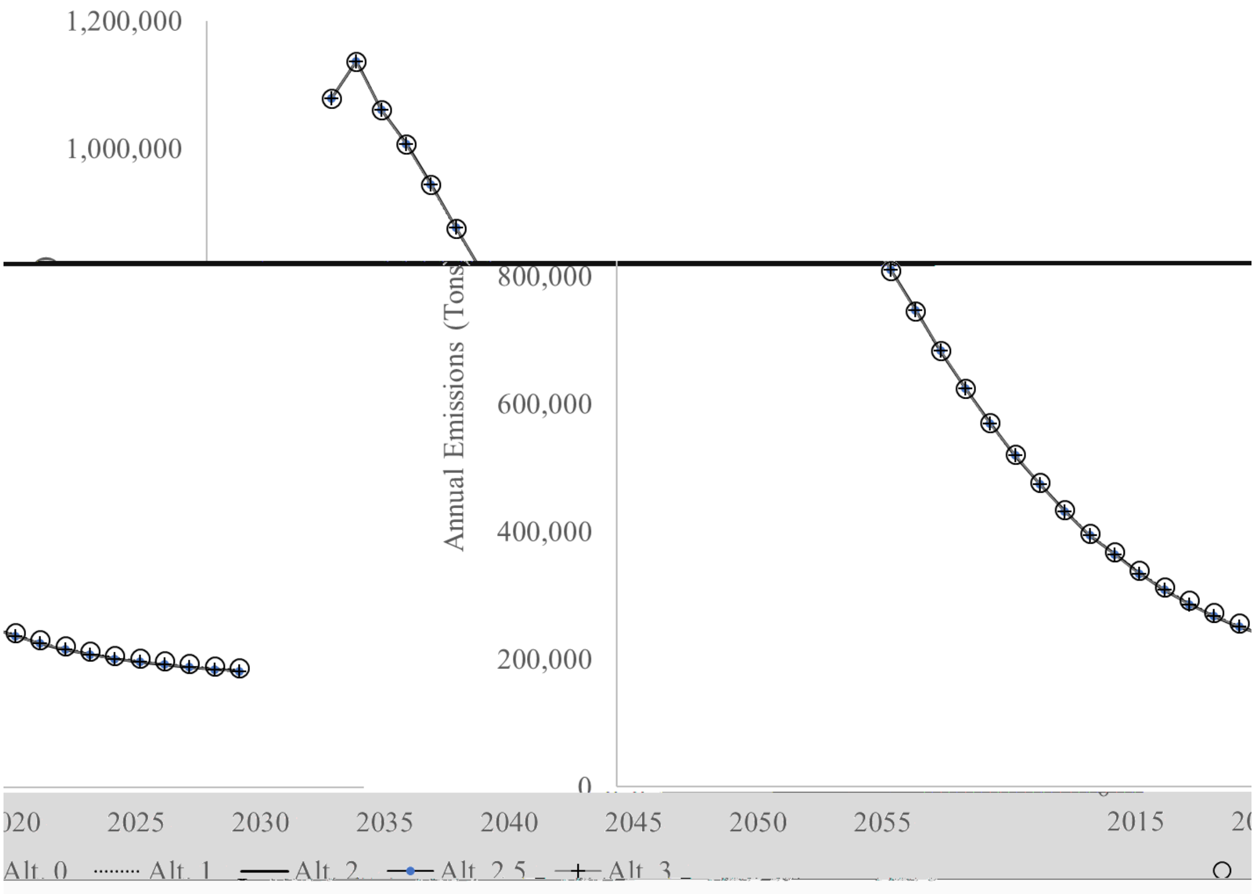

Figure 1-2 – Estimated Annual NO_X Emissions Attributable to Light-Duty On-Road Fleet

On the other hand, as discussed in the Final Regulatory Impact Analysis (FRIA) and Final Supplemental Environmental Impact Statement (Final SEIS), NHTSA projects that annual SO_2 emissions attributable to the light-duty on-road fleet could increase modestly under the action alternatives, because, as discussed above, NHTSA projects that each of the action alternatives could lead to greater use of electricity (for plug-in hybrid electric vehicles [PHEVs] and battery electric vehicles [BEVs]). The adoption of actions—such as actions prompted by President Biden's E.O. directing agencies to develop a Federal Clean Electricity and Vehicle Procurement Strategy—to reduce electricity generation emission rates beyond projections underlying NHTSA's analysis (discussed in Chapter 5) could dramatically reduce SO_2 emissions under all regulatory alternatives considered in the final rule.[2]

For the "standard setting" analysis, the FRIA accompanying today's notice provides additional detail regarding projected criteria pollutant emissions and health effects, as well as the inclusion of these impacts in the benefit-cost analysis. For the "unconstrained" or "EIS" type of analysis, the Final SEIS accompanying the final rule presents much more information regarding projected criteria pollutant emissions, as well as model-based estimates of corresponding impacts on several measures of urban air quality and public health. As mentioned above, these estimates of

[2] https://www.whitehouse.gov/briefing-room/presidential-actions/2021/01/27/executive-order-on-tackling-the-climate-crisis-at-home-and-abroad/. (Accessed: February 14, 2022).

criteria pollutant emissions are based on a complex analysis involving interacting simulation techniques and a myriad of input estimates and assumptions. Especially extending well past 2040, the analysis involves a multitude of uncertainties. Therefore, actual criteria pollutant emissions could ultimately be different from NHTSA's current estimates for this final rule.

This Technical Support Document (TSD) describes the supporting technical analysis that informed agency decision-makers in deciding to establish this rate of stringency increase for the CAFE standards for MYs 2024-2026.

Chapter 1 of this TSD explains how NHTSA develops footprint-based curves for the regulatory alternatives that represent different levels of possible CAFE stringency. Chapter 1 also presents the regulatory alternatives themselves and explains how the CAFE Model uses inputs to conduct the analysis.

Chapter 2 of this TSD describes the development of the inputs that the CAFE Model ("the model") uses, including the analysis fleet, the zero emissions vehicle (ZEV) Module, compliance credits, technology effectiveness values, technology adoption and availability, technology costs, and other inputs.

Chapter 3 of this TSD describes the technology paths within the model.

Chapter 4 of this TSD describes consumer responses to manufacturer compliance strategies, including macroeconomic assumptions that affect and describe consumer behavior, changes in fleet composition (including new vehicle sales and retirement or scrappage of existing vehicles), changes in vehicle miles traveled (VMT), and changes in fuel consumption.

Chapter 5 of this TSD describes how the model simulates the environmental effects of the different regulatory alternatives, including greenhouse gas emissions effects, criteria pollutant emissions effects, and how health effects flow from those changes.

Chapter 6 of this TSD describes how the model simulates the economic effects of the different regulatory alternatives, in terms of costs and benefits that accrue to consumers and to society.

Chapter 7 of this TSD describes how the model simulates the safety effects of the different regulatory alternatives.

1.1 Why does NHTSA conduct this analysis?

When NHTSA promulgates new regulations, it generally presents an analysis that estimates the impacts of such regulations, and the impacts of other regulatory alternatives. These analyses derive from statutes such as the Administrative Procedure Act (APA) and National Environmental Policy Act (NEPA), from Executive Orders (such as E.O. 12866 and E.O. 13653), and from other administrative guidance (*e.g.*, Office of Management Budget Circular A-4). For CAFE, the Energy Policy and Conservation Act (EPCA), as amended by the Energy Independence and Security Act (EISA), contains a variety of provisions that require NHTSA to consider certain compliance elements in certain ways and avoid considering other things, in determining maximum feasible CAFE standards. Collectively, capturing all of these requirements and guidance elements analytically means that, at least for CAFE, NHTSA presents an analysis that spans a meaningful range of regulatory alternatives, that quantifies a range of technological, economic, and environmental impacts, and that does so in a manner that accounts for EPCA's express requirements for the CAFE program (*e.g.*, that passenger cars and light trucks are regulated separately, and that the standard for each fleet must be set at the maximum feasible level in each model year).

NHTSA's decision regarding the final standards is thus supported by, although not dictated by, extensive analysis of potential impacts of the regulatory alternatives under consideration. Along with the preamble to the final rule, this TSD, a FRIA, and a Final SEIS, together provide an extensive and detailed enumeration of related methods, estimates, assumptions, and results. NHTSA's analysis has been constructed specifically to reflect various aspects of governing law applicable to CAFE standards and has been expanded and improved in response to comments received to the proposal, to the prior rulemaking, and based on additional work conducted over the last several months. Further improvements, which could not be incorporated in this final rule analysis due to timeline considerations, scope of notice, and/or complexity, may be made in the future based on comments received to the proposal, the 2021 National Academy of Sciences (NAS) Report[3] and other additional work generally previewed in these rulemaking documents. The analysis for this final rule aided NHTSA in implementing its statutory obligations, including the weighing of various considerations, by reasonably informing decision-makers about the estimated effects of choosing different regulatory alternatives.

NHTSA's analysis makes use of a range of data (*i.e.*, observations of things that have occurred), estimates (*i.e.*, things that may occur in the future), and models (*i.e.*, methods for making estimates). Two examples of *data* include (1) records of actual odometer readings used to estimate annual mileage accumulation at different vehicle ages and (2) CAFE compliance data used as the foundation for the "analysis fleet" containing, among other things, production volumes and fuel economy levels of specific configurations of specific vehicle models produced for sale in the United States. Two examples of *estimates* include (1) forecasts of future gross domestic product (GDP) growth used, with other estimates, to forecast future vehicle sales volumes and (2) the "retail price equivalent" (RPE) factor used to estimate the ultimate cost to consumers of a given fuel-saving technology, given accompanying estimates of the technology's "direct cost," as adjusted to account for estimated "cost learning effects" (*i.e.*, the tendency that it will cost a manufacturer less to apply a technology as the manufacturer gains more experience doing so).

NHTSA uses the CAFE Compliance and Effects Modeling System (usually shortened to the "CAFE Model") to estimate manufacturers' potential responses to new CAFE and CO_2 standards and to estimate various impacts of those responses. DOT's Volpe National Transportation Systems Center (often simply referred to as the "Volpe Center") develops, maintains, and applies the model for NHTSA. NHTSA has used the CAFE Model to perform analyses supporting every

[3] National Academies of Sciences, Engineering, and Medicine, 2021. *Assessment of Technologies for Improving Fuel Economy of Light-Duty Vehicles – 2025-2035,* Washington, DC: The National Academies Press (hereinafter, "2021 NAS Report"). *Available at* https://www.nationalacademies.org/our-work/assessment-of-technologies-for-improving-fuel-economy-of-light-duty-vehicles-phase-3, and for hard copy review at DOT headquarters. (Accessed: February 14, 2022).

CAFE rulemaking since 2001. The 2016 rulemaking regarding heavy-duty pickup and van fuel consumption and CO_2 emissions also used the CAFE Model for analysis.

The basic design of the CAFE Model is as follows: the system first estimates how vehicle manufacturers might respond to a given regulatory scenario, and from that potential compliance solution, the system estimates what impact that response will have on fuel consumption, emissions, and economic externalities. In a highly summarized form, the following diagram shows the basic categories of CAFE Model procedures, and the sequential flow between different stages of the modeling. The diagram does not present specific model inputs or outputs, as well as many specific procedures and model interactions. The model documentation accompanying this TSD presents these details.

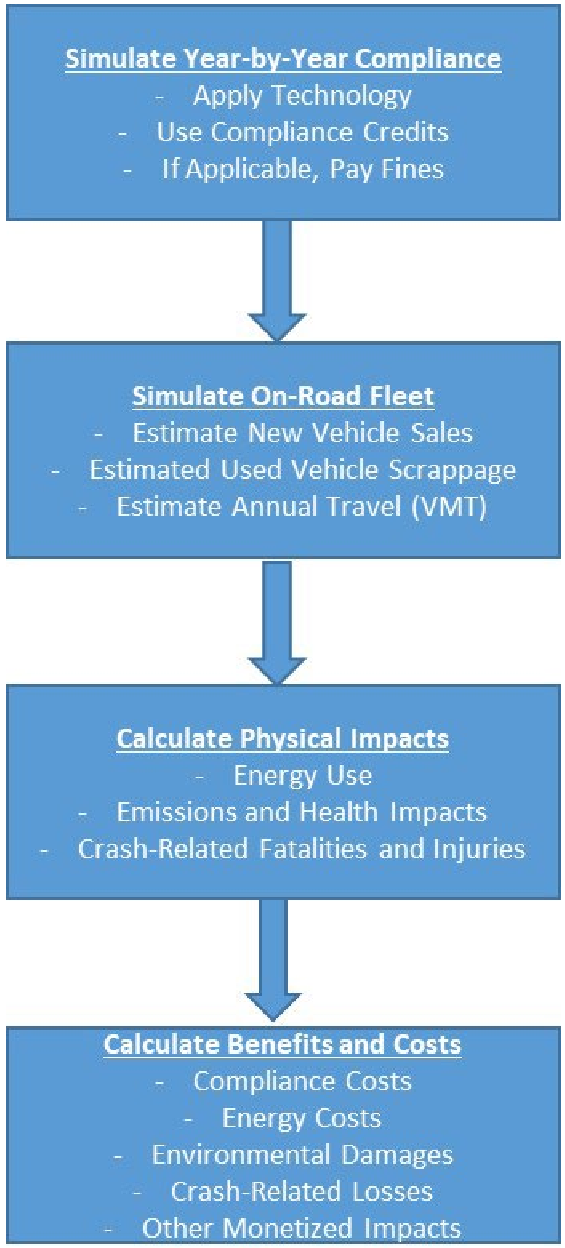

Figure 1-3 – CAFE Model Procedures and Logical Flow

More specifically, the model may be characterized as an integrated system of models. For example, one model estimates manufacturers' responses, another estimates resultant changes in total vehicle sales, and still another estimates resultant changes in fleet turnover (*i.e.*, scrappage). A regulatory scenario involves specification of the form, or shape, of the standards (*e.g.*, flat standards, or linear or logistic attribute-based standards), scope of passenger car and light truck regulatory classes, and stringency of the CAFE standards for each model year to be analyzed. For example, a regulatory scenario may define CAFE standards that increase in stringency by 8 percent per year for 3 consecutive years. Additionally, and importantly, the model does not determine the form or stringency of the standards. Instead, the model applies *inputs* specifying the form and stringency of standards to be analyzed and produces *outputs* showing the impacts of manufacturers working to meet those standards. Those outputs then become the basis for comparing between different potential stringencies.

Manufacturer compliance simulation and the ensuing effects estimation, collectively referred to as compliance modeling, encompass numerous subsidiary elements. Compliance simulation begins with a detailed user-provided[4] initial forecast of the vehicle models offered for sale during the simulation period. The compliance simulation then attempts to bring each manufacturer into compliance with the standards[5] defined by the regulatory scenario contained within an input file developed by the user.

Estimating impacts involves calculating resultant changes in new vehicle costs, estimating a variety of costs (*e.g.*, for fuel) and effects (*e.g.*, CO_2 emissions from fuel combustion) occurring as vehicles are driven over their lifetimes before eventually being scrapped, and estimating the monetary value of these effects. Estimating impacts also involves consideration of consumer responses – *e.g.*, the impact of vehicle fuel economy, operating costs, and vehicle price on consumer demand for passenger cars and light trucks. Both basic analytical elements involve the application of many analytical inputs. Many of these inputs are developed *outside* of the model and not *by* the model.

NHTSA also uses EPA's Motor Vehicle Emissions Simulator (MOVES) model to estimate "tailpipe" (a.k.a. "vehicle" or "downstream") emission factors for criteria pollutants,[6] and uses four DOE and DOE-sponsored models to develop inputs to the CAFE Model, including three developed and maintained by DOE's Argonne National Laboratory. The agency uses the DOE Energy Information Administration's (EIA's) National Energy Modeling System (NEMS) to estimate fuel prices,[7] and uses Argonne's Greenhouse gases, Regulated Emissions, and Energy use in Transportation (GREET) model to estimate emissions rates from fuel production and distribution processes.[8] DOT also sponsored DOE/Argonne to use Argonne's Autonomie full-vehicle modeling and simulation system to estimate the fuel economy impacts for over a million

[4] Because the CAFE Model is publicly available, anyone can develop their own initial forecast (or other inputs) for the model to use. The DOT-developed Market Data file that contains the forecast used for this final rule is available on NHTSA's website at https://www.nhtsa.gov/corporate-average-fuel-economy/cafe-compliance-and-effects-modeling-system#downloads. (Accessed: March 22, 2022).
[5] With appropriate inputs, the model can also be used to estimate impacts of manufacturers' potential responses to new CO_2 standards and to California's ZEV program.
[6] *See* https://www.epa.gov/moves. (Accessed: February 14, 2022). Today's final rule uses version MOVES3, available at https://www.epa.gov/moves/latest-version-motor-vehicle-emission-simulator-moves. (Accessed: February 14, 2022).
[7] *See* https://www.eia.gov/outlooks/aeo/info_nems_archive.php. (Accessed: February 14, 2022). Today's final rule uses fuel prices estimated using the AEO 2021 version of NEMS (see https://www.eia.gov/outlooks/aeo/pdf/02%20AEO2021%20Petroleum.pdf). (Accessed: February 14, 2022)
[8] Information regarding GREET is available at https://greet.es.anl.gov/index.php. (Accessed: February 14, 2022). Today's final rule uses the 2021 version of GREET.

combinations of technologies and vehicle types.[9,10] Other chapters in this TSD and discussion in the accompanying FRIA describe details of the agency's use of these models. In addition, as discussed in the Final SEIS accompanying today's final rule, DOT relied on a range of climate models to describe impacts on climate, air quality, and public health. The Final SEIS discusses and describes the use of these models.

The CAFE Model, therefore, serves as a "hub" that connects and holds together a wide range of inputs, processes, and other models that all inform DOT's analysis, and that, in turn, provides essential model results underlying the Final SEIS accompanying today's final rule. Though not exhaustive, the diagram on the following page shows most of the important connections between different elements of DOT's analysis.

[9] As part of the Argonne simulation effort, individual technology combinations simulated in Autonomie were paired with Argonne's BatPaC model to estimate the battery cost associated with each technology combination based on characteristics of the simulated vehicle and its level of electrification. Information regarding Argonne's BatPaC model is available at https://www.anl.gov/cse/batpac-model-software. (Accessed: February 14, 2022).

[10] In addition, the impact of engine technologies on fuel consumption, torque, and other metrics was characterized using GT-POWER simulation modeling in combination with other engine modeling that was conducted by IAV Automotive Engineering, Inc. (IAV). The engine characterization "maps" resulting from this analysis were used as inputs for the Autonomie full-vehicle simulation modeling. Information regarding GT-POWER is available at https://www.gtisoft.com/gt-suite-applications/propulsion-systems/gt-power-engine-simulation-software. (Accessed: February 14, 2022).

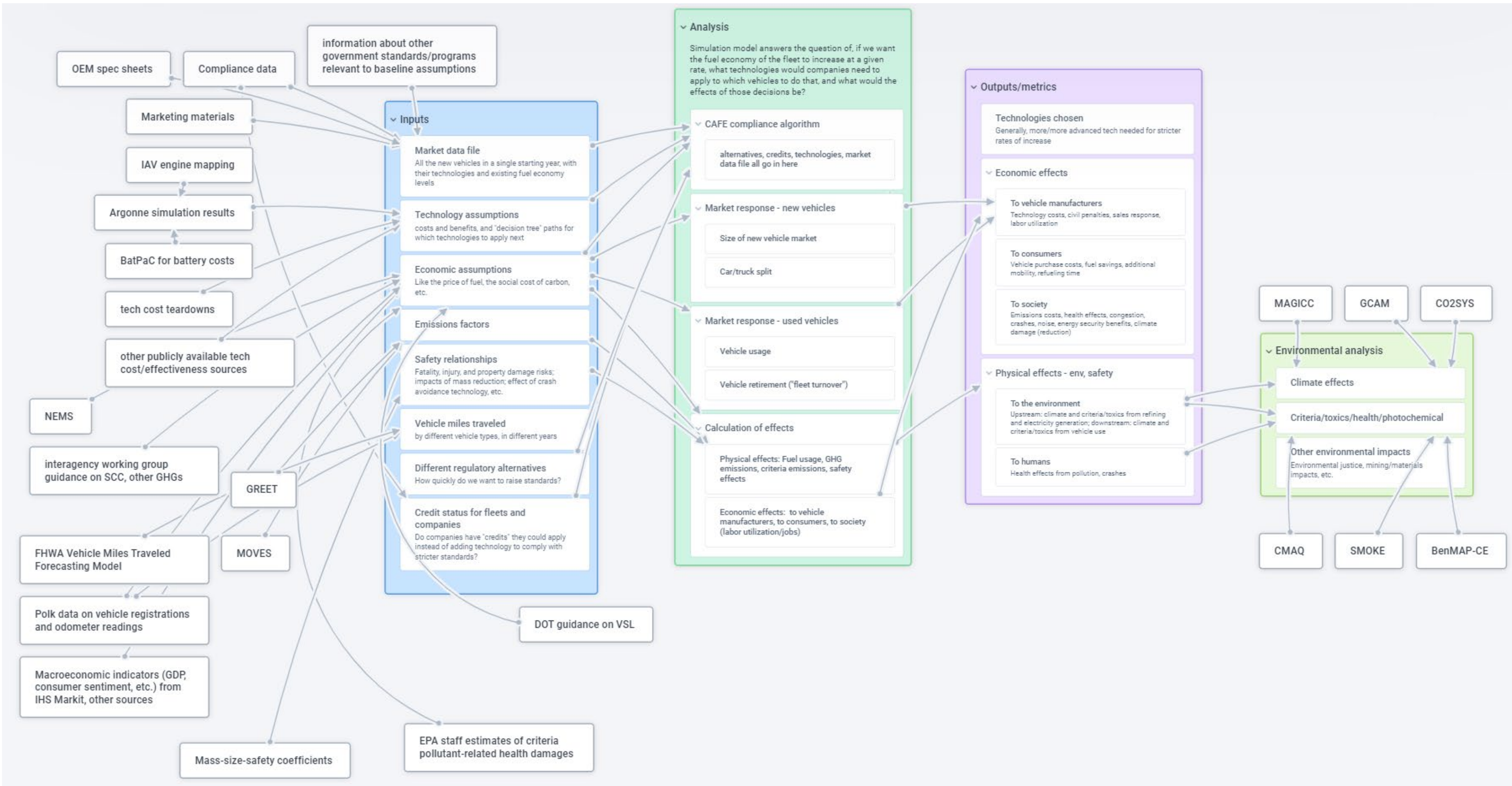

Figure 1-4 – Key Elements of DOT's Analysis

To prepare for analysis supporting today's final rule, DOT has refined and expanded the CAFE Model through ongoing development. Examples of such changes, some informed by past external comments, made since early 2020 include:

- Inclusion of 400- and 500-mile BEVs;
- Inclusion of high compression ratio (HCR) engines with cylinder deactivation;
- Accounting for manufacturers' responses to both CAFE and CO_2 standards jointly (rather than only separately);
- Accounting for the ZEV mandates applicable in California and the Section 177 states;
- Accounting for some vehicle manufacturers' (BMW, Ford, Honda, VW, and Volvo) voluntary adoption of the California Framework Agreements through MY 2026, with greater rates of electrification than would have been required under the 2020 Federal final rule;[11]
- Including CAFE civil penalties in the "effective cost" metric used when simulating manufacturers' potential application of fuel-saving technologies;
- Including refined procedures to estimate health effects and corresponding monetized damages attributable to criteria pollutant emissions;
- Adding new procedures to estimate the impacts and corresponding monetized damages of highway vehicle crashes that do not result in fatalities;
- Establishing procedures to ensure that modeled technology application and production volumes are the same across all regulatory alternatives in the earliest model years; and
- Revising procedures to more precisely focus application of EPCA's "standard setting constraints" (*i.e.*, regarding the consideration of compliance credits and additional dedicated alternative fueled vehicles) to only those model years for which NHTSA is proposing or finalizing new standards.

These changes reflect DOT's long-standing commitment to ongoing refinement of its approach to estimating the potential impacts of new CAFE standards. Following the proposal preceding today's notice, NHTSA made several further changes to the CAFE Model, including:

- Including new options for applying a dynamic fleet share model (of the relative shares passenger cars and light trucks comprise of the total U.S. new vehicle market);

[11] For more information on the Framework Agreements for Clean Cars, including the specific agreements signed by individual manufacturers, please see https://ww2.arb.ca.gov/news/framework-agreements-clean-cars. (Accessed: February 14, 2022).

- Adding provisions allowing direct input of the number of miles to be included when valuing avoided fuel outlays in the models used to estimate impacts on the total sales of new vehicles and the scrappage of used vehicles;

- Expanding reporting to include all estimates (for today's analysis) of the social cost of carbon dioxide emissions (i.e., the SCC) when reporting total and net benefits to society;

- Calculating and reporting the value of miles reallocated between new and used vehicles (when holding overall travel demand before accounting for the rebound effect constant between regulatory alternatives);

- Including adjustments to reduce exclude finance costs from reported incremental costs to consumers, and reduce reported insurance costs by 20 percent (to prevent double-counting of the costs to replace totaled vehicles); and

- Incorporating revisions to allow direct specification of total VMT even in years for which the CAFE Model estimates new vehicle sales (in particular, for today's analysis, 2021, to account for VMT recovering rapidly following the decline in the early months of the coronavirus disease of 2019 (COVID-19) pandemic.

These changes reflect DOT's long-standing commitment to ongoing refinement of its approach to estimating the potential impacts of new CAFE standards and, since the early 2000s, refining the CAFE Model DOT maintains to make such estimates, as shown in Figure 1-5.

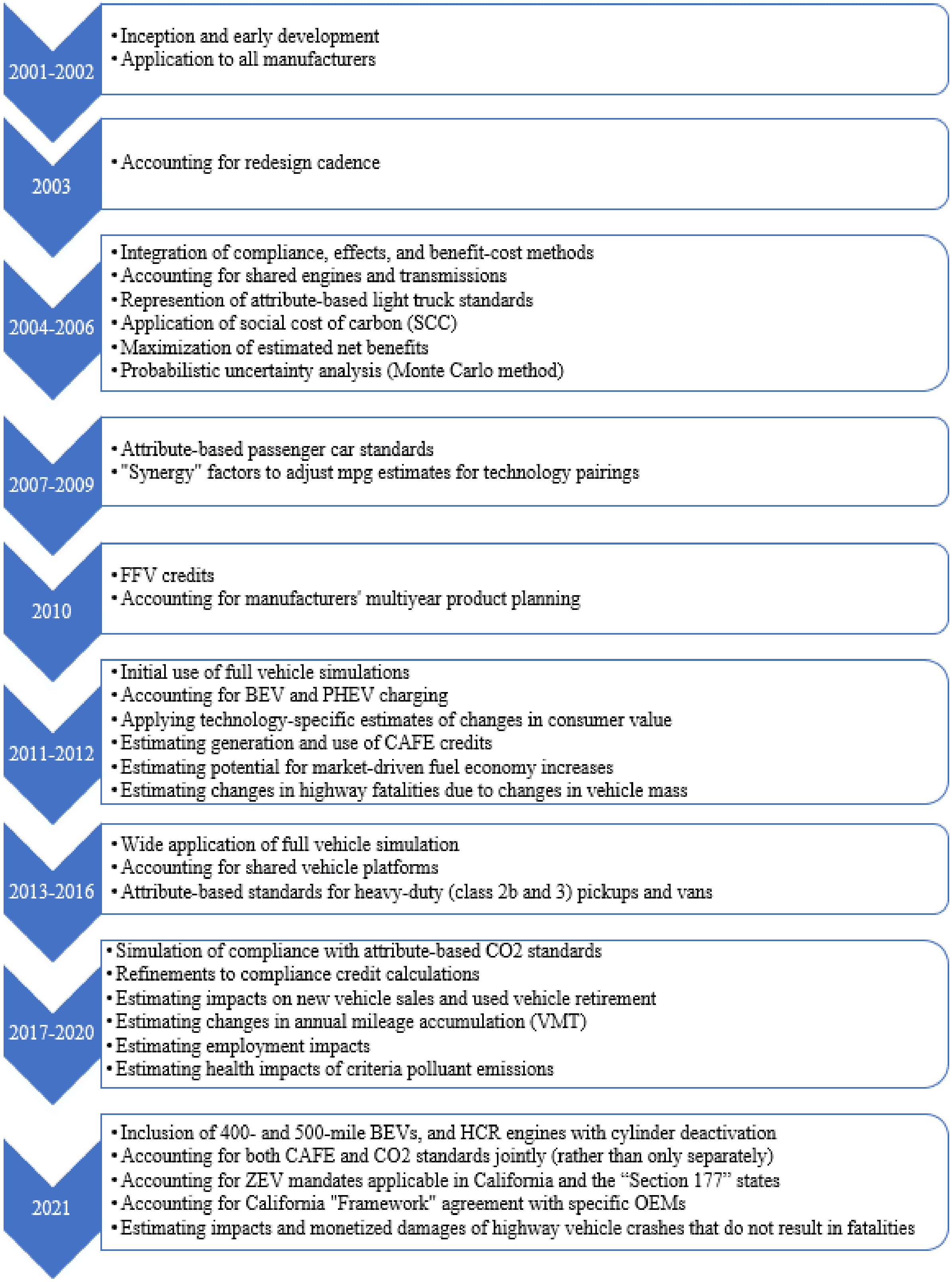

Figure 1-5 – CAFE Model Refinement Milestones

Because the CAFE Model simulates a wide range of actual constraints and practices related to automotive engineering, planning, and production, such as common vehicle platforms, sharing of engines among different vehicle models, and timing of major vehicle redesigns, the analysis produced by the CAFE Model provides a transparent and realistic basis to show pathways manufacturers could follow over time in applying new technologies, which helps better assess impacts of potential future standards. Furthermore, because the CAFE Model also accounts for regulatory compliance provisions (now including CO_2 compliance provisions), such as adjustments for reduced refrigerant leakage, production "multipliers" for some specific types of vehicles (*e.g.*, PHEVs), and carried-forward (*i.e.*, banked) credits, the CAFE Model provides a transparent and realistic basis to estimate how such technologies might be applied over time in response to CAFE or CO_2 standards.

Considering the technological heterogeneity of manufacturers' current product offerings, and the wide range of ways in which the many fuel economy-improving technologies included in the analysis can be combined, the CAFE Model has been designed to use inputs that provide an estimate of the fuel economy achieved for many tens of thousands of different potential combinations of fuel-saving technologies. Across the range of technology classes encompassed by the analysis fleet, today's analysis involves more than a million such estimates. While the CAFE Model requires no specific approach to developing these inputs, the NAS has recommended, and stakeholders have commented, that full-vehicle simulation provides the best balance between realism and practicality. DOE/Argonne has spent several years developing, applying, and expanding means to use distributed computing to exercise its Autonomie full-vehicle modeling and simulation tool over the scale necessary for realistic analysis of CAFE. This scalability and related flexibility (in terms of expanding the set of technologies to be simulated) makes Autonomie well-suited for developing inputs to the CAFE Model.

In addition, DOE/Argonne's Autonomie also has a long history of development and widespread application by a wide range of users in government, academia, and industry. Many of these users apply Autonomie to inform funding and design decisions. These real-world exercises have contributed significantly to aspects of Autonomie important to producing realistic estimates of fuel economy levels, such as estimation and consideration of performance, utility, and drivability metrics (*e.g.*, towing capability, shift busyness, frequency of engine on/off transitions). This steadily increasing realism has, in turn, steadily increased confidence in the appropriateness of using Autonomie to make significant investment decisions. Notably, DOE uses Autonomie for analysis supporting budget priorities and plans for programs managed by its Vehicle Technologies Office (VTO).

Like any model, both Autonomie and the CAFE Model benefit from ongoing refinement. However, NHTSA is confident that this combination of models produces a realistic characterization of the potential impacts of potential new standards. The majority of stakeholders that have supported the agency's reliance on the DOE/Argonne Autonomie tool and DOT CAFE Model noted not only technical reasons to use these models, but also other reasons such as efficiency, transparency, and ease with which outside parties can exercise models and replicate the agency's analysis.

Today's analysis exercises the CAFE Model in a manner that explicitly accounts for the fact that vehicle manufacturers face the *combination* of CAFE standards, EPA CO_2 standards, and ZEV mandates, and five manufacturers voluntary adoption of the California Framework Agreements (also applicable to these manufacturers' total production for the U.S. market) through model year 2026. These regulations and contracts have important structural and other differences that affect the strategy a manufacturer could use to comply with each of the above, and NHTSA believes, as discussed at more length in the final rule preamble, that it is important for agency decision-makers to be as informed as possible about the effects of the regulatory landscape in which future CAFE compliance would be occurring.

As explained, the analysis is designed to reflect several statutory and regulatory requirements applicable to CAFE and tailpipe CO_2 standard setting. EPCA contains several requirements governing the scope and nature of CAFE standard setting. Among these, some have been in place since EPCA was first signed into law in 1975, and some were added in 2007, when Congress passed EISA and amended EPCA. The Clean Air Act (CAA), as discussed elsewhere, provides EPA with very broad authority under Section 202(a), and does not contain EPCA/EISA's prescriptions. In the interest of harmonization, however, EPA has adopted some of the EPCA/EISA requirements into its tailpipe CO_2 regulations, and NHTSA, in turn, has created some additional flexibilities by regulation not expressly included by EPCA/EISA in order to harmonize better with some of EPA's programmatic decisions. EPCA/EISA requirements regarding the technical characteristics of CAFE standards and the analysis thereof include, but are not limited to, the following, and the analysis reflects these requirements as summarized:

<u>Corporate Average Standards</u>: 49 U.S.C. 32902 requires that standards apply to the average fuel economy levels achieved by each corporation's fleets of vehicles produced for sale in the United States.[12] EPA has adopted a similar approach under Section 202(a) of the CAA in the interest of harmonization. The CAFE Model calculates the CAFE and CO_2 levels of each manufacturer's fleets based on estimated production volumes and characteristics, including fuel economy levels, of distinct vehicle models that could be produced for sale in the United States.

<u>Separate Standards for Passenger Cars and Light Trucks</u>: 49 U.S.C. 32902 requires the Secretary of Transportation (the Secretary) to set CAFE standards separately for passenger cars and light trucks. EPA has adopted a similar approach under Section 202(a) of the CAA. The CAFE Model accounts separately for passenger cars and light trucks, including differentiated standards and compliance.

<u>Attribute-Based Standards</u>: 49 U.S.C. 32902 requires the Secretary of Transportation to define CAFE standards as mathematical functions expressed in terms of one or more vehicle attributes related to fuel economy. This means that for a given manufacturer's fleet of vehicles produced for sale in the United States in a given regulatory class and model year, the applicable minimum CAFE requirement (*i.e.*, the numerical value of the requirement) is computed based on the applicable mathematical function, and the mix and attributes of vehicles in the manufacturer's fleet. EPA has also adopted attribute-based standards under its broad CAA Section 202(a)

[12] This differs from safety standards and traditional emissions standards, which apply separately to each vehicle. For example, every vehicle produced for sale in the United States must, on its own, meet all applicable federal motor vehicle safety standards (FMVSS), but no vehicle produced for sale must, on its own, meet federal fuel economy standards. Rather, each manufacturer is required to produce a mix of vehicles that, taken together, achieve an average fuel economy level no less than the applicable minimum level.

authority in its current GHG standards. The CAFE Model accounts for such functions and vehicle attributes explicitly.

Separately Defined Standards for Each Model Year: 49 U.S.C. 32902 requires the Secretary to set CAFE standards (separately for passenger cars and light trucks[13]) at the maximum feasible levels in each model year. CAA Section 202(a) allows EPA to establish CO_2 standards separately for each model year, and EPA has chosen to do this in the previous light-duty vehicle CO_2 standard-setting rules. The CAFE Model represents each model year explicitly, and accounts for the production relationships between model years.[14]

Separate Compliance for Domestic and Imported Passenger Car Fleets: 49 U.S.C. 32904 requires the EPA Administrator to determine CAFE compliance separately for each manufacturers' fleets of domestic passenger cars and imported passenger cars, which manufacturers must consider as they decide how to improve the fuel economy of their passenger car fleets. EPA does not face a similar requirement for CO_2 standard compliance. The CAFE Model accounts explicitly for this requirement when simulating manufacturers' potential responses to CAFE standards and combines any given manufacturer's domestic and imported cars into a single fleet when simulating that manufacturer's potential response to CO_2 standards.

Minimum CAFE Standards for Domestic Passenger Car Fleets: 49 U.S.C. 32902 requires that domestic passenger car fleets meet a minimum standard, which is calculated as 92 percent of the industry-wide average level required under the applicable attribute-based CAFE standard, as projected by the Secretary at the time the standard is promulgated. EPA's GHG program does not contain a similar requirement. The CAFE Model accounts explicitly for this requirement for CAFE standards and sets this requirement aside for CO_2 standards.

Civil Penalties for Noncompliance: 49 U.S.C. 32912 (and implementing regulations) prescribes a rate (in dollars per tenth of a mpg) at which the Secretary is to levy civil penalties if a manufacturer fails to comply with a CAFE standard for a given fleet in a given model year, after considering available credits. Some manufacturers have historically demonstrated a willingness to pay civil penalties rather than achieving full numerical compliance across all fleets. The CAFE Model calculates civil penalties for CAFE shortfalls and provides means to estimate that a manufacturer might stop adding fuel-saving technologies once continuing to do so would be effectively more "expensive" (after accounting for fuel prices and buyers' willingness to pay for fuel economy) than paying civil penalties. In contrast, the CAA does not authorize the EPA Administrator to allow manufacturers to sell noncompliant fleets and pay civil penalties; manufacturers who have chosen to pay civil penalties for CAFE compliance instead have tended to employ EPA's more-extensive programmatic flexibilities to meet CO_2 emissions standards. Thus, the CAFE Model does not allow civil penalty payment as an option for CO_2 standards.

[13] 49 U.S.C. chapter 329 uses the term "non-passenger automobiles," while NHTSA uses the term "light trucks" in its CAFE regulations. The terms' meanings are identical.

[14] For example, a new engine first applied to given vehicle model/configuration in model year 2020 will most likely be "carried forward" to model year 2021 of that same vehicle model/configuration, in order to reflect the fact that manufacturers do not apply brand-new engines to a given vehicle model every single year. The CAFE Model is designed to account for these real-world factors.

Dual-Fueled and Dedicated Alternative Fuel Vehicles: For purposes of calculating CAFE levels used to determine compliance, 49 U.S.C. 32905 and 32906 specify methods for calculating the fuel economy levels of vehicles operating on alternative fuels to gasoline or diesel through MY 2020. After MY 2020, methods for calculating alternative fuel vehicle (AFV) fuel economy are governed by regulation. The CAFE Model can account for these requirements explicitly for each vehicle model. However, 49 U.S.C. 32902 prohibits consideration of the fuel economy of dedicated AFV models when NHTSA determines what levels of CAFE standards are maximum feasible. The CAFE Model therefore has an option to be run in a manner that excludes the additional application of dedicated AFV technologies in model years for which maximum feasible standards are under consideration. As allowed under NEPA for analysis appearing in EISs informing decisions regarding CAFE standards, the CAFE Model can also be run without this analytical constraint. CAA Section 202(a) does not similarly require EPA to avoid consideration of dedicated AFVs when setting CO_2 standards. The CAFE Model thus accounts for dual- and AFVs when simulating manufacturers' potential responses to CO_2 standards.[15]

ZEV Mandates: The CAFE Model can simulate manufacturers' compliance with ZEV mandates applicable in California and Section 177[16] states. The approach involves identifying specific vehicle model/configurations that could be replaced with PHEVs or BEVs, and immediately making these changes in each model year, before beginning to consider the potential that other technologies could be applied toward compliance with CAFE or CO_2 standards.

Creation and Use of Compliance Credits: 49 U.S.C. 32903 provides that manufacturers may earn CAFE "credits" by achieving a CAFE level beyond that required of a given fleet in a given model year, and specifies how these credits may be used to offset the amount by which a different fleet falls short of its corresponding requirement. These provisions allow credits to be "carried forward" and "carried back" between model years, transferred between regulated classes (domestic passenger cars, imported passenger cars, and light trucks), and traded between manufacturers. However, credit use is also subject to specific statutory limits. For example, CAFE compliance credits can be carried forward a maximum of five model years and carried back a maximum of three model years. Also, EPCA/EISA caps the amount of credit that can be transferred between passenger car and light truck fleets and prohibits manufacturers from applying traded or transferred credits to offset a failure to achieve the applicable minimum standard for domestic passenger cars. The CAFE Model explicitly simulates manufacturers' potential use of credits carried forward from prior model years or transferred from other fleets.[17]

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[15] For today's analysis, NHTSA has exercised the CAFE Model accounting for EPA regulatory flexibilities.

[16] The term "Section 177 states" refers to states which have elected to adopt California's standards in lieu of Federal requirements, as allowed under Section 177 of the CAA.

[17] The CAFE Model does not explicitly simulate the potential that manufacturers would carry CAFE or CO_2 credits back (*i.e.*, borrow) from future model years, or acquire and use CAFE compliance credits from other manufacturers. At the same time, because EPA has currently elected not to limit credit trading or transferring, the CAFE Model can be exercised in a manner that simulates unlimited (a.k.a. "perfect") CO_2 compliance credit trading throughout the industry (or, potentially, within discrete trading "blocs"). NHTSA believes there is significant uncertainty in how manufacturers may choose to employ these particular flexibilities in the future: for example, while it is reasonably foreseeable that a manufacturer who over-complies in one year may "coast" through several subsequent years relying on those credits rather than continuing to make technology improvements, it is harder to assume with

49 U.S.C. 32902 prohibits consideration of manufacturers' potential application of CAFE compliance credits when setting maximum feasible CAFE standards. The CAFE Model can be operated in a manner that excludes the application of CAFE credits for a given model year under consideration for standard setting. CAA 202(a) does not preclude the EPA Administrator from adopting analogous provisions. With some exceptions, EPA's baseline regulations limit the "life" of compliance credits from most model years to 5 years, and to limit borrowing to 3 years, but has not adopted any limits on transfers (between fleets) or trades (between manufacturers) of compliance credits. The CAFE Model accounts for the absence of limits on transfers of CO_2 standards. Insofar as the CAFE Model can be exercised in a manner that simulates trading of CO_2 compliance credits, such simulations treat trading as unlimited.[18]

Statutory Basis for Stringency: 49 U.S.C. 32902 requires the Secretary to set CAFE standards at the maximum feasible levels, considering technological feasibility, economic practicability, the need of the Nation to conserve energy, and the impact of other government standards. EPCA/EISA authorizes the Secretary to interpret these factors, and as the Department's interpretation has evolved, NHTSA has continued to expand and refine its qualitative and quantitative analysis to account for these statutory factors. For example, the Autonomie simulations reflect the agency's judgment that it would not be economically practicable for a manufacturer to "split" an engine shared among many vehicle model/configurations into myriad versions each optimized to a single vehicle model/configuration.

National Environmental Policy Act: In addition, NEPA requires the Secretary to issue an EIS that documents the estimated impacts of regulatory alternatives under consideration. The Final SEIS accompanying today's final rule documents changes in emission inventories as estimated using the CAFE Model, but also documents corresponding estimates—based on the application of other models documented in the Final SEIS, of impacts on the global climate, on tropospheric air quality, and on human health.

Other Aspects of Compliance: Beyond these statutory requirements applicable to DOT and/or EPA are several specific technical characteristics of CAFE and/or CO_2 regulations that are also relevant to the construction of today's analysis. For example, EPA has defined procedures for

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confidence that manufacturers will rely on future technology investments to offset prior-year shortfalls, or whether/how manufacturers will trade credits with market competitors rather than making their own technology investments. Historically, carry-back and trading have been much less utilized than carry-forward, for a variety of reasons including higher risk and preference not to 'pay competitors to make fuel economy improvements we should be making' (to paraphrase one manufacturer), although NHTSA recognizes that carry-back and trading are used more frequently when standards increase more rapidly in stringency. Given the uncertainty just discussed, and given also the fact that the agency has yet to resolve some of the analytical challenges associated with simulating use of these flexibilities, the agency considers borrowing and trading to involve sufficient risk that it is prudent to support today's final rule with analysis that sets aside the potential that manufacturers could come to depend widely on borrowing and trading. While compliance costs in real life may be somewhat different from what is modeled today as a result of this analytical decision, that is broadly true no matter what, and the agency does not believe that the difference would be so great that it would change the policy outcome. Furthermore, a manufacturer employing a trading strategy would presumably do so because it represents a lower-cost compliance option. Thus, the estimates derived from this modeling approach are likely to be conservative in this respect, with real-world compliance costs possibly being lower.

[18] To avoid making judgments about possible future trading activity, when exercising the model in this way, the agency combines all manufacturers into a single entity, so that the most cost-effective choices are made for the fleet as a whole.

calculating average CO_2 levels, and has revised procedures for calculating CAFE levels, to reflect manufacturers' application of "off-cycle" technologies that increase fuel economy. Although too little information is available to account for these provisions explicitly in the same way that the agency has accounted for other technologies, the CAFE Model does include and makes use of inputs reflecting the agency's expectations regarding the extent to which manufacturers may earn such credits, along with estimates of corresponding costs. Similarly, the CAFE Model includes and makes use of inputs regarding credits EPA has elected to allow manufacturers to earn toward CO_2 levels (not CAFE) based on the use of air conditioner refrigerants with lower global warming potential, or on the application of technologies to reduce refrigerant leakage. In addition, EPA has elected to provide that through certain model years, manufacturers may apply "multipliers" to plug-in hybrid electric vehicles, dedicated electric vehicles, fuel cell vehicles, and hydrogen vehicles, such that when calculating a fleet's average CO_2 levels (not CAFE), the manufacturer may, for example, "count" each electric vehicle twice. The CAFE Model accounts for these multipliers, based on current regulatory provisions or on alternative approaches. Although these are examples of regulatory provisions that arise from the exercise of discretion rather than specific statutory mandate, they can materially impact outcomes.

Besides the updates to the model described above, any analysis of regulatory actions that will be implemented several years in the future, and whose benefits and costs accrue over decades, requires many assumptions. Over such time horizons, many, if not most, of the relevant assumptions in such an analysis are inevitably uncertain.[19] It is natural that each successive CAFE analysis should update assumptions to reflect better the current state of the world and the best current estimates of future conditions.

Several assumptions have been updated since the 2020 final rule for today's final rule. While NHTSA would have made these updates as a matter of course, we note that that the COVID-19 pandemic has been profoundly disruptive, including in ways directly material to major analytical inputs such as fuel prices, GDP, vehicle production and sales, and highway travel. As discussed below, for the analysis supporting the notice of proposed rulemaking (NPRM) preceding today's notice, NHTSA updated its "analysis fleet" from a model year 2017 reference to a model year 2020 reference, updated estimates of manufacturers' compliance credit "holdings," updated fuel price projections to reflect the U.S. Energy Information Administration's (EIA's) 2021 Annual Energy Outlook (AEO), updated projections of GDP and related macroeconomic measures, and updated projections of future highway travel. Since that time, NHTSA has further updated macroeconomic and highway travel projections, reflecting the fact that these have recovered more rapidly than initially anticipated. However, today's analysis continues to rely on AEO 2022 fuel price projections, as EIA did not issue AEO 2022 until after NHTSA had already completed today's analysis.

In addition, through E.O. 13990, President Biden has required the formation of an Interagency Working Group (IWG) on the Social Cost of Greenhouse Gases and charged this body with updating estimates of the social costs of carbon, nitrous oxide, and methane. As discussed below, NHTSA has applied the IWG's interim guidance, which contains cost estimates (per ton

[19] As often stated, "It's difficult to make predictions, especially about the future." *See*, *e.g.*, https://quoteinvestigator.com/2013/10/20/no-predict/. (Accessed: February 14, 2022).

of emissions) considerably greater than those applied in the analysis supporting the 2020 SAFE rule. These and other updated analytical inputs are discussed in detail in the remainder of this TSD.

1.2 What is NHTSA analyzing?

1.2.1 Attribute-Based Standards

As in the CAFE and CO_2 rulemakings in 2010, 2012, and 2020, NHTSA is setting attribute-based CAFE standards defined by a mathematical function of vehicle footprint, which has an observable correlation with fuel economy. EPCA, as amended by EISA, expressly requires that CAFE standards for passenger cars and light trucks be based on one or more vehicle attributes related to fuel economy and be expressed in the form of a mathematical function.[20] Thus, the final standards (and regulatory alternatives) take the form of fuel economy targets expressed as functions of vehicle footprint (the product of vehicle wheelbase and average track width) that are separate for passenger cars and light trucks. Chapter 1.2.3 below discusses NHTSA's continued reliance on footprint as the relevant attribute in this final rule.

Under the footprint-based standards, the function defines a fuel economy performance target for each unique footprint combination within a car or truck model type. Using the functions, each manufacturer thus will have a CAFE average standard for each year that is almost certainly unique to each of its fleets,[21] based upon the footprints and production volumes of the vehicle models produced by that manufacturer. A manufacturer will have separate footprint-based standards for cars and for trucks, consistent with 49 U.S.C. 32902(b)'s direction that NHTSA must set separate standards for cars and for trucks. The functions are mostly sloped, so that generally, larger vehicles (*i.e.*, vehicles with larger footprints) will be subject to lower mpg targets than smaller vehicles. This is because, generally speaking, smaller vehicles are more capable of achieving higher levels of fuel economy, mostly because they tend not to have to work as hard (and therefore to require as much energy) to perform their driving task. Although a manufacturer's fleet average standards could be estimated throughout the model year based on the projected production volume of its vehicle fleet (and are estimated as part of EPA's certification process), the standards with which the manufacturer must comply are determined by its final model year production figures. A manufacturer's calculation of its fleet average standards, as well as its fleets' average performance at the end of the model year, will thus be based on the production-weighted average target and performance of each model in its fleet.[22]

For passenger cars, consistent with prior rulemakings, NHTSA is defining fuel economy targets as shown in Equation 1-1.

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[20] 49 U.S.C. 32902(a)(3)(A).

[21] EPCA/EISA requires NHTSA and EPA to separate passenger cars into domestic and import passenger car fleets for CAFE compliance purposes (49 U.S.C. 32904(b)), whereas EPA combines all passenger cars into one fleet.

[22] As discussed in prior rulemakings, a manufacturer may have some vehicle models that exceed their target and some that are below their target. Compliance with a fleet average standard is determined by comparing the fleet average standard (based on the production-weighted average of the target levels for each model) with fleet average performance (based on the production-weighted average of the performance of each model).

$$TARGET_{FE} = \frac{1}{MIN\left[MAX\left(c \times FOOTPRINT + d, \frac{1}{a}\right), \frac{1}{b}\right]}$$

Equation 1-1 – Passenger Car Fuel Economy Footprint Target Curve

Where:

$TARGET_{FE}$ is the fuel economy target (in mpg) applicable to a specific vehicle model type with a unique footprint combination,

a is a minimum fuel economy target (in mpg),

b is a maximum fuel economy target (in mpg),

c is the slope (in gallons per mile per square foot, or gpm, per square foot) of a line relating fuel consumption (the inverse of fuel economy) to footprint, and

d is an intercept (in gpm) of the same line.

Here, *MIN* and *MAX* are functions that take the minimum and maximum values, respectively, of the set of included values. For example, *MIN*[40, 35] = 35 and *MAX*(40, 25) = 40, such that *MIN*[*MAX*(40, 25), 35] = 35.

The resultant functional form is reflected below in graphs displaying the passenger car target function in each model year for each regulatory alternative.

For light trucks, also consistent with prior rulemakings, NHTSA is defining fuel economy targets as shown in Equation 1-2.

$$TARGET_{FE} = MAX\left(\frac{1}{MIN\left[MAX\left(c \times FOOTPRINT + d, \frac{1}{a}\right), \frac{1}{b}\right]}, \frac{1}{MIN\left[MAX\left(g \times FOOTPRINT + h, \frac{1}{e}\right), \frac{1}{f}\right]}\right)$$

Equation 1-2 – Light Truck Fuel Economy Target Curve

Where:

$TARGET_{FE}$ is the fuel economy target (in mpg) applicable to a specific vehicle model type with a unique footprint combination,

a, *b*, *c*, and *d* are as for passenger cars, but taking values specific to light trucks,

e is a second minimum fuel economy target (in mpg),

f is a second maximum fuel economy target (in mpg), *g* is the slope (in gpm per square foot) of a second line relating fuel consumption (the inverse of fuel economy) to footprint, and

h is an intercept (in gpm) of the same second line.

As for the passenger car target function, the resultant functional form is reflected below in graphs displaying the light truck target function in each model year for each regulatory alternative.

Although the general model of the target function equation is the same for each vehicle category (passenger cars and light trucks) and each model year, the parameters of the function equation differ for cars and trucks.

To be clear, as has been the case since NHTSA began establishing attribute-based standards, no vehicle needs meet the specific applicable fuel economy target, because compliance with CAFE standards is determined, per statute, based on corporate average fuel economy. In this respect, CAFE standards are unlike, for example, Federal Motor Vehicle Safety Standards (FMVSS) and certain vehicle criteria pollutant emissions standards where each car must meet the requirements. CAFE standards apply to the average fuel economy levels achieved by manufacturers' entire fleets of vehicles produced for sale in the United States. Safety standards apply on a vehicle-by-vehicle basis, such that every single vehicle produced for sale in the United States must, on its own, comply with minimum FMVSS. When first mandating CAFE standards in the 1970s, Congress specified a more flexible averaging-based approach that allows some vehicles to "under-comply" (*i.e.*, fall short of the overall flat standard, or fall short of their target under attribute-based standards) as long as a manufacturer's overall fleet is in compliance.

The required CAFE level applicable to a given fleet in a given model year is determined by calculating the production-weighted harmonic average of fuel economy targets applicable to specific vehicle model configurations in the fleet, as shown in Equation 1-3.

$$CAFE_{required} = \frac{\sum_i PRODUCTION_i}{\sum_i \frac{PRODUCTION_i}{TARGET_{FE,i}}}$$

Equation 1-3 – Calculation for Required CAFE Level

Where:

$CAFE_{required}$ is the CAFE level the fleet is required to achieve,

i refers to specific vehicle model/configurations in the fleet,

$PRODUCTION_i$ is the number of model configuration *i* produced for sale in the United States, and

$TARGET_{FE,I}$ is the fuel economy target (as defined above) for model configuration *i*.

Chapter 1.2.2 describes the advantages of attribute-based standards, generally. Chapter 1.2.3 explains the specific decision, in past rules and for the current rule, to continue to use vehicle footprint as the attribute over which to vary stringency. Chapter 1.2.4 discusses the methodologies used to develop the current attribute-based standards. Chapter 1.2.5 discusses methodologies previously used to reconsider the mathematical function for CAFE standards, while Chapters 1.2.6 and 1.2.7 discuss the approach used in the 2020 final rule, which has largely been retained for this rule. Chapter 1.2.8 explains NHTSA's decision for this final rule to continue to set standards of similar shape for MYs 2024-2026.

1.2.2 Why attribute-based standards, and what are the benefits?

As explained above, Congress expressly requires the CAFE standards to be attribute-based. Under attribute-based standards, every vehicle model has a fuel economy target, the levels of which depend on the level of that vehicle's determining attribute (for the MY 2024-2026 standards, footprint will continue to be the determining attribute, as discussed below). The manufacturer's fleet average CAFE performance is calculated by the harmonic production-weighted average of those targets, as shown in Equation 1-4.

$$Required\ CAFE = \frac{\sum_{i\,\in\,OEM\ Fleet} Production_i}{\sum_{i\,\in\,OEM\ Fleet} \frac{Production_i}{Target_i}}$$

Equation 1-4 – Attribute-Based CAFE Requirement

Here, *i* represents a given model[23] in a manufacturer's fleet, $Production_i$ represents the U.S. production of that model, and $Target_i$ represents the target as defined by the attribute-based standards. This means no vehicle is required to meet its target; instead, manufacturers are free to balance improvements however they deem best within (and, given credit transfers, at least partially across) their fleets.

While Congress expressly requires CAFE standards to be specified as a mathematical function dependent on one or more attributes related to fuel economy, Congress has provided NHTSA the authority to select specific attribute(s) and mathematical functions. Before Congress amended EPCA to introduce these requirements, CAFE standards were specified as single values (*e.g.*, 27.5 mpg for passenger cars and 20.7 for light trucks). Being wholly independent of fleet composition, these requirements posed a significantly greater technical challenge for manufacturers producing more larger vehicles for the U.S. market than for manufacturers focused more on smaller vehicles, because all else equal, smaller vehicles achieve greater fuel economy levels. Therefore, these single-value requirements presented an inherent incentive to shift production toward smaller vehicles rather than increasing the application of fuel-saving technologies across their fleets. In carrying out the Congressional requirement to adopt attribute-based standards defined as a mathematical function, NHTSA has sought to reflect the trade-off—*i.e.*, the relationship—between the attribute and fuel economy, consistent with the overarching purpose of EPCA/EISA to conserve energy. If the shape captures these trade-offs, every manufacturer is more likely to continue adding fuel-efficient technology across the distribution of the attribute within their fleet, instead of potentially changing the attribute—and other correlated attributes, including fuel economy—as a part of their compliance strategy.

[23] If a model has more than one footprint variant, here each of those variants is treated as a unique model, *i*, since each footprint variant will have a unique target.

1.2.3 Choosing Footprint as the Attribute

49 U.S.C. 32902(b)(3)(A) states that the attribute used to set CAFE standards must be a "vehicle attribute related to fuel economy." While there are many vehicle attributes that are related to fuel economy, NHTSA (and EPA) have chosen to use vehicle footprint as the attribute since MY 2011, the first year of CAFE standards set under EISA, and NHTSA is continuing this approach for MYs 2024-2026. Footprint has an observable correlation to fuel economy. There are several policy and technical reasons why NHTSA believes that footprint remains the most appropriate attribute on which to base the final standards for the vehicles covered by this rulemaking, even though some other vehicle attributes (notably, curb weight) are better correlated to fuel economy, and even though the 2021 NAS Report suggested adding another attribute.

First, the 2002 NAS Report described at length and quantified the potential safety problem with average fuel economy standards that specify a single numerical requirement for the entire industry,[24] identifying that smaller and lighter vehicles incentivized by those standards could be less safe for their occupants. Since that report, NHTSA has sought to set CAFE standards with an eye toward possible safety effects associated with the standards. Because vehicle size is correlated with vehicle safety for the occupants of that vehicle, and because CAFE standards can affect vehicle size when manufacturers are considering how to improve the fuel economy of their vehicles, it is important to choose an attribute correlated with vehicle size (mass or some dimensional measure).

Vehicle mass is strongly correlated with fuel economy; on a per-mile basis, a vehicle with more mass takes more energy to move than a vehicle with less mass. Footprint has some positive correlation with frontal surface area, likely a negative correlation with aerodynamics, and therefore fuel economy, but the relationship is less deterministic. Mass and crush space are both important safety considerations. Mass disparity in particular can affect crash outcomes. Although mass is more strongly correlated with fuel economy than footprint, NHTSA continues to believe that there is less risk of artificial manipulation (*i.e.*, changing the attribute(s) to achieve a more favorable target) by increasing footprint under footprint-based standards than there would be by increasing vehicle mass under mass-based standards. It is relatively easy for a manufacturer to add enough mass to a vehicle to decrease its applicable fuel economy target by a significant amount – even infotainment systems add weight through components, wiring, etc. – as compared to increasing vehicle footprint, which is a much more complicated change that typically takes place only with a vehicle redesign. A mass-based attribute would be the wrong incentive if EPCA's objective is energy conservation. Changes in footprint can affect vehicle dynamics, for example, requiring reevaluation of compliance with certain FMVSS and safety system performance, among other things. Mass-based standards can also discourage manufacturers from applying mass-efficient materials and designs, because their standards would become more stringent as mass is reduced.

As discussed in NHTSA's MY 2011 CAFE final rule,[25] when first electing to adopt footprint-based standards for both passenger cars and light trucks, NHTSA carefully considered other alternatives, including vehicle mass and "shadow" (overall width multiplied by overall length).

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[24] *See* 2002 NAS Report at p. 5, finding 12.
[25] *See* 74 Fed. Reg. 14359 (Mar. 30, 2009).

Compared to both of these other alternatives, footprint is much less susceptible to gaming, because while there is some potential to adjust track width, wheelbase is more difficult (and expensive) to change, at least outside a planned vehicle redesign. This is not to say that a footprint-based system eliminates manipulation, or that a footprint-based system eliminates the possibility that manufacturers will change vehicles in ways that compromise occupant protection. NHTSA is aware of research suggesting that the footprints of vehicles in the on-road fleet have been increasing over time. Because many American consumers value utility (size and capability), larger vehicles are encouraged (relative to a mass-based approach). Both the current footprint-based standards and the pre-EISA flat standards allow(ed) manufacturers to change the sizes and shapes of individual vehicles, if average standards were met.

The question has also arisen periodically of whether NHTSA should instead consider multi-attribute standards, such as those that also depend on weight, torque, power, towing capability, and/or off-road capability. To date, every time NHTSA has considered options for which attribute(s) to select, the agency has concluded that a properly-designed footprint-based approach provides the best means of achieving the basic policy goals (*i.e.*, by increasing the likelihood of improved fuel economy across the entire fleet of vehicles; by reducing disparities between manufacturers' compliance burdens; and by reducing incentives for manufacturers to respond to standards by reducing vehicle size in ways that could compromise overall highway safety) involved in applying an attribute-based standard. At the same time, footprint-based standards can be structured in a way that furthers the energy and environmental policy goals of EPCA by not creating inappropriate incentives to increase vehicle size in ways that could increase fuel consumption.

In the 2021 NAS Report, the committee recommended that if Congress does not act to remove the prohibition at 49 U.S.C. 32902(h) on considering the fuel economy of dedicated AFVs (like BEVs) in determining maximum feasible CAFE standards, then NHTSA should account for the fuel economy benefits of ZEVs by "setting the standard as a function of a second attribute in addition to footprint – for example, the expected market share of ZEVs in the total U.S. fleet of new light-duty vehicles – such that the standards increase as the share of ZEVs in the total U.S. fleet increases."[26]

NHTSA considered this recommendation carefully and suggested an approach to implementing it in the Draft TSD, which would have included the expected market share of ZEVs as an attribute on which fuel economy could be based. In doing so, NHTSA sought comment on whether the described approach would be consistent with the prohibition in 49 U.S.C. 32902(h) on considering the fuel economy of dedicated AFVs in setting maximum feasible CAFE standards. As is discussed further in the preamble, many commenters disagreed that the described approach would be consistent with NHTSA's statutory authority. In considering the question further, NHTSA agrees. While the agency appreciates the recommendation from the NAS committee, we remain uncertain that including electrification as an attribute on which to

[26] National Academies of Sciences, Engineering, and Medicine, 2021. *Assessment of Technologies for Improving Fuel Economy of Light-Duty Vehicles – 2025-2035,* Washington, DC: The National Academies Press (hereinafter, "2021 NAS Report"), at Summary Recommendation 5. *Available at* https://www.nationalacademies.org/our-work/assessment-of-technologies-for-improving-fuel-economy-of-light-duty-vehicles-phase-3 and for hard copy review at DOT headquarters. (Accessed: February 14, 2022).

base fuel economy standards could be done in a way consistent with our authority. The described approach was thus not pursued for the final rule.

1.2.4 Choosing the Mathematical Function to Specify Footprint-Based Standards

In requiring NHTSA to "prescribe by regulation separate average fuel economy standards for passenger and non-passenger automobiles based on 1 or more vehicle attributes related to fuel economy and express each standard in the form of a mathematical function," EPCA/EISA provides discretion regarding not only the selection of the attribute(s), but also regarding the nature of the function. While NHTSA is continuing to employ the curve shapes that have been used since the 2012 final rule, which did not change under the 2020 final rule, the discussion is reiterated for purposes of completeness.

The relationship between fuel economy and footprint, though directionally clear (*i.e.*, fuel economy tends to decrease with increasing footprint), is theoretically vague, and quantitatively uncertain; in other words, not so precise as to *a priori* yield only a single possible curve. The decision of how to specify this mathematical function therefore reflects some amount of judgment. The function can be specified with a view toward achieving different environmental and petroleum reduction goals, encouraging different levels of application of fuel-saving technologies, avoiding any adverse effects on overall highway safety, reducing disparities of manufacturers' compliance burdens, and preserving consumer choice, among other aims. The following are among the specific technical concerns and resultant policy tradeoffs that NHTSA and EPA have previously considered in selecting the details of specific past and future curve shapes:

1. Steeper footprint-based standards may create incentives to upsize vehicles, potentially oversupplying vehicles of certain footprints beyond what the market would naturally demand, and thus increasing the possibility that fleetwide (or total) fuel savings benefits will be forfeited artificially.

2. Flatter standards (*i.e.*, curves) increase the risk that the size of vehicles will be reduced, reducing any utility consumers would have gained from a larger vehicle.

3. Given the same industry-wide average required fuel economy standard, flatter standards tend to place greater compliance burdens on full-line manufacturers, although this is not necessarily true if the vehicles are ZEVs.

4. Given the same industry-wide average required fuel economy standard, dramatically steeper standards tend to place greater compliance burdens on limited-line manufacturers (depending, of course, on which vehicles are being produced), although this is not necessarily true if the vehicles are ZEVs.

5. If cutpoints (*i.e.*, locations of rapid change in slope, as with piecewise-linear functions) are adopted, given the same industry-wide average required fuel economy, moving small-vehicle cutpoints to the left (*i.e.*, up in terms of fuel economy) discourages the introduction of small vehicles, and reduces the incentive to downsize small vehicles.

6. If cutpoints are adopted, given the same industry-wide average required fuel economy, moving large-vehicle cutpoints to the right (*i.e.*, down in terms of fuel economy) better accommodates the design requirements of larger vehicles – especially large pickups – and extends the size range over which downsizing is discouraged in ways that could compromise overall highway safety.

1.2.5 Mathematical Functions that Have Been Used Previously

Notwithstanding the aforementioned discretion under EPCA/EISA, data should inform consideration of potential mathematical functions, but how relevant data are defined and interpreted, and the choice of methodology for fitting a curve to those data, can and should include some consideration of specific policy goals. This chapter summarizes the methodologies and policy concerns that were considered in developing previous target curves (for a complete discussion see the 2012 FRIA).

As discussed below, the MY 2011 final curves followed a constrained logistic function defined specifically in the final rule.[27] The MY 2012-2021 final standards and the MY 2022-2025 augural standards were defined by constrained linear target functions of footprint, as shown in Equation 1-5.[28]

$$Target = \frac{1}{\min\left(\max\left(c * Footprint + d, \frac{1}{a}\right), \frac{1}{b}\right)}$$

Equation 1-5 – Constrained Linear Target Function

Here, *Target* is the fuel economy target applicable to vehicles of a given footprint in square feet (*Footprint*). The upper asymptote, *a*, and the lower asymptote, *b*, are specified in mpg; the reciprocal of these values represent the lower and upper asymptotes, respectively, when the curve is instead specified in gallons per mile (gpm). The slope, *c*, and the intercept, *d*, of the linear portion of the curve are specified as gpm per change in square feet, and gpm, respectively.

The min and max functions will take the minimum and maximum values within their associated parentheses. Thus, the max function will first find the maximum of the fitted line at a given footprint value and the lower asymptote from the perspective of gpm. If the fitted line is below the lower asymptote it is replaced with the floor, which is also the minimum of the floor and the ceiling by definition, so that the target in mpg space will be the reciprocal of the floor in mpg space, or simply, *a*. If, however, the fitted line is not below the lower asymptote, the fitted value is returned from the max function and the min function takes the minimum value of the upper asymptote (in gpm space) and the fitted line. If the fitted value is below the upper asymptote, it is between the two asymptotes and the fitted value is appropriately returned from the min

[27] *See* 74 Fed. Reg. 14196, 14363-14370 (Mar. 30, 2009) for NHTSA discussion of curve fitting in the MY 2011 CAFE final rule.

[28] The right cutpoint for the light truck curve was moved further to the right for MYs 2017-2021, so that more possible footprints would fall on the sloped part of the curve. In order to ensure that, for all footprints, future standards would be at least as high as MY 2016 levels, standards for light trucks for MYs 2017-2020 are the maximum of a “floor” target curve and the target curves for the given MY standard. This is defined further in the 2012 final rule. *See* 77 Fed. Reg. 62624, at 62699-700 (Oct. 15, 2012), and in Table VII of 49 CFR 533.5(a).

function, making the overall target in mpg the reciprocal of the fitted line in gpm. If the fitted value is above the upper asymptote, the upper asymptote is returned from the min function, and the overall target in mpg is the reciprocal of the upper asymptote in gpm space, or *b*.

In this way, curves specified as constrained linear functions are specified by the following parameters in Equation 1-5.

a = upper limit (mpg)

b = lower limit (mpg)

c = slope (gpm per ft^2)

d = intercept (gpm)

The slope and intercept are specified as gpm per sq. ft. and gpm, instead of mpg per sq. ft. and mpg, because fuel consumption and emissions appear roughly linearly related to gallons per mile (the reciprocal of miles per gallon).

1.2.5.1 NHTSA in MY 2008 and MY 2011 CAFE (Constrained Logistic)

In 2009, for the MY 2011 CAFE rule, NHTSA estimated fuel economy levels by footprint from the MY 2008 fleet after normalization for differences in technology,[29] but did not make adjustments to reflect other vehicle attributes (*e.g.*, power-to-weight ratios). Starting with the technology-adjusted passenger car and light truck fleets, NHTSA used minimum absolute deviation (MAD) regression without sales weighting to fit a logistic form as a starting point to develop mathematical functions defining the standards. NHTSA then identified footprints at which to apply minimum and maximum values (rather than letting the standards extend without limit) and transposed those functions vertically (*i.e.*, on a gallons per mile basis, uniformly downward) to produce the promulgated standards. In the preceding 2006 rule for MY 2008-2011 light truck standards, NHTSA examined a range of potential functional forms, and concluded that, compared to other considered forms, the constrained logistic form provided the expected and appropriate trend (decreasing fuel economy as footprint increases), but avoided creating "kinks" that the agency was then concerned would provide distortionary incentives for vehicle with neighboring footprints.[30]

1.2.5.2 MY 2012-2016 Standards (Constrained Linear)

In 2010, for the MY 2012-2016 rule, potential methods for specifying mathematical functions to define fuel economy and CO_2 standards were reevaluated. These methods were fit to the same MY 2008 data as the MY 2011 standard. Considering these further specifications, the constrained logistic form, if applied to post-MY 2011 standards, would have likely contained a steep mid-section that would have provided undue incentive to increase the footprint of midsize

[29] *See* 74 Fed. Reg. 14196, 14363-14370 (Mar. 30, 2009) for NHTSA discussion of curve fitting in the MY 2011 CAFE final rule.

[30] *See* 71 Fed. Reg. 17556, 17609-17613 (Apr. 6, 2006) for NHTSA discussion of "kinks" in the MYs 2008-2011 light truck CAFE final rule (there described as "edge effects"). A "kink," as used here, is a portion of the curve where a small change in footprint results in a disproportionally large change in stringency.

passenger cars.[31] A range of methods to fit the curves would have been reasonable, and a minimum absolute deviation (MAD) regression without sales weighting on a technology-adjusted car and light truck fleet was used to fit a linear equation. This equation was used as a starting point to develop mathematical functions defining the standards. Footprints were then identified at which to apply minimum and maximum values (rather than letting standards extend without limit. Finally, these constrained/piecewise linear functions were transposed vertically (*i.e.*, on a gpm or CO_2 basis, uniformly downward) by multiplying the initial curve by a single factor for each MY standard to produce the final attribute-based targets for passenger cars and light trucks described in the final rule.[32] These transformations are typically presented as percentage improvements over a previous MY target curve.

1.2.5.3 MY 2017 and Beyond Standards (Constrained Linear) – 2012 Final Rule

The mathematical functions finalized in 2012 for MYs 2017 and beyond changed somewhat from the functions for the MY 2012-2016 standards. These changes were made both to address comments from stakeholders, and to consider further some of the technical concerns and policy goals judged more preeminent under the increased uncertainty of the impacts of finalizing and proposing standards for model years further into the future.[33] Recognizing the concerns raised by full-line OEMs, it was concluded that continuing increases in the stringency of the light truck standards would be more feasible if the light truck curve for MYs 2017 and beyond was made steeper than the MY 2016 truck curve and the right (large footprint) cutpoint was extended only gradually to larger footprints. To accommodate these considerations, the 2012 final rule finalized the slope fit to the MY 2008 fleet using a sales-weighted, ordinary least-squares regression, using a fleet that had technology applied to make the technology application across the fleet more uniform, and after adjusting the data for the effects of weight-to-footprint. Information from an updated MY 2010 fleet was also considered to support this decision. As the curve was vertically shifted (with fuel economy specified as mpg instead of gpm or CO_2 emissions) upwards, the right cutpoint was progressively moved for the light truck curves with successive model years, reaching the final endpoint for MY 2021.

1.2.6 NHTSA's Process for Reconsidering the Mathematical Functions in the 2020 Final Rule

1.2.6.1 Why did NHTSA reconsider the mathematical functions?

By shifting the developed curves by a single factor, it is assumed that the underlying relationship of fuel consumption (in gallons per mile) to vehicle footprint does not change significantly from the model year data used to fit the curves to the range of model years for which the shifted curve shape is applied to develop the standards. However, it must be recognized that the relationship between vehicle footprint and fuel economy is not necessarily constant over time; newly developed technologies, changes in consumer demand, and even the curves themselves could influence the observed relationships between the two vehicle characteristics. For example, if certain technologies are more effective or more marketable for certain types of vehicles, their

[31] 75 Fed. Reg. 25362 (May 7, 2010).
[32] *See* generally 74 Fed. Reg. 49491-96 (Sept. 28, 2009); 75 Fed. Reg. 25357-62 (May 7, 2010).
[33] The MYs 2012-2016 final standards were signed April 1st, 2010—putting 6.5 years between its signing and the last affected model year, while the MYs 2017-2021 final standards were signed August 28th, 2012—giving just more than nine years between signing and the last affected final standards.

application may not be uniform over the range of vehicle footprints. Further, if market demand has shifted between vehicle types, so that certain vehicles make up a larger share of the fleet, any underlying technological or market restrictions that inform the average shape of the curves could change. That is, changes in the technology or market restrictions themselves, or a mere re-weighting of different vehicle types, could change the observed unweighted or production-weighted relationship between footprint and fuel economy.

For the above reasons, the curve shapes were reconsidered in the 2018 proposal using the newest available data (at that time, from MY 2016). With a view toward corroboration through different techniques, a range of descriptive statistical analyses were conducted that did not require underlying engineering models of how fuel economy and footprint might be related, and a separate analysis that used vehicle simulation results as the basis to estimate the relationship from a perspective more explicitly informed by engineering theory was conducted as well. Despite changes in the new vehicle fleet both in terms of technologies applied and in market demand, that analysis found that the underlying statistical relationship between footprint and fuel economy had not changed significantly since the MY 2008 fleet used for the 2012 final rule; therefore, EPA and NHTSA proposed in 2018 to continue to use the curve shapes fit in 2012. The analysis and reasoning supporting that decision, which this final rule also relies on, follows. Chapter 1.2.8 explains why NHTSA is continuing to employ these curve shapes for MYs 2024-2026.

1.2.6.2 What statistical analyses were considered?

In considering previously how to address the various policy concerns discussed above, NHTSA considered data from the MY 2016 fleet, and performed a number of descriptive statistical analyses (*i.e.*, involving observed fuel economy levels and footprints) using various statistical methods, weighting schemes, and adjustments to the data to make the fleets less technologically heterogeneous. There were several adjustments to the data that were common to all the statistical analyses considered.

With a view toward isolating the relationship between fuel economy and footprint, NHTSA excluded the few diesels in the fleet, as well as the limited number of vehicles with partial or full electric propulsion; when the fleet is normalized so that technology is more homogenous, application of these technologies is not allowed. This is consistent with the methodology used in the 2012 final rule.

NHTSA applied the above adjustments to all statistical analyses, regardless of the specifics of each of the methods, weights, and technology level of the data, considered to view the relationship of vehicle footprint and fuel economy. Table 1-1 summarizes the different assumptions considered and the key attributes of each. NHTSA considered all possible combinations of these assumptions, producing a total of eight footprint curves.

Table 1-1 – Summary of Assumptions Considered in the Statistical Analysis of the Footprint-Fuel Economy (FE) Relationship

Varying Assumptions:	Regression Type		Regression Weights		Technology Level	
Alternatives Considered:	**OLS**	**MAD**	**Production-weighted**	**Model-weighted**	**Existing Technology**	**Max. Technology**
Details	Ordinary Least Squares Regression	Minimum Absolute Deviation Regression	Points weighted by production volumes of each model.	Equal weight for each model; collapses points with similar: footprint, FE, and curb weight.	MY 2016 tech., excluding: HEV, PHEV, BEV, and FCV.	Maximum tech. applied, excluding: HEV, PHEV, BEV, and FCV.
Key Attributes	Describes the average relationship between footprint and fuel economy; outliers can skew results.	Describes the median relationship between footprint and fuel economy; does not give outliers as much weight.	Tends towards higher-volume models; may systematically disadvantage manufacturers who produce fewer vehicles.	Tends towards the space of the joint distribution of footprint and FE with the most models; gives low-volume models equal weight.	Describes existing market, including demand factors; may miss changes in curve shape due to advanced technology application.	Captures relationship with homogenous technology application; may miss varying demand considerations for different segments.

1.2.6.2.1 Existing Technology Level Curves

The "existing technology" level curves excluded diesels and vehicles with electric propulsion, as discussed above, but made no other changes to each model year fleet. Comparing the MY 2016 curves to ones built under the same methodology from previous model year fleets showed whether the observed curve shape had changed significantly over time as standards became more stringent. Importantly, those curves included any market forces that made technology application variable over the distribution of footprint. Those market forces were not present in the "maximum technology" level curves: by making technology levels homogenous, this variation was removed. The existing technology level curves, built using both regression types and both regression weight methodologies from the MY 2008, MY 2010, and MY 2016 fleets, shown in more detail in Chapter 4.4.2.1 of the 2018 Preliminary Regulatory Impact Analysis (PRIA), supported the curve slopes finalized in the 2012 final rule. The curves built from most methodologies using each fleet generally shifted but remained very similar in slope. This suggested that the relationship of footprint to fuel economy, including both technology and market limits, did not significantly change after the 2012 final rule.

1.2.6.2.2 Maximum Technology Level Curves

As in prior rulemakings, NHTSA considered technology differences between vehicle models to be a significant factor producing uncertainty regarding the relationship between fuel consumption and footprint. Because attribute-based standards are intended to encourage the application of additional technology to improve fuel economy across the distribution of footprint in the fleet, NHTSA considered approaches in which technology application was simulated for purposes of the curve fitting analysis to produce fleets that are less varied in technology content. This approach helped to reduce "noise" (*i.e.*, dispersion) in the plot of vehicle footprints and fuel consumption levels and to identify a more technology-neutral relationship between footprint and fuel consumption. The results of that analysis for maximum technology level curves are also shown in Chapter 4.4.2.2 of the 2018 PRIA. Especially if vehicles progress over time toward more similar size-specific efficiency, further removing variation in technology application both better isolated the relationship between fuel consumption and footprint and further supported the curve slopes established in the 2012 final rule.

1.2.7 What other methodologies were considered?

The methods discussed above are descriptive in nature, using statistical analysis to relate observed fuel economy levels to observed footprints for known vehicles. As such, these methods were clearly based on actual data, answering the question of "how does fuel economy appear to be related to footprint?" However, being independent of explicit engineering theory, they did not answer the question of "how might one expect fuel economy to be related to footprint?" Therefore, in addition to the above methods, an alternative methodology was also developed and applied, using full vehicle simulation, to come closer to answering the second question, providing a basis either to corroborate answers to the first, or to suggest that further investigation could be important.

As discussed in the 2012 final rule, several manufacturers have confidentially shared with NHTSA what they describe as "physics-based" curves, with each original equipment manufacturer (OEM) showing significantly different shapes for the footprint-fuel economy relationships. This variation affirms that while footprint is related to fuel economy, many other things are also related to fuel economy. In reconsidering the shapes of the curves for the 2018 NPRM, NHTSA developed a similar estimation of physics-based curves leveraging third-party simulation work from Argonne National Laboratories (Argonne). Estimating physics-based curves helped to ensure that technology and performance were held constant for all footprints. This process augmented the largely-statistical analysis described above with an analysis that more explicitly incorporated engineering theory, which helped to corroborate that the relationship between fuel economy and footprint was in fact being characterized.

A tractive energy prediction model was also developed to support the 2018 proposal. Tractive energy is the amount of energy it will take to move a vehicle.[34] Given a vehicle's mass, frontal area, aerodynamic drag coefficient, and rolling resistance as inputs, the model predicted the amount of tractive energy required for the vehicle to complete the Federal test cycle. This model

[34] Thomas, J. "Drive Cycle Powertrain Efficiencies and Trends Derived from EPA Vehicle Dynamometer Results," *SAE Int. J. Passeng. Cars - Mech. Syst.* 7(4):2014, doi:10.4271/2014-01-2562. Available at https://www.sae.org/publications/technical-papers/content/2014-01-2562/ and for hard copy review at DOT headquarters. (Accessed: February 14, 2022).

was used to predict the tractive energy required for the average vehicle of a given footprint[35] and "body technology package" to complete the cycle. The body technology packages considered are defined in Table 1-2.

Using the absolute tractive energy predicted and tractive energy effectiveness values spanning possible internal combustion engines, fuel economy values were then estimated for different body technology packages and engine tractive energy effectiveness values. Here, tractive energy effectiveness is defined as the share of the energy content of fuel consumed, which is converted into mechanical energy and used to move a vehicle – for internal combustion engine (ICE) vehicles, this will vary with the relative efficiency of specific engines. Data from Argonne simulations suggested that the limits of tractive energy effectiveness are approximately 25 percent for ICE vehicles that do not possess integrated starter generator, other hybrid, plug-in, pure electric, or fuel cell technology.

Table 1-2 – Summary of Body Technology Packages Considered for Tractive Energy Analysis

Body Tech. Package	Mass Reduction Level	Aerodynamics Level	Roll Resistance Level
1	0%	0%	0%
2	0%	10%	10%
3	10%	10%	10%
4	10%	15%	20%
5	15%	20%	20%

Chapter 6 of the 2018 PRIA shows the resultant CAFE levels estimated for the vehicle classes Argonne simulated for this analysis, at different footprint levels and by vehicle "box." Pickups are considered 1-box, hatchbacks and minivans are 2-box, and sedans are 3-box. These estimates were compared with the MY 2021 standards finalized in 2012. The general trend of the simulated data points followed the pattern of the MY 2021 standards set in 2012 for all technology packages and tractive energy effectiveness values presented in the 2018 PRIA. The tractive energy curves were intended to validate the curve shapes against a physics-based alternative, and the analysis suggested that the curve shapes tracked the physical relationship between fuel economy and tractive energy for different footprint values.

The relationship between fuel economy and footprint remains directionally discernible but quantitatively uncertain. Nevertheless, each standard must commit to only one function. Approaching the question "how is fuel economy related to footprint" from different directions and applying different approaches has given NHTSA confidence that the function we are continuing to apply appropriately and reasonably reflects the relationship between fuel economy and footprint.

[35]The mass reduction curves used elsewhere in the 2018 analysis were used to predict the mass of a vehicle with a given footprint, body style box, and mass reduction level. The 'Body style Box' is 1 for hatchbacks and minivans, 2 for pickups, and 3 for sedans, and is an important predictor of aerodynamic drag. Mass is an essential input in the tractive energy calculation.

1.2.8 Maintaining the Existing Footprint Curves for MYs 2024-2026

Changes in the market that have occurred since NHTSA last examined the appropriateness of the footprint curves have been, for the most part, consistent with the trends in 2018. For the most part, vehicle manufacturers have continued over the past several years to reduce their offerings of smaller footprint vehicles and increase their sales of larger footprint vehicles and continue to sell many small to mid-size crossovers and sport utility vehicles (SUVs). While this trend may not be as optimal for reducing fuel consumption and carbon dioxide emissions as compared to manufacturers increasing their offerings of smaller footprint vehicles and reducing their sales of larger footprint vehicles, it does not appear that the trend has changed so dramatically over the last three years to warrant a detailed re-examination of that relationship as part of this final rule. Moreover, changes to the footprint curves can significantly affect manufacturers' ability to comply. Given the available lead time between now and the beginning of MY 2024, NHTSA believes it is unlikely any potential benefit of changing the shape of the footprint curves (when we are already significantly changing standard stringency) would outweigh the costs of doing so. NHTSA may explore changes to curve shapes in a future action.

1.3 What does the CAFE Model need to conduct this analysis?

To conduct the analysis described above, the CAFE Model needs a variety of inputs. At a high level, the model needs the following regulatory alternatives: an analysis fleet (see Chapter 2.2), technology effectiveness values (see Chapter 2.4), technology cost information, (see Chapter 2.6), and economic assumptions (see Chapter 4.1 for macroeconomic assumptions and Chapter 6 for all others). Additionally, for this final rule, NHTSA has added the specific inputs to enable the model to simulate compliance with California's ZEV program (see Chapter 2.3). Chapter 2 discusses the required inputs in more detail.

1.4 What are the regulatory alternatives under consideration in this final rule?

Agencies typically consider regulatory alternatives in rulemaking analyses as a way of evaluating the comparative effects of different potential ways of accomplishing their desired goal. NEPA requires agencies to compare the potential environmental impacts of their regulatory actions to those of a reasonable range of alternatives. E.O. 12866 and E.O. 13563, as well as Office of Management and Budget (OMB) Circular A-4, also encourage agencies to evaluate regulatory alternatives in their rulemaking analyses.

Alternatives analysis begins with a "No-Action" Alternative, typically described as what would occur in the absence of any regulatory action. This final rule includes a No-Action Alternative, described below, and three "action alternatives." The final standards may, in places, be referred to as the "Preferred Alternative," which is NEPA parlance, but NHTSA intends "final standards" and "Preferred Alternative" to be used interchangeably for purposes of this rulemaking.

Regulations regarding implementation of NEPA require agencies to "rigorously explore and objectively evaluate all reasonable alternatives, and for alternatives which were eliminated from detailed study, briefly discuss the reasons for their having been eliminated."[36] This does not

[36] 40 CFR 1502.14.

amount to a requirement that agencies evaluate the widest conceivable spectrum of alternatives. Rather, the range of alternatives must be reasonable and consistent with the purpose and need of the action.

The different regulatory alternatives are defined in terms of percent-increases in CAFE stringency from year to year. Readers should recognize that those year-over-year changes in stringency are *not* measured in terms of mile per gallon differences (as in, 1 percent more stringent than 30 miles per gallon in one year equals 30.3 miles per gallon in the following year), but rather in terms of shifts in the *footprint functions* that form the basis for the *actual* CAFE standards (as in, on a gallon per mile basis, the CAFE standards change by a given percentage from one model year to the next). Under some alternatives, the rate of change is the same from year to year, while under others, it differs, and under some alternatives, the rate of change is different for cars and for trucks. One action alternative is more stringent than the Preferred Alternative, while two are less stringent than the Preferred Alternative. The alternatives considered in this final rule represent a reasonable range of possible agency actions.

The regulatory alternatives for this final rule are presented here as the percent-increases-per-year that they represent. The sections that follow will present the alternatives as the literal coefficients which define standards curves increasing at the given percentage rates and will also explain the basis for the alternatives selected.

Table 1-3 – Regulatory Alternatives Considered in this Final Rule

Regulatory Alternative	**Year-Over-Year Stringency Increases (Passenger Cars)**			**Year-Over-Year Stringency Increases (Light Trucks)**		
	2024	2025	2026	2024	2025	2026
Alternative 0 (No-Action)	1.5%	1.5%	1.5%	1.5%	1.5%	1.5%
Alternative 1	9.14%	3.26%	3.26%	11.02%	3.26%	3.26%
Alternative 2	8%	8%	8%	8%	8%	8%
Alternative 2.5 (Preferred)	8%	8%	10%	8%	8%	10%
Alternative 3	10%	10%	10%	10%	10%	10%

As for past rulemaking analyses, NHTSA has analyzed each of the regulatory alternatives in a manner that estimates manufacturers' potential application of technology in response to the corresponding CAFE requirements and the estimated market demand for fuel economy, considering estimated fuel prices, estimated product development cadence, and the estimated availability, applicability, cost, and effectiveness of fuel-saving technologies. The analysis sometimes shows that specific manufacturers could increase CAFE levels beyond requirements in ways estimated to, through avoided fuel outlays, "pay buyers back" very quickly (*i.e.*, within 30 months) for the corresponding additional costs to purchase new vehicles. Consistent with the analysis published with the 2020 final rule, today's analysis shows that if battery costs decline as projected while fuel prices increase as projected, BEVs should become increasingly attractive on this basis, such that the modeled application of BEVs (and some other technologies) clearly outstrips regulatory requirements after the mid-2030s.

Our No-Action Alternative is more nuanced than in any prior rulemaking. In this analysis, Alternative 0 includes the national standards finalized in 2020 for both CAFE and GHG, as well as the voluntary California Framework Agreements (which affects five manufacturers – BMW, Ford, Honda, Volkswagen, and Volvo, together about 30 percent of the market) and the ZEV mandate that California and the Section 177 states have adopted. NHTSA continues to believe that to properly estimate fuel economies (and achieved GHG emissions) in the No-Action Alternative, it is necessary to simulate all of these legal requirements affecting automakers and vehicle design simultaneously. Consequently, the CAFE Model evaluates each requirement in each model year, for each manufacturer/fleet. Differences among fleets and compliance provisions often creates over-compliance in one program, even if a manufacturer is able to exactly comply (or under-comply) in the other program. This is similar to how manufacturers approach the question of concurrent compliance in the real world – when faced with multiple regulatory programs, the most cost-effective path may be to focus efforts on meeting one or two sets of requirements, even if that results in "more effort" than would be necessary for another set of requirements, in order to ensure that all regulatory obligations are met. We elaborate on these new model capabilities below. Generally speaking, the model treats each manufacturer as applying the following logic when making technology decisions:

1. What do I need to carry over from last year?

2. What should I apply more widely in order to continue sharing (of, *e.g.*, engines) across different vehicle models?

3. What new PHEVs or BEVs do I need to build in order to satisfy the ZEV mandates?

4. What further technology, if any, could I apply that would enable buyers to recoup additional costs within 30 months after buying new vehicles?

5. What additional technology, if any, should I apply in order to respond to CAFE and CO_2 standards?

All the regulatory alternatives considered here include, for passenger cars, the following coefficients defining the combination of baseline federal CO_2 standards and the California Framework Agreements.

Table 1-4 – Passenger Car CO_2 Target Function Coefficients

	2021	**2022**	**2023**	**2024**	**2025**	**2026**
a (g/mi)	162	159	156	154	151	149
b (g/mi)	221	217	214	210	207	203
c (g/mi per s.f.)	3.94	3.88	3.82	3.77	3.71	3.65
d (g/mi)	0.2	-0.1	-0.4	-0.6	-0.9	-1.2
e (s.f.)	41	41	41	41	41	41
f (s.f.)	56	56	56	56	56	56
g (g/mi)	157	151	146	140	135	130
h (g/mi)	215	207	199	192	185	178
i (g/mi per s.f.)	3.84	3.70	3.56	3.43	3.30	3.18
j (g/mi)	-0.4	-0.4	-0.4	-0.4	-0.3	-0.3

Coefficients *a, b, c, d, e*, and *f* define the current federal CO_2 standards for passenger cars. Analogous to coefficients defining CAFE standards, coefficients *a* and *b* specify minimum and maximum passenger car CO_2 targets in each model year. Coefficients *c* and *d* specify the slope and intercept of the linear portion of the CO_2 target function, and coefficients *e* and *f* bound the region within which CO_2 targets are defined by this linear form. Coefficients *g, h, i,* and *j* define the CO_2 targets applicable to BMW, Ford, Honda, Volkswagen, and Volvo, pursuant to the agreements these manufacturers have reached with California. Beyond 2026, the MY 2026 federal standards apply to all manufacturers, including these five manufacturers. The coefficients shown in Table 1-5 define the corresponding CO_2 standards for light trucks.

Table 1-5 – Light Truck CO_2 Target Function Coefficients

	2021	2022	2023	2024	2025	2026
a (g/mi)	207	203	200	196	193	190
b (g/mi)	329	324	319	314	309	304
c (g/mi per s.f.)	4.51	4.44	4.37	4.31	4.23	4.17
d (g/mi)	21.5	20.6	20.2	19.6	19.6	19.0
e (s.f.)	41	41	41	41	41	41
f (s.f.)	68	74	74	74	74	74
g (g/mi)	195	188	181	174	168	162
h (g/mi)	335	324	312	300	289	278
i (g/mi per s.f.)	4.28	4.12	3.97	3.82	3.68	3.54
j (g/mi)	19.8	19.1	18.4	17.7	17.0	16.4

All of the regulatory alternatives considered here also include NHTSA's estimates of ways each manufacturer could introduce new PHEVs and BEVs in response to ZEV mandates.[37] As discussed in greater detail below, these estimates force the model to convert specific vehicle model/configurations to either a BEV200, BEV300, or BEV400 at the earliest estimated redesign. These "ZEV Candidates" define an *incremental* response to ZEV mandates (*i.e.*, beyond PHEV and BEV production through MY 2020) comprise the following shares of manufacturers' MY 2020 production for the U.S. market as shown in Table 1-6.

[37] NHTSA interprets EPCA/EISA as allowing consideration of already-built fully electric vehicles in its analytical baseline because (1) 49 U.S.C. 32902(h) clearly applies to the "maximum feasible" determination, which NHTSA has long held is *informed* by analytical results but not *dictated* by them; and (2) it would be arbitrary for NHTSA to interpret 32902(h) as requiring it to ignore already-built fully electric vehicles, because doing so would be unrealistic, would make the analysis less informative by biasing the cost-benefit results, and would be inconsistent with OMB guidance in Circular A-4.

Table 1-6 – ZEV "Candidates" as Share of MY 2020 Production

Manufacturer	BEV200	BEV300	BEV400
BMW		1.9%	
Daimler	2.6%		0.8%
FCA		1.1%	
Ford	0.1%	1.1%	
GM		1.0%	
Honda		1.8%	
Hyundai		1.3%	
Kia	1.7%	0.5%	
Jaguar – Land Rover	0.2%	1.4%	
Mazda	3.1%		
Mitsubishi	0.6%	1.2%	
Nissan		0.5%	
Subaru		2.2%	
Tesla			
Toyota	1.2%	0.7%	
Volvo	2.3%	0.7%	
VWA		1.5%	

For example, while Tesla obviously need not introduce additional BEVs to comply with ZEV mandates, our analysis indicates Nissan could need to increase BEV offerings modestly to do so, and Mazda and some other manufacturers may need to do considerably more than Nissan to introduce new BEV offerings.

This representation of the Framework Agreements, CO_2 standards and ZEV mandates applies equally to all regulatory alternatives, and NHTSA's analysis applies the CAFE Model to examine each alternative treating each manufacturer as responding jointly to the entire set of requirements.

1.4.1 "No-Action" Alternative

The No-Action Alternative (also sometimes referred to as "Alternative 0") applies the CAFE target curves set in 2020 for MYs 2024-2026, which raised stringency by 1.5 percent per year for both passenger cars and light trucks.

Table 1-7 – Characteristics of No-Action Alternative – Passenger Cars

	2024	2025	2026
a (mpg)	51.78	52.57	53.37
b (mpg)	38.74	39.33	39.93
c (gpm per s.f.)	0.000433	0.000427	0.000420
d (gpm)	0.00155	0.00152	0.00150

Table 1-8 – Characteristics of No-Action Alternative – Light Trucks

	2024	2025	2026
a (mpg)	41.55	42.18	42.82
b (mpg)	26.82	27.23	27.64
c (gpm per s.f.)	0.000484	0.000477	0.000469
d (gpm)	0.00423	0.00417	0.00410

These equations are presented graphically in Figure 1-6 and Figure 1-7, where the x-axis represents vehicle footprint and the y-axis represents fuel economy, showing that in "CAFE space," targets are higher in fuel economy for smaller footprint vehicles and lower for larger footprint vehicles.

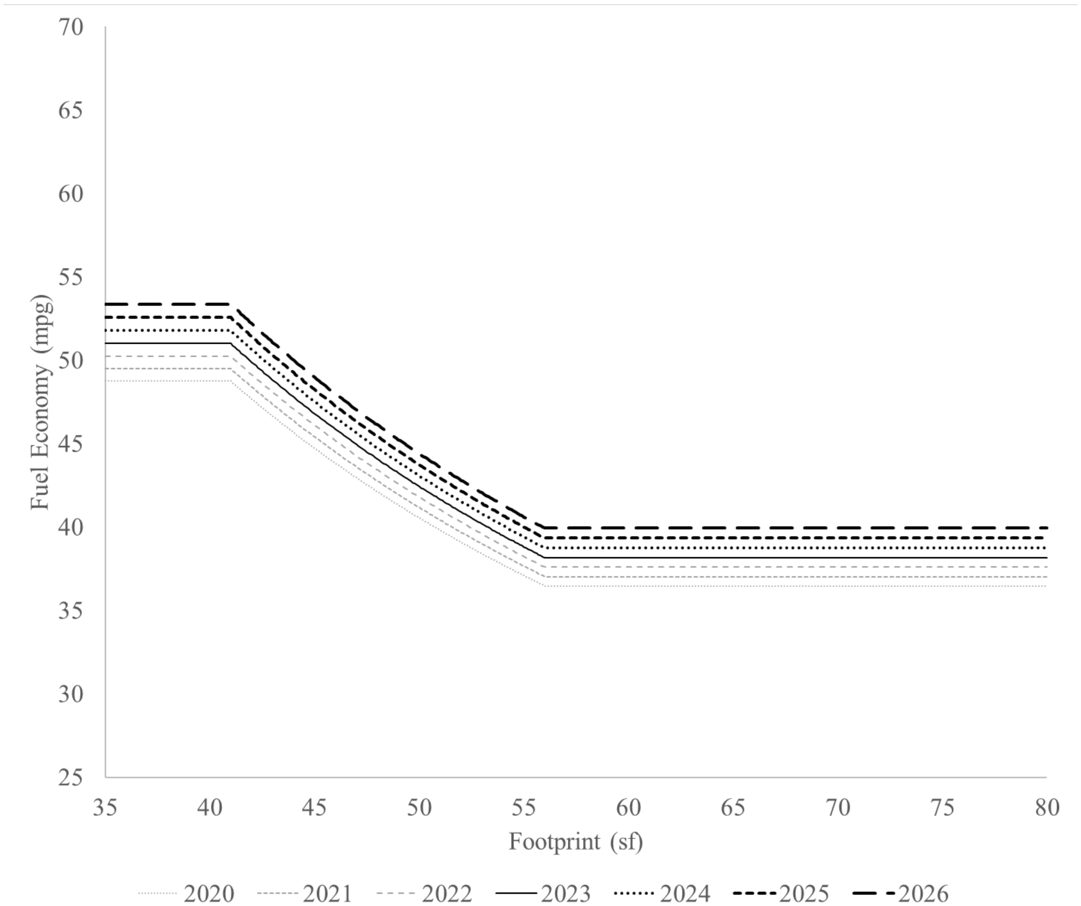

Figure 1-6 – No-Action Alternative, Passenger Car Fuel Economy Target Curves

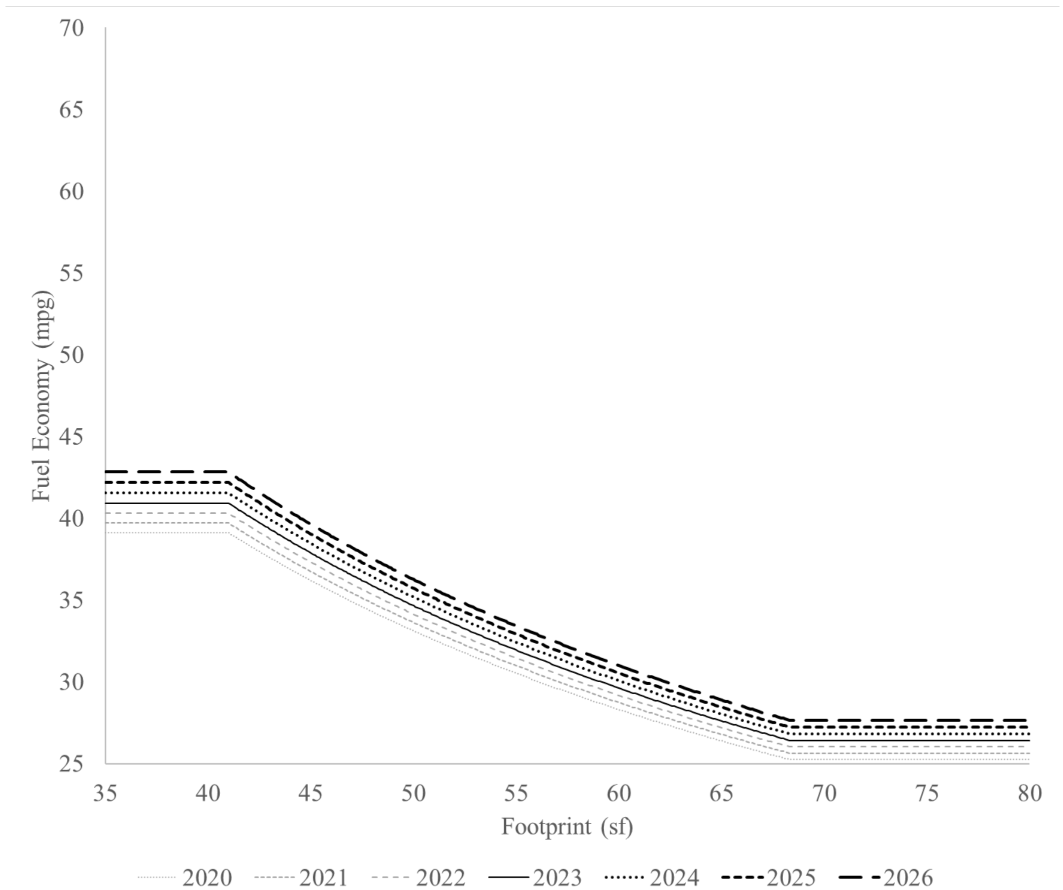

Figure 1-7 – No-Action Alternative, Light Truck Fuel Economy Target Curves

EPCA, as amended by EISA, requires that any manufacturer's domestically-manufactured passenger car fleet must meet the greater of either 27.5 mpg on average, or 92 percent of the average fuel economy projected by the Secretary for the combined domestic and non-domestic passenger automobile fleets manufactured for sale in the United States by all manufacturers in the model year. The projection shall be published in the Federal Register when the standard for that model year is promulgated in accordance with 49 U.S.C. 32902(b).[38] Any time NHTSA establishes or changes a passenger car standard for a model year, the minimum domestic passenger car standard (MDPCS) must also be evaluated or re-evaluated and established accordingly, but for purposes of the No-Action Alternative, the MDPCS is as it was established in the 2020 final rule, as shown in Table 1-9.

Table 1-9 – No-Action Alternative – Minimum Domestic Passenger Car Standard

2024	2025	2026
41.8 mpg	42.4 mpg	43.1 mpg

[38] 49 U.S.C. 32902(b)(4).

As the baseline against which the Action Alternatives are measured, the No-Action Alternative also includes several other actions that NHTSA believes will occur in the absence of further regulatory action, as discussed above.

NHTSA accomplished much of this through expansion of the CAFE Model after the 2020 final rule. The previous version of the model had been extended to apply to GHG standards as well as CAFE standards but had not been published in a form that simulated simultaneous compliance with both sets of standards. As discussed at greater length in the current CAFE Model documentation, the updated version of the model simulates all the following simultaneously:

1. Compliance with CAFE standards.

2. Compliance with GHG standards applicable to all manufacturers.

3. Compliance with alternative GHG emission reduction commitments applicable to a subset of manufacturers.

4. Compliance with ZEV mandates.

5. Further fuel economy improvements applied if sufficiently cost-effective for buyers.

Inclusion of these actions in the No-Action Alternative means that they are necessarily included in each of the Action Alternatives. That is, the impacts of all the alternatives evaluated in the final rule are against the backdrop of these State and voluntary actions by automakers. This is important to remember, because it means that automakers will be taking actions that affect the technology mix on vehicles—which in some situations will alter fuel economy and the assessment of what is technological feasible to improve fuel economy even in the absence of new CAFE standards, and that costs and benefits attributable to those actions are therefore *not* attributable to possible future CAFE standards.

One of the effects of the costs and benefits attributable to those actions not being attributable to possible future CAFE standards is that the effects of the final rule appear less cost-beneficial than they would otherwise. The apparent "over-compliance" with the No-Action Alternative alluded to above, in particular, reduces the benefits attributable to the final standards. There are several causes for this apparent over-compliance, as also listed above. The following text explores one of them in more detail.

Among the realities that face manufacturers is consumer demand for fuel economy. While this topic creates much debate, for purposes of *compliance simulations*, the final rule analysis assumes that market demand for fuel economy can be represented by a 30-month payback (meaning that the value of future fuel savings (undiscounted) fully offsets the cost of the technology). However, the benefit cost analysis accounts for the full lifetime fuel savings that accrue to vehicles affected by the final standards.

NHTSA staff believe that manufacturers do improve fuel economy even in the absence of standards, because:

1) <u>The last 15 years' worth of CAFE compliance data show that they do.</u>

From 2004 – 2017 (the last year for which NHTSA has final compliance data and certified compliance positions), Figure 1-8 illustrates the extent of certified over-compliance by each manufacturer and fleet (as a percentage of the standard). While some manufacturers' compliance history, Jaguar Land Rover (JLR) for example, support the theory that manufacturers do not exceed their standards, some of these manufacturers serve a portion of the market (e.g., Jaguar buyers) almost certainly less concerned with fuel outlays than the bulk of the U.S. market, and the majority of the data tell a different story. Some manufacturers have even exceeded their standards in certain fleets by 20 percent or more over many consecutive years (Honda passenger cars, or Subaru trucks, for example). Others have similarly observed the auto industry's secular march toward higher fuel economy over time, even in the absence of standards."[39]

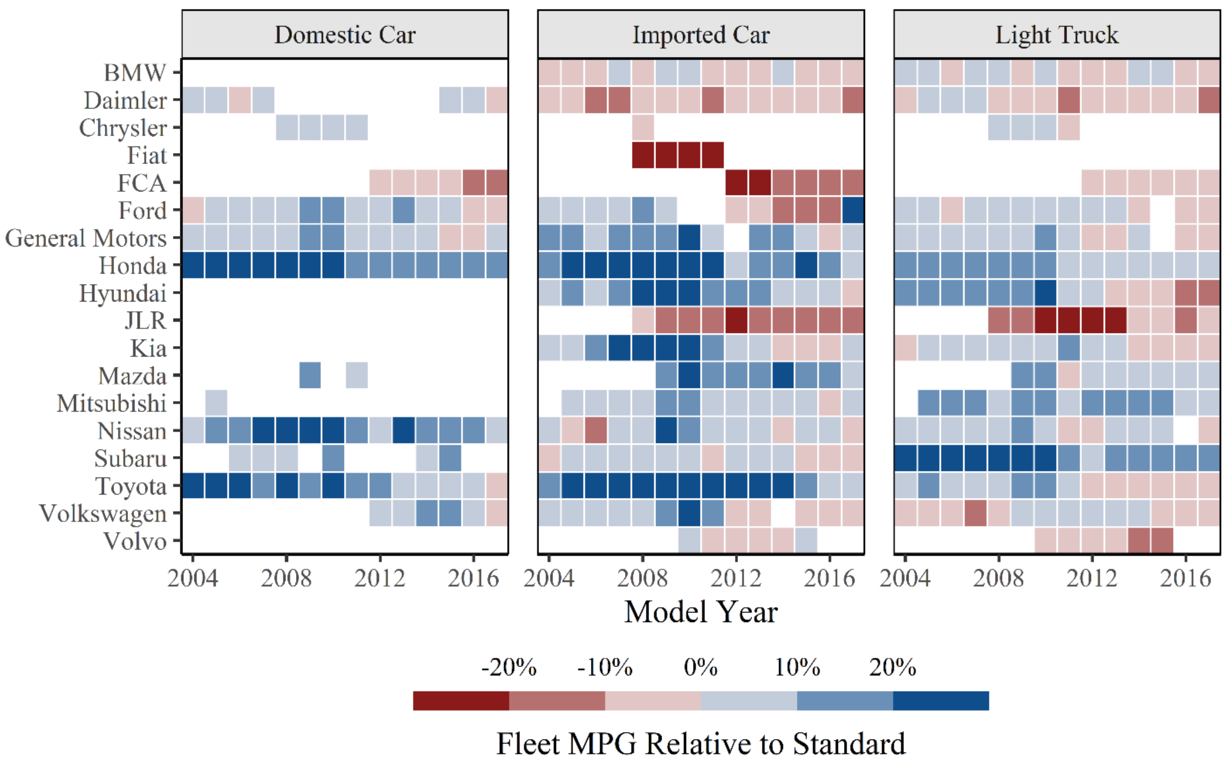

Figure 1-8 – Percent Over-Compliance with CAFE Over Time

2) <u>Manufacturers have consistently told NHTSA that they make any fuel economy improvements for which the cost can be fully recovered within the first 2-3 years of ownership. They have said that consumers typically shift toward improvements in other attributes after that point.</u>

[39] https://www.theatlantic.com/science/archive/2020/04/trumps-auto-rollback-will-eliminate-13500-jobs-cafe/609748/. (Accessed: February 14, 2022).

The 2015 NAS report discussed this assumption explicitly, stating: "There is also empirical evidence supporting loss aversion as a possible cause of the energy paradox. Greene (2011) showed that if consumers accurately perceived the upfront cost of fuel economy improvements and the uncertainty of fuel economy estimates, the future price of fuel, and other factors affecting the present value of fuel savings, the loss-averse consumers among them would appear to act as if they had very high discount rates or required payback periods of about 3 years."[40] Naturally, there are heterogeneous preferences for vehicle attributes in the marketplace, only one of which is the focus of this program. At the same time that we are observing record sales of battery electric vehicles, we are also seeing sustained demand for pickup trucks with higher payloads and towing capacity. This analysis, like all the CAFE analyses preceding it, uses an average value to represent these preferences across the market.

3) <u>As in previous CAFE analyses, our fuel price projections assume sustained increases in real fuel prices over the course of the rule (and beyond).</u>

As readers are certainly aware, fuel prices have changed over time – sometimes quickly, sometimes slowly, generally upward (see Figure 1-9).

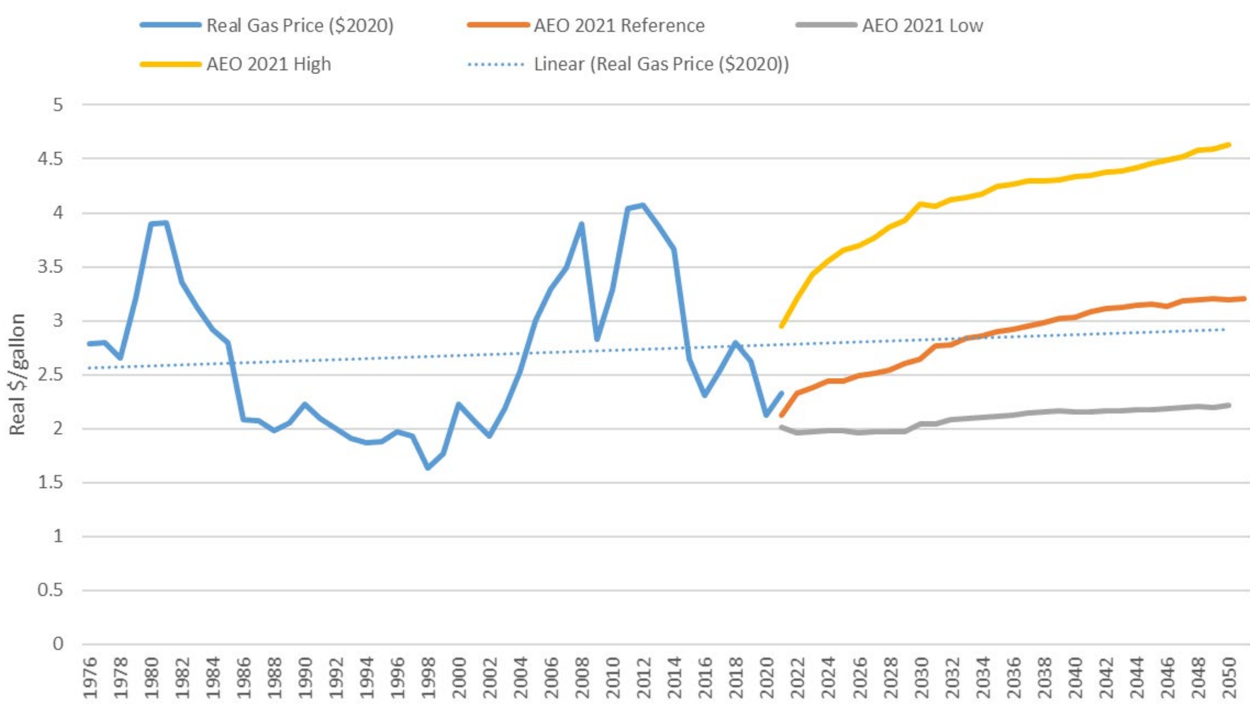

Figure 1-9 – Real Fuel Prices over Time

In the 1990s, when fuel prices were historically low (as shown in Figure 1-9), manufacturers did not tend to improve their fuel economy, likely because there simply was very little consumer demand for improved fuel economy. In subsequent decades, when fuel prices were higher, many

[40] National Research Council 2015, *Cost, Effectiveness, and Deployment of Fuel Economy Technologies for Light-Duty Vehicles*, at p. 317. Washington, DC: The National Academies Press. https://doi.org/10.17226/21744. (Accessed: February 14, 2022). Available for review in hard copy at DOT headquarters.

of them have exceeded their standards in multiple fleets, and for multiple years (see Figure 1-8). Our current fuel price projections look more like the last two decades, where prices have been more volatile, but also closer to $3/gallon on average.

In general, during periods of either less stringent standards or consistently higher fuel prices, manufacturers across the industry have over-complied by varying amounts across regulatory classes. In recent years, as fuel prices have steadily declined on average and CAFE standards have continued to increase (since 2008 for light trucks and since 2011 for passenger cars), fewer manufacturers have exceeded their standards. However, our compliance data shows that that at least some manufacturers do improve their fuel economy if fuel prices are high enough, even if they are not able to respond perfectly to fluctuations precisely when they happen. In many cases, specific manufacturers have exceeded their standards by significantly larger margins than we simulate in the rulemaking analysis, as the graphs above illustrate. This highlights the importance of fuel price assumptions both in the analysis and in the real world on the future of fuel economy improvements.

4) Rulemaking analysis attempts to isolate the impact of the action being considered, which means that we need to capture accurately what else is happening *besides* the action.

Given that fuel prices influence the degree to which manufacturers will increase fuel economy in the absence of regulation, the characterization of that behavior must be sufficiently flexible to accommodate multiple fuel price projections. If, instead of our central analysis assumptions about fuel prices, we assumed fuel prices more like the historically low prices of the 1990s, this analysis would show little, if any, over-compliance. Similarly, a multi-year spike in prices like the one that occurred from 2012 – 2014 should result in additional consumer demand for fuel economy – which we observed during that period.

While the assumption in this analysis does result in some manufacturers continuing to improve fuel economy beyond the levels required in the baseline, the amount of this that occurs is generally small.

Who is over-complying in the analysis, and by how much?

Manufacturers separate into three distinct groups: the manufacturers in the Framework Agreements; manufacturers projected to be bound by the baseline GHG and/or CAFE standards; and manufacturers projected to exceed baseline requirements through the additional application of cost-effective technology (i.e., the 30-month payback assumption).

Table 1-10 – Simulated (and Recent) Compliance for CA Agreement Companies

Manufacturer	Regulatory Class	CAFE 2020	CAFE 2026	CAFE 2029	CO2 2020	CO2 2026	CO2 2029
BMW	Domestic Car				-17%	3%	8%
	Imported Car	-14%	16%	17%			
	Light Truck	-1%	13%	13%	0%	-3%	12%
	TOTAL	-9%	15%	16%	-9%	1%	10%
Ford	Domestic Car	-12%	10%	12%	-16%	-3%	6%
	Imported Car	-19%	51%	51%			
	Light Truck	2%	17%	17%	3%	1%	15%
	TOTAL	-1%	15%	16%	-1%	0%	13%
Honda	Domestic Car	3%	12%	12%	2%	-3%	9%
	Imported Car	2%	15%	16%			
	Light Truck	5%	20%	20%	6%	4%	17%
	TOTAL	4%	16%	16%	4%	0%	12%
Volvo	Domestic Car	-11%	-4%	0%	-16%	-14%	1%
	Imported Car	-14%	10%	15%			
	Light Truck	-1%	21%	25%	2%	6%	19%
	TOTAL	-3%	15%	20%	-2%	1%	14%
VWA	Domestic Car	-17%	1%	3%	-14%	4%	13%
	Imported Car	-12%	23%	26%			
	Light Truck	-8%	13%	14%	-8%	-3%	12%
	TOTAL	-10%	15%	17%	-10%	0%	12%

Table 1-10 shows that, for the Framework companies, the CA requirement is the binding constraint under the No-Action Alternative. For example, in MY 2026, BMW over-complies with its passenger car (PC) GHG requirement but slightly under-complies with its light truck (LT) GHG requirement. (Within the context of the simulation, under or over-complying by one percent is the equivalent of a gram or two per mile. This is well within the precision of these simulations.) Also in MY 2026, other Framework manufacturers achieve average CO_2 levels generally closer to average CO_2 requirements than in the past. However, in every case, compliance with the Framework Agreements leads to significant over-compliance in the CAFE program.

Also under the No-Action Alternative, some other manufacturers are generally bound by the baseline standards, as Table 1-11 shows. However, while the Framework Agreements makes baseline GHG requirements unambiguously more challenging than baseline CAFE standards for participating manufacturers, results for these other manufacturers are less definitively one-sided. For example, while results suggest baseline GHG requirements could be more challenging for Hyundai than baseline CAFE requirements, MY 2026 results for some other manufacturers show similar degrees of overcompliance with CAFE and GHG requirements.

Table 1-11 – Simulated (and Recent) Compliance for Companies Bound by National GHG

Manufacturer	Regulatory Class	2020	2026	2029	2020	2026	2029
Daimler	Domestic Car				-29%	3%	1%
	Imported Car	-18%	5%	7%			
	Light Truck	-6%	4%	6%	-9%	4%	5%
	TOTAL	-11%	4%	7%	-17%	4%	3%
FCA	Domestic Car	-27%	4%	7%	-39%	4%	2%
	Imported Car	-23%	13%	14%			
	Light Truck	-7%	2%	5%	-7%	2%	4%
	TOTAL	-9%	2%	5%	-10%	2%	3%
GM	Domestic Car	-7%	3%	2%	-8%	1%	-2%
	Imported Car	-13%	0%	2%			
	Light Truck	-4%	1%	4%	-5%	0%	3%
	TOTAL	-5%	1%	4%	-6%	0%	1%
Hyundai	Domestic Car	12%	26%	27%	-13%	0%	1%
	Imported Car	-10%	2%	3%			
	Light Truck	-6%	4%	4%	-10%	1%	2%
	TOTAL	-9%	3%	4%	-13%	0%	1%
JLR	Domestic Car				-21%	-2%	-2%
	Imported Car	-15%	0%	2%			
	Light Truck	-11%	1%	3%	-10%	2%	1%
	TOTAL	-11%	1%	3%	-11%	2%	1%
Mitsubishi	Domestic Car				-9%	1%	-3%
	Imported Car	-8%	2%	3%			
	Light Truck	0%	3%	3%	0%	3%	3%
	TOTAL	-3%	3%	3%	-3%	2%	1%

For some OEMs, over-compliance is instead the result of technology application. For example, while Mazda PC over-complies with both CAFE and GHG, the GHG over-compliance (the binding standard here) is less than Mazda's historical compliance. However, Mazda's LT fleet is over-complying through the application of cost-effective technology. The same is generally true of Toyota's PC fleet, though the LT fleet over-complies more than in recent years.

Looking at the actual technologies that the CAFE Model is applying voluntarily, we see that in general, the model applies technologies that increase fuel economy for less than $40 per percent improvement – this is the amount that will pay back within the defined period. An important exception is Subaru, which barely complies with its PC standard (in both programs), but significantly exceeds its LT standard in both programs. While Subaru has historically exceeded its LT CAFE standard by comparable degrees, the over-compliance here is not driven by technology application, but rather by the assumed application of off-cycle (and air conditioning [AC]) credits. As the figures below demonstrate, Subaru is not actually applying much on-cycle technology, but simply making the economic decision to maximize AC/OC, as some companies do. Reliance on AC leakage and off-cycle credits has little impact on estimated real-world fuel savings (at least in the CAFE Model). In fact, all of the companies in Table 1-12 are characterized by rapid increases in deployment of AC/OC credits toward compliance, which leaves many cost-effective technologies available.

Table 1-12 – Simulated Over-Compliance through Cost-Effective Technology Application

<table>
<tr><th rowspan="2">Manufacturer</th><th rowspan="2">Regulatory Class</th><th colspan="3">CAFE</th><th colspan="3">CO2</th></tr>
<tr><th>2020</th><th>2026</th><th>2029</th><th>2020</th><th>2026</th><th>2029</th></tr>
<tr><td rowspan="4">Kia</td><td>Domestic Car</td><td></td><td></td><td></td><td rowspan="2">-7%</td><td rowspan="2">2%</td><td rowspan="2">2%</td></tr>
<tr><td>Imported Car</td><td>-5%</td><td>4%</td><td>5%</td></tr>
<tr><td>Light Truck</td><td>-7%</td><td>5%</td><td>8%</td><td>-8%</td><td>5%</td><td>7%</td></tr>
<tr><td>TOTAL</td><td>-6%</td><td>4%</td><td>6%</td><td>-7%</td><td>4%</td><td>4%</td></tr>
<tr><td rowspan="4">Mazda</td><td>Domestic Car</td><td>-14%</td><td>21%</td><td>21%</td><td rowspan="2">-23%</td><td rowspan="2">3%</td><td rowspan="2">1%</td></tr>
<tr><td>Imported Car</td><td>-11%</td><td>4%</td><td>4%</td></tr>
<tr><td>Light Truck</td><td>0%</td><td>9%</td><td>9%</td><td>-4%</td><td>6%</td><td>8%</td></tr>
<tr><td>TOTAL</td><td>-5%</td><td>7%</td><td>8%</td><td>-12%</td><td>5%</td><td>5%</td></tr>
<tr><td rowspan="4">Nissan</td><td>Domestic Car</td><td>1%</td><td>5%</td><td>5%</td><td rowspan="2">-5%</td><td rowspan="2">2%</td><td rowspan="2">1%</td></tr>
<tr><td>Imported Car</td><td>-12%</td><td>0%</td><td>0%</td></tr>
<tr><td>Light Truck</td><td>-5%</td><td>8%</td><td>10%</td><td>-9%</td><td>7%</td><td>9%</td></tr>
<tr><td>TOTAL</td><td>-3%</td><td>5%</td><td>6%</td><td>-7%</td><td>4%</td><td>4%</td></tr>
<tr><td rowspan="4">Subaru</td><td>Domestic Car</td><td></td><td></td><td></td><td rowspan="2">-24%</td><td rowspan="2">4%</td><td rowspan="2">2%</td></tr>
<tr><td>Imported Car</td><td>-15%</td><td>6%</td><td>6%</td></tr>
<tr><td>Light Truck</td><td>12%</td><td>29%</td><td>30%</td><td>11%</td><td>25%</td><td>24%</td></tr>
<tr><td>TOTAL</td><td>6%</td><td>23%</td><td>23%</td><td>5%</td><td>20%</td><td>19%</td></tr>
<tr><td rowspan="4">Toyota</td><td>Domestic Car</td><td>4%</td><td>3%</td><td>7%</td><td rowspan="2">3%</td><td rowspan="2">6%</td><td rowspan="2">10%</td></tr>
<tr><td>Imported Car</td><td>6%</td><td>11%</td><td>18%</td></tr>
<tr><td>Light Truck</td><td>-6%</td><td>10%</td><td>12%</td><td>-9%</td><td>10%</td><td>11%</td></tr>
<tr><td>TOTAL</td><td>-1%</td><td>9%</td><td>13%</td><td>-4%</td><td>8%</td><td>10%</td></tr>
</table>

The following tables show the technologies that the CAFE Model actually applies for a subset of manufacturers, showing the model year in which the technology is applied, the technology applied, and the ratio of the incremental costs to apply the technology to the affected vehicles divided by the fuel savings estimated to be realized during the first 30 months of vehicle operation. For example, in the following table, the first voluntary application of improved accessories (IACC) incurs $0.70 of technology cost for every $1.00 of fuel savings (counting only fuel savings during the first 30 months of vehicle operation), and the first voluntary application of AERO15 <u>reduces</u> technology costs by $5.50 for every $1.00 of fuel savings.

Table 1-13 – Kia Voluntary Technology Application

Model Year	Technology	Costs/Savings
2022	IACC	0.7
2024	AERO15	-5.5
2024	AERO15	-5.3
2024	AERO20	-5.0
2024	AERO20	-4.9
2024	AERO15	-3.5
2024	AERO15	-2.8
2024	AERO20	-1.9
2024	AERO20	-1.5
2024	ROLL10	0.1
2024	HCR1	0.4
2024	ROLL20	0.4
2024	IACC	0.5
2024	ROLL20	0.5
2024	IACC	0.6
2024	ROLL20	0.7
2024	HCR1	0.8
2024	ROLL20	0.9
2024	AT10L2	0.9
2024	MR1	1.0
2024	AERO15	1.0
2025	HCR1	1.0
2027	TURBO1	0.9
2029	BEV200	-3.3
2029	AERO20	0.2

In theory, the technologies whose cost of application is negative should be applied regardless of regulatory pressure (or even fuel prices), because it would literally save manufacturers money to apply them. Kia's table illustrates a common theme—that a number of technologies appear to have attractive cost-effectiveness – notably aerodynamic improvements and low rolling resistance tires. Given that Hyundai-Kia is targeting its share of HEV/PHEV/BEV to be closer to 25 percent by 2025 (and we simulate less than 3 percent in the baseline), our estimated over-compliance in the baseline is almost certainly too *low*, rather than too *high*.[41] (We do show one

[41] https://hyundainews.com/en-us/releases/2982. (Accessed: January 18, 2022).

application of BEV being cost-effective enough to occur without a regulatory prompt as soon as MY 2029 for Kia.)

Table 1-14 – Mazda Voluntary Technology Application

Model Year	Technology	Costs/Savings
2023	ROLL20	0.8
2023	AT8	0.9
2025	AERO10	-4.2
2025	AERO15	-3.5
2025	AERO20	-1.4
2026	MR1	0.6
2026	AERO15	0.8
2026	AERO15	0.9

Mazda's table tells a similar story – minor technologies that are either cost-saving, or very cost-effective.

Table 1-15 – Nissan Voluntary Technology Application

Model Year	Technology	Costs/Savings
2023	MR3	0.7
2023	ROLL10	0.1
2023	IACC	0.2
2023	ROLL20	0.3
2023	AT8L2	0.7
2023	AT10L2	0.7
2023	AERO15	0.9
2023	TURBOD	0.9
2024	AERO15	-5.0
2024	AERO20	-4.6
2024	AERO15	-4.8
2024	AERO20	-4.4
2024	IACC	0.6
2024	IACC	0.7
2024	ROLL20	0.7
2024	HCR1	0.9
2024	AERO15	1.0
2025	MR1	-2.0
2025	AERO20	-1.4
2026	ROLL10	0.1
2026	IACC	0.2
2026	ROLL20	0.3
2027	SAX	1.6
2028	MR1	0.6
2028	AERO15	0.8
2028	AERO15	1.0
2029	AERO10	1.2

2029	AERO15	1.0

Nissan's technology application is broader than the first two, but features many of the same technologies – aero, tires, certain cost-effective transmissions, certain cost-effective engines.

As stated above, Subaru's over-compliance is not a function of technology application, although we show this overcompliance leaves opportunities for Subaru to apply some additional technology not necessitated by baseline standards.

Table 1-16 – Subaru Voluntary Technology Application

Model Year	Technology	Costs/Savings
2023	AERO15	-5.3
2023	AERO15	-4.3
2023	TURBO1	-0.4
2023	ROLL10	0.1
2023	IACC	0.4
2023	ROLL20	0.5
2023	IACC	0.6
2023	ROLL20	0.6
2023	ROLL20	0.7
2023	ROLL20	0.6
2023	IACC	0.6
2024	HCR1	0.8
2024	AERO15	1.0
2029	AERO15	0.9

Rather, Subaru exceeds both standards because we assume (a priori) that most manufacturers will make increasing use of AC/OC credits toward compliance in both programs. Subaru's OC credits are assumed to nearly triple during the rulemaking timeframe, and AC leakage credits to nearly double. While CAFE does not account for AC leakage credits, manufacturers who opt to comply with GHG standards through their application leave cost-effective fuel economy technology on the table. If instead, they opt to pursue compliance only through on-cycle fuel economy improvements, our analysis will still show some over-compliance in the LT fleet, but less than Subaru has typically exhibited.

Table 1-17 – Toyota Voluntary Technology Application

Model Year	Technology	Costs/Savings	Model Year	Technology	Costs/Savings
2022	HCR0	0.8	2024	HCR1	0.8
2022	ROLL20	0.8	2025	AERO15	-5.8
2022	AT8	0.8	2025	AERO20	-5.4
2022	ROLL20	0.8	2026	ROLL10	0.1
2022	AERO15	1.0	2026	IACC	0.2
2022	AERO15	2.1	2026	ROLL20	0.4
2022	HCR1	1.0	2026	AT8	0.4

2023	ROLL10	0.1	2026	ROLL20	0.4
2023	IACC	0.4	2026	AT8	0.4
2023	ROLL20	0.5	2026	ROLL20	0.4
2023	ROLL10	0.1	2026	MR1	0.7
2023	IACC	0.4	2026	AERO10	0.7
2023	IACC	0.3	2026	AERO10	0.8
2023	IACC	0.3	2026	AERO10	0.9
2023	IACC	0.4	2026	TURBO1	1.0
2023	ROLL20	0.4	2026	MR1	1.0
2023	IACC	0.4	2026	EFR	1.0
2023	AT8	0.4	2027	BEV200	-2.8
2023	ROLL20	0.5	2027	MR1	0.9
2023	IACC	0.5	2028	IACC	0.9
2023	ROLL20	0.5	2028	AERO15	0.9
2023	AT10L2	0.8	2028	AERO15	1.0
2023	AERO15	1.0	2029	HCR1	0.1
2024	AERO15	-3.8	2029	BEV200	0.3
2024	AERO15	-3.4	2029	AERO10	-1.9
2024	AERO15	-3.2	2029	AERO15	-1.4
2024	AERO20	-1.6	2029	AERO20	0.1
2024	AERO20	-1.5	2029	AERO15	0.9
2024	AERO20	-1.4	2029	TURBO1	0.9
2024	DEAC	0.6	2029	AERO15	0.9
2024	IACC	0.8	2029	MR1	1.0

We show Toyota applying more technology than the other manufacturers in this set. Toyota has old truck engines that are infrequently redesigned (in the pickup segment), and the model takes advantage of cost-effective opportunities to upgrade them, as seems reasonable to expect that they will.[42] The same technologies that appear cost-effective for other manufacturers, also appear cost-effective for Toyota (including several whose cost is negative). And, similar to Subaru, we show Toyota nearly doubling their application of both OC and AC leakage credits during the rulemaking period. If instead, they choose to comply through the application of fuel economy technology, many of these cost-effective technologies would be applied in service of compliance, rather than in excess of it.

<u>What does this over-compliance mean for costs and benefits attributable to the final rule?</u>

[42] As discussed below, technology-related inputs to the agency's analysis—in particular, inputs providing the basis for estimates of the fuel economy benefit achieved by applying a given combination of technologies—are based on applying technologies in a manner that holds vehicle performance and utility nominally constant. Manufacturers could instead apply technologies in a manner that balances changes in fuel economy with changes in vehicle performance, utility, and cost, instead of using all of a given technology's potential to improve fuel economy. However, the agency is unaware of any practicable means to simulate such tradeoffs and optimization for different categories of vehicles, or any practicable means to estimate how buyers' valuation of different categories of vehicles could change in response to simultaneous changes in fuel economy, different measures of vehicle performance, and different measures of vehicle utility.

Today's analysis treats manufacturers' decisions as being informed by fuel prices, applying the same functional approach for all regulatory alternatives and all fuel prices—that is, offsetting technology costs by fuel savings estimated to accrue over the first 30 months of vehicle operation. Because less stringent standards tend to leave more technology "on the table" than more stringent standards, this approach attributes some costs and benefits to the No-Action Alternative, rather than to the incremental impact of more stringent action alternative. Notwithstanding uncertainties regarding manufacturers' and buyers' future decision making, NHTSA considers this the best practicable approach available at this time.

NHTSA could have instead treated manufacturers' decisions as being uninformed by fuel prices.[43] With other inputs (including fuel prices) left at reference case value, doing so would have increased the agency's estimates of additional costs and benefits attributable to the final rule by about 7.5 billion dollars (6 percent) and 6 billion dollars (4 percent), respectively, thus reducing the agencies estimates of net benefits by about 1.5 billion dollars (9 percent).[44]

1.4.2 Action Alternatives

In addition to the aforementioned No-Action Alternative, NHTSA has considered four "action" alternatives, each of which is more stringent than the No-Action Alternative during MYs 2024-2026. These action alternatives are as specified below, with Alternative 1 being the least stringent in MY 2026, Alternative 3 being the most stringent, and Alternative 2.5 (the Preferred Alternative) falling between Alternatives 2 and 3 in terms of MY 2026 stringency.

1.4.2.1 Alternative 1

Alternative 1 would increase CAFE stringency for MY 2024 by 9.14 percent for passenger cars and 11.02 percent for light trucks and increase stringency in MYs 2025 and 2026 by 3.26 percent per year for both passenger cars and light trucks.

[43] Such an approach would, for example, produce the same fuel economy changes when gasoline costs $4.00 per gallon (the 2030 price, in 2018 dollars, in the high oil price case considered in today's sensitivity analysis) as when gasoline costs $2.00 per gallon (the corresponding low oil price value).
[44] These estimates reflect a 3 percent discount rate for climate-related damages, and a 3 percent discount rate for all other benefits and costs.

Table 1-18 – Characteristics of Alternative 1 – Passenger Cars

	2024	2025	2026
a (mpg)	56.15	58.04	60.00
b (mpg)	42.00	43.41	44.88
c (gpm per s.f.)	0.000400	0.000387	0.000374
d (gpm)	0.00141	0.00136	0.00132

Table 1-19 – Characteristics of Alternative 1 – Light Trucks

	2024	2025	2026
a (mpg)	46.17	47.73	49.34
b (mpg)	27.73	28.67	29.63
c (gpm per s.f.)	0.000436	0.000422	0.000408
d (gpm)	0.00377	0.00365	0.00353

These equations are represented graphically below:

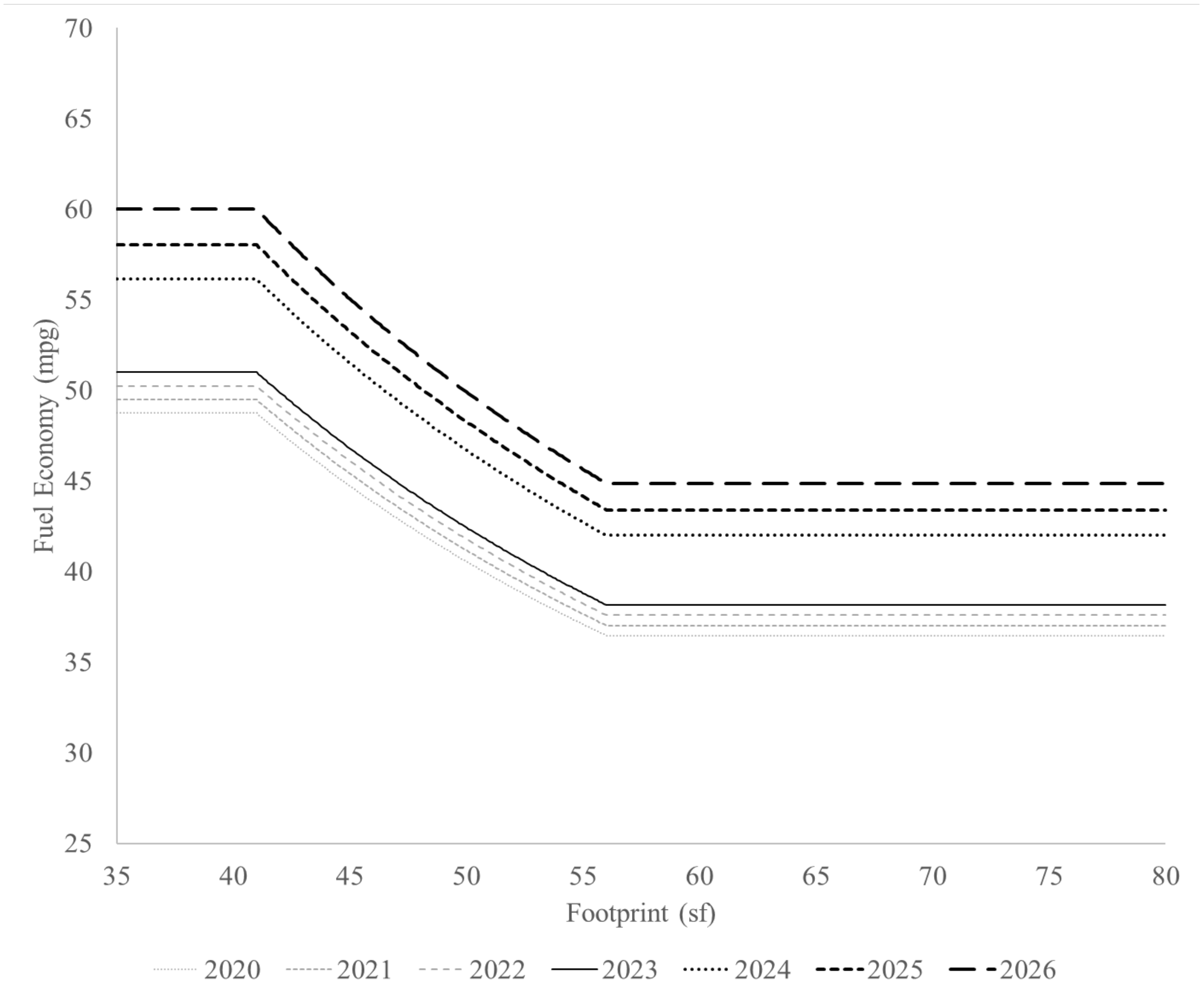

Figure 1-10 – Alternative 1, Passenger Car Fuel Economy, Target Curves

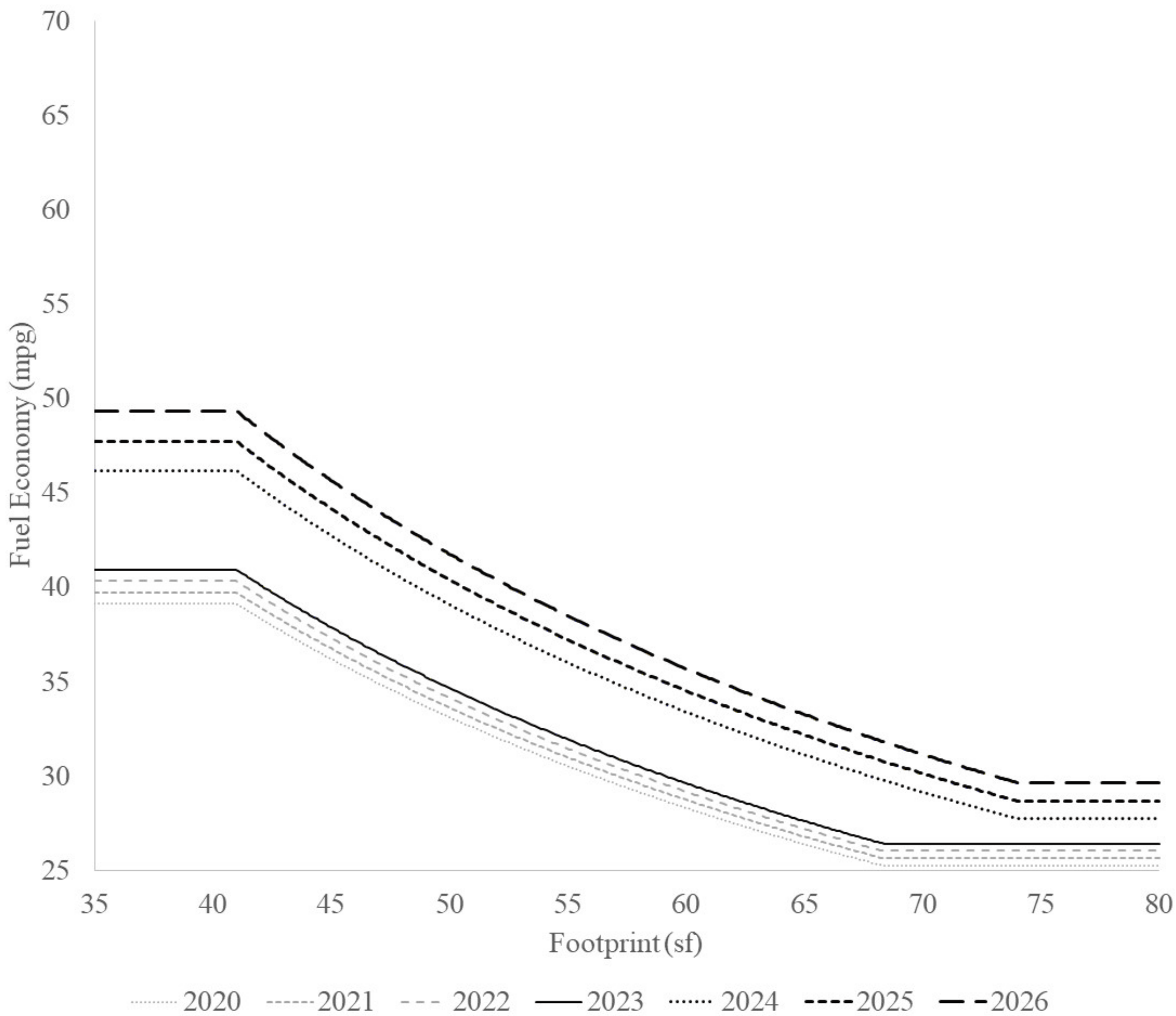

Figure 1-11 – Alternative 1, Light Truck Fuel Economy, Target Curves

Under this alternative, the MDPCS is as follows:

Table 1-20 – Alternative 1 - Minimum Domestic Passenger Car Standard

2024	2025	2026
44.9 mpg	46.4 mpg	47.9 mpg

1.4.2.2 Alternative 2

Alternative 2 would increase CAFE stringency at 8 percent per year.

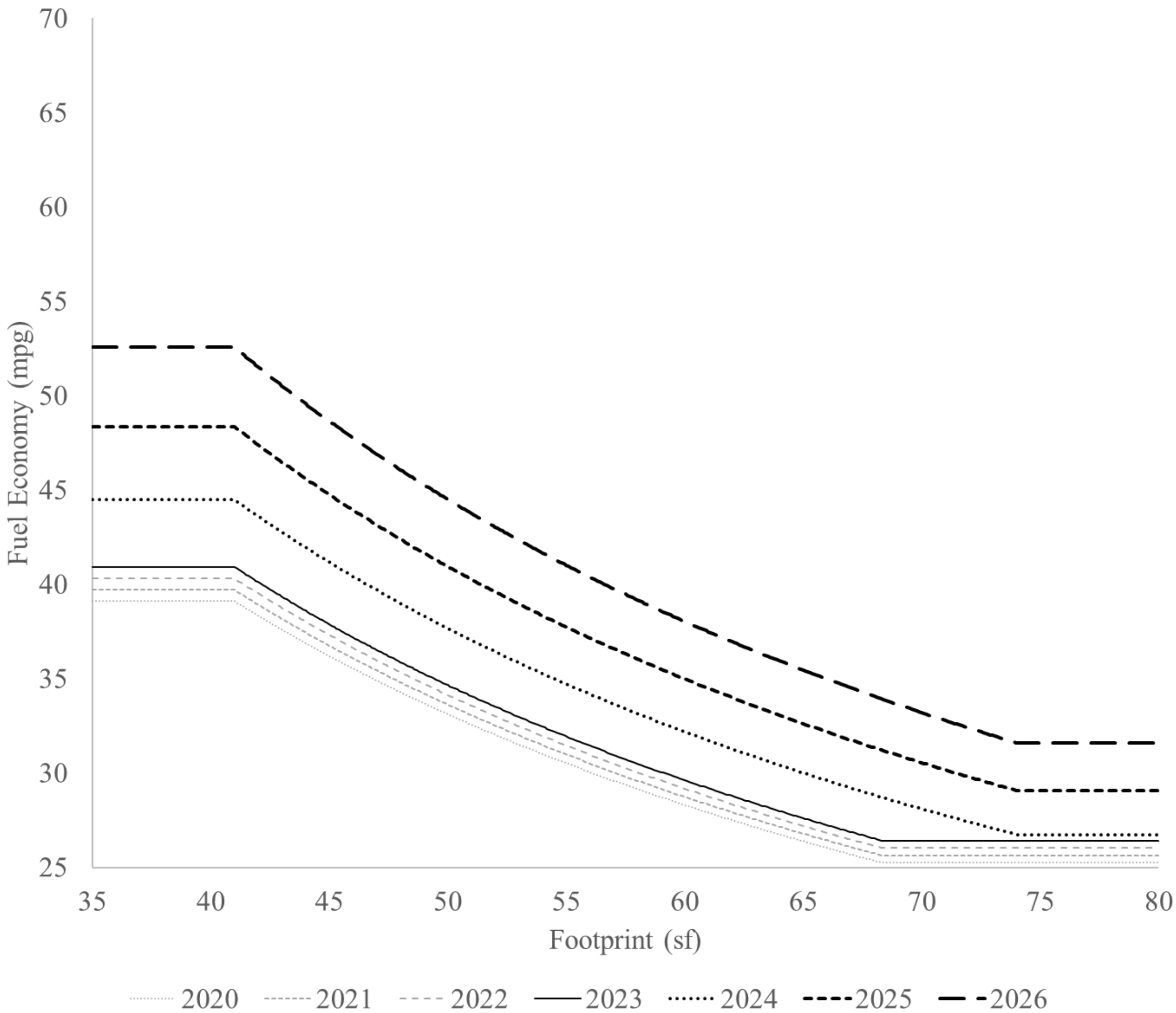

Figure 1-13 – Alternative 2, Light Truck Fuel Economy, Target Curves

Under this alternative, the MDPCS is as follows:

Table 1-23 – Alternative 2 – Minimum Domestic Passenger Car Standard

2024	2025	2026
44.4 mpg	48.1 mpg	52.3 mpg

1.4.2.3 Alternative 2.5 – Preferred Alternative

In the proposal preceding this final rule, NHTSA sought comment on a possible modification to Alternative 2, which would have increased the stringency of CAFE standards by 10 percent between model years 2025 and 2026, rather than by 8 percent. Shown graphically, this possibility appears as shown below:

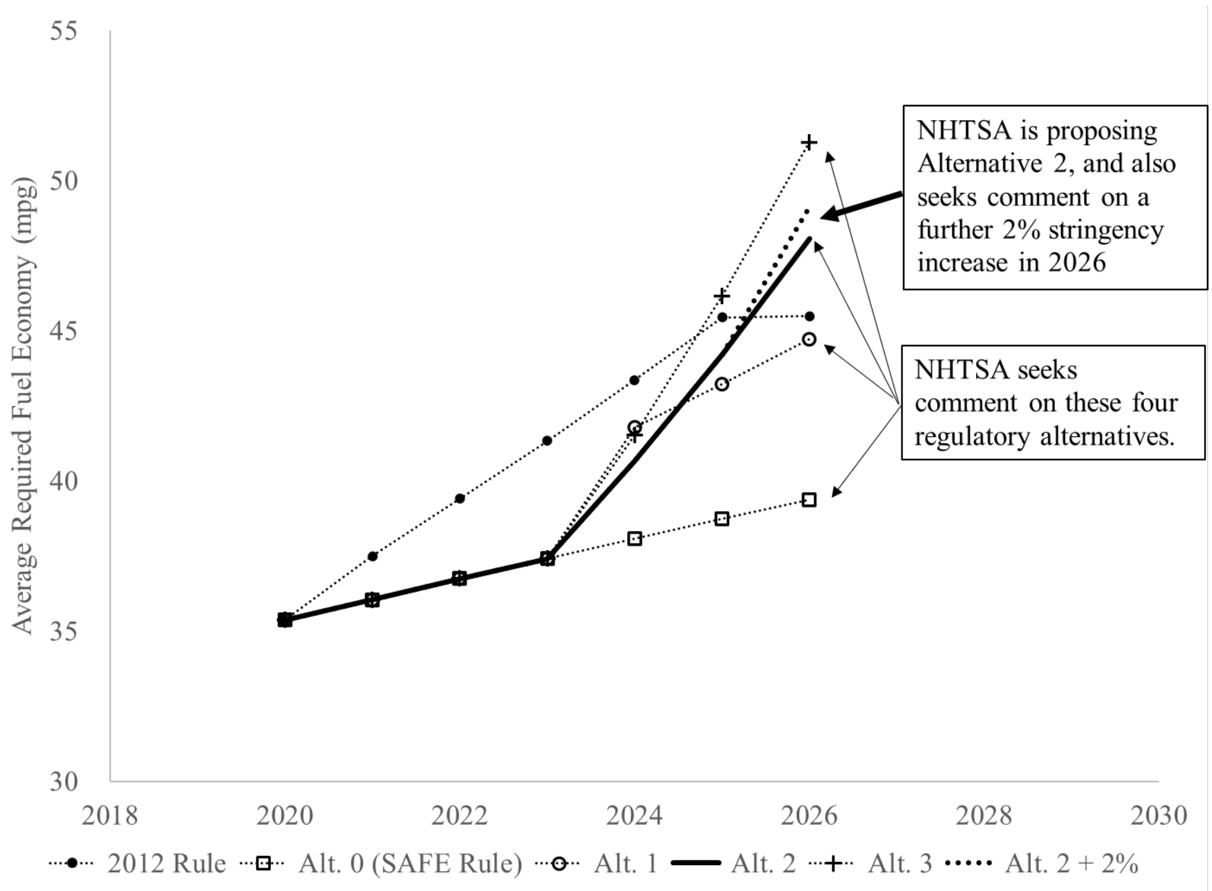

Figure 1-14 – Graphic Representation of Possible Other Alternative

The coefficients associated with this alternative have been determined as follows:

Table 1-24 – Characteristics of Alternative 2.5 – Passenger Cars

	2024	2025	2026
a (mpg)	55.44	60.26	66.95
b (mpg)	41.48	45.08	50.09
c (gpm per s.f.)	0.000405	0.000372	0.000335
d (gpm)	0.00144	0.00133	0.00120

Table 1-25 – Characteristics of Alternative 2.5 – Light Trucks

	2024	2025	2026
a (mpg)	44.48	48.35	53.73

b (mpg)	26.74	29.07	32.30
c (gpm per s.f.)	0.000452	0.000416	0.000374
d (gpm)	0.00395	0.00364	0.00327

These equations are represented graphically below:

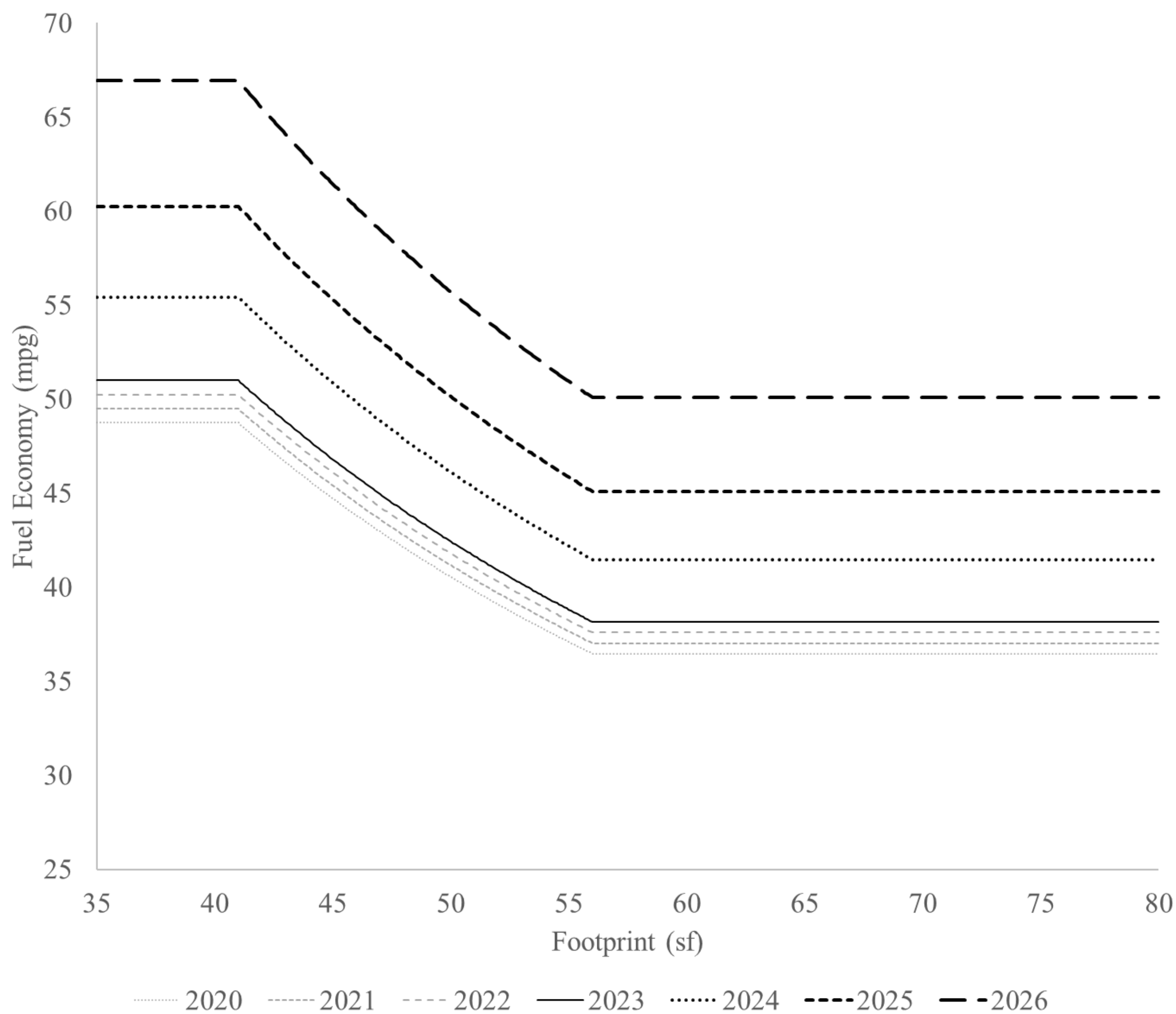

Figure 1-15 – Alternative 2.5, Passenger Car Fuel Economy, Target Curves

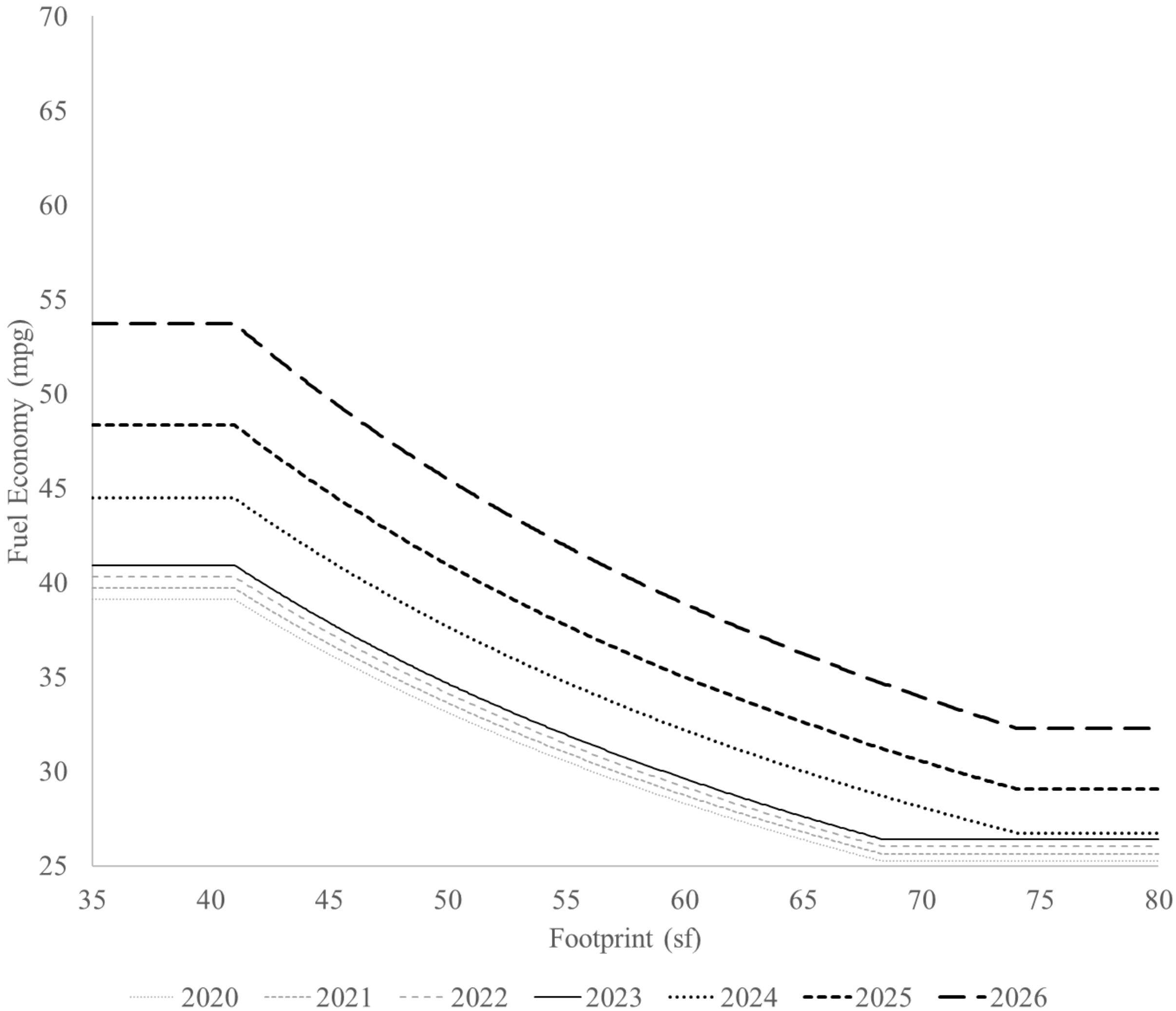

Figure 1-16 – Alternative 2.5, Light Truck Fuel Economy, Target Curves

Under this alternative, the MDPCS is as follows:

Table 1-26 – Alternative 2.5 – Minimum Domestic Passenger Car Standard

2024	2025	2026
44.3 mpg	48.2 mpg	53.5 mpg

NHTSA considered this alternative as a way to evaluate the effects of CAFE standards could be considered a middle ground between Alternative 2 and Alternative 3 allowing for a slower ramp in stringency than Alternative 3 but providing additional lead time to return to a fuel consumption trajectory exemplified by the standards announced in 2012.

1.4.2.4 Alternative 3

Alternative 3 would increase CAFE stringency at 10 percent per year. When developing regulatory alternatives for consideration in the published NPRM, NHTSA calculated this would result in total fuel economy savings from vehicles produced during MYs 2021-2029 similar to total lifetime fuel economy savings that would have occurred if NHTSA had promulgated final CAFE standards for MYs 2021-2025 at the augural levels announced in 2012 and, in addition, if NHTSA had also promulgated MY 2026 standards that reflected a continuation of that average rate of stringency increase (4.48 percent for passenger cars and 4.54 percent for light trucks).

Table 1-27 – Characteristics of Alternative 3 – Passenger Cars

	2024	**2025**	**2026**
a (mpg)	56.67	62.97	69.96
b (mpg)	42.40	47.11	52.34
c (gpm per s.f.)	0.000396	0.000356	0.000321
d (gpm)	0.00141	0.00127	0.00114

Table 1-28 – Characteristics of Alternative 3 – Light Trucks

	2024	**2025**	**2026**
a (mpg)	45.47	50.53	56.14
b (mpg)	27.34	30.38	33.75
c (gpm per s.f.)	0.000442	0.000398	0.000358
d (gpm)	0.00387	0.00348	0.00313

These equations are represented graphically below:

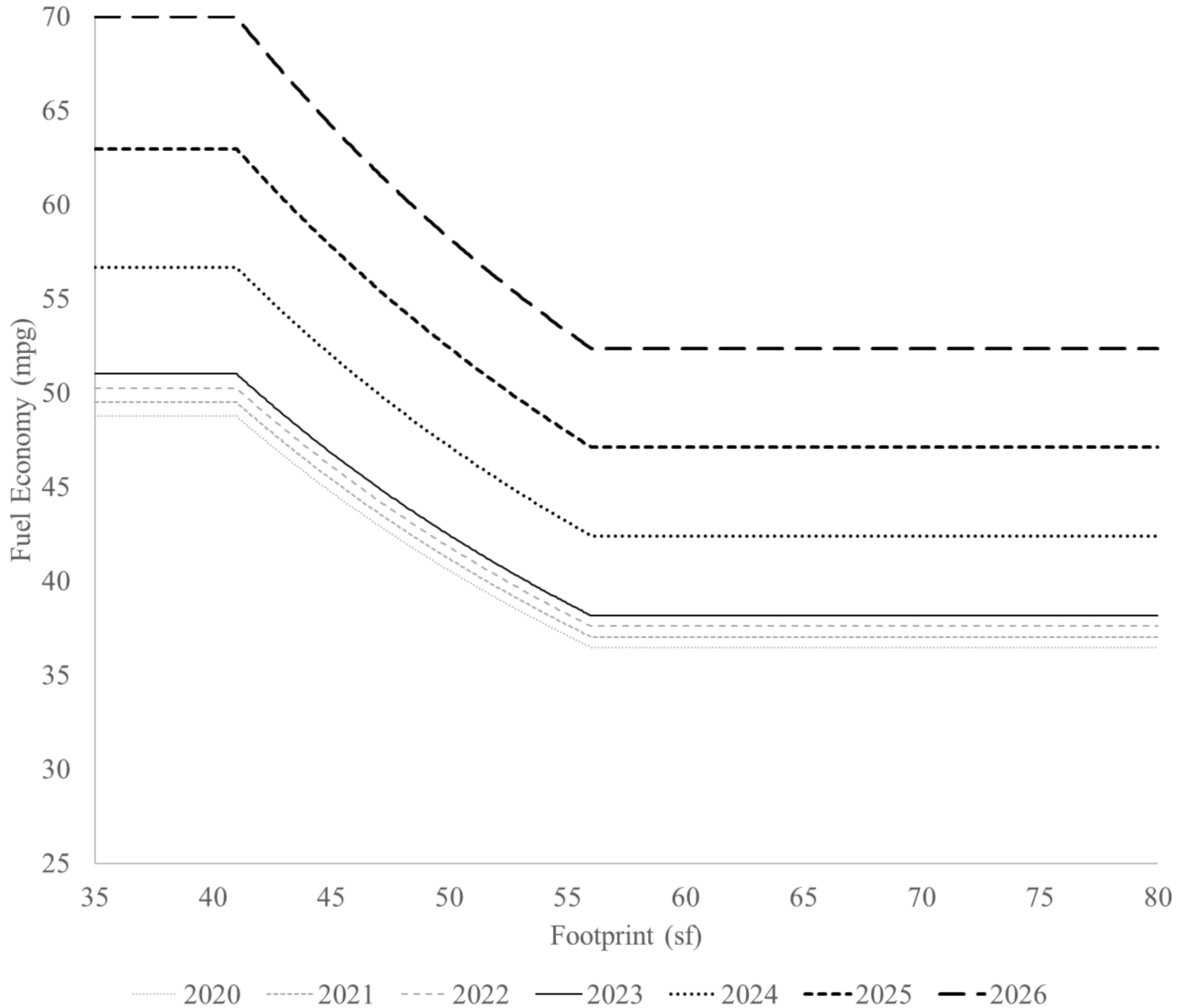

Figure 1-17 – Alternative 3, Passenger Car Fuel Economy, Target Curves

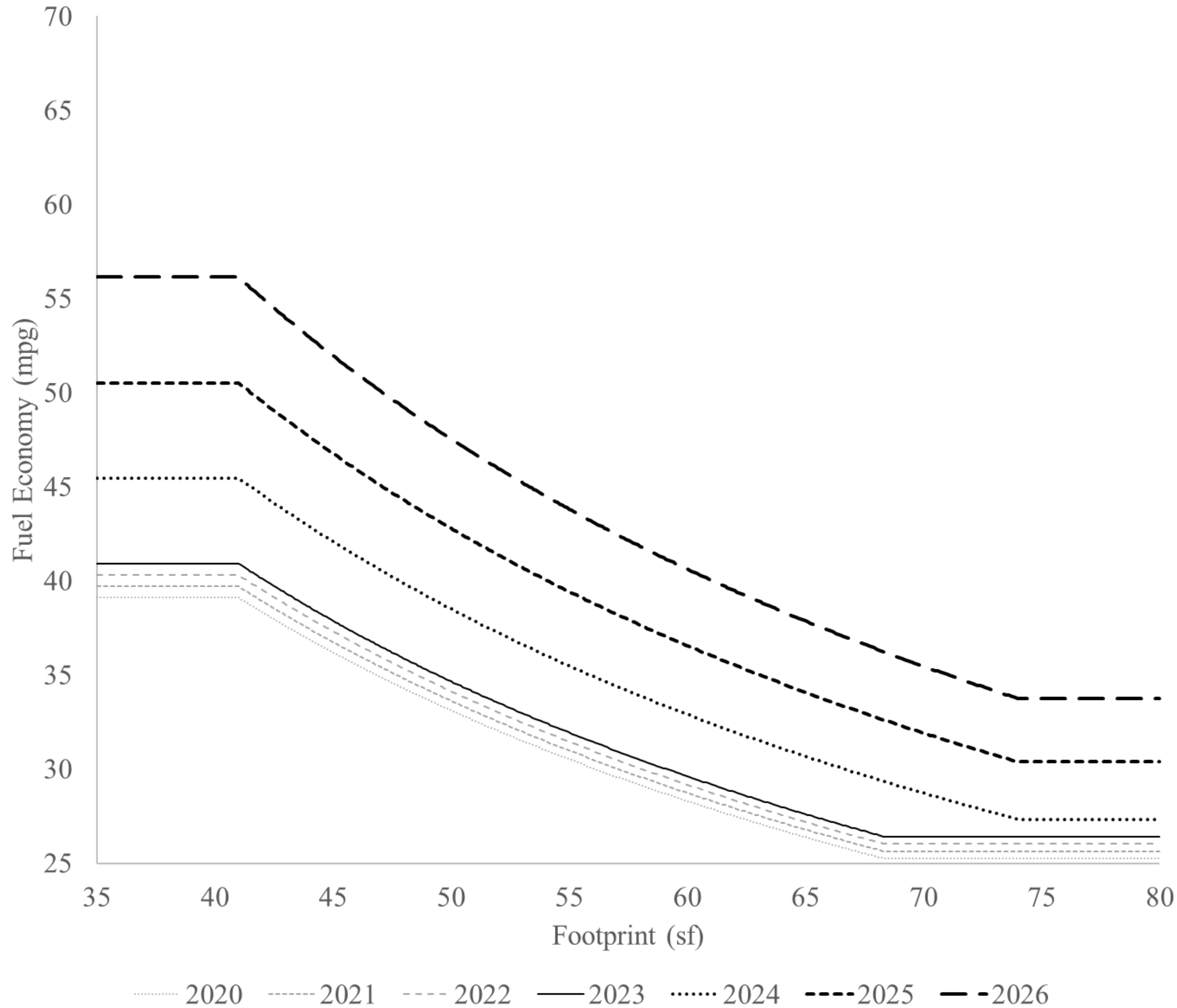

Figure 1-18 – Alternative 3, Light Truck Fuel Economy, Target Curves

Under this alternative, the MDPCS is as follows:

Table 1-29 – Alternative 3 – Minimum Domestic Passenger Car Standard

2024	2025	2026
45.2 mpg	50.3 mpg	55.9 mpg

NHTSA considered this alternative as a way to evaluate the effects of CAFE standards that would return to a fuel consumption trajectory exemplified by the standards announced in 2012.

2 What inputs does the compliance analysis require?

The CAFE Model applies various technologies to different vehicle models in each manufacturer's product line to simulate how each manufacturer might make progress toward compliance with the specified standard. Subject to a variety of user-controlled constraints, the model applies technologies based on their relative cost-effectiveness, as determined by several input assumptions regarding the cost and effectiveness of each technology, the cost of compliance (determined by the change in CAFE or CO_2 credits, CAFE-related civil penalties, or value of CO_2 credits, depending on the compliance program being evaluated), and the value of avoided fuel expenses. For a given manufacturer, the compliance simulation algorithm applies technologies either until the manufacturer runs out of cost-effective technologies,[45] until the manufacturer exhausts *all* available technologies, or, if the manufacturer is assumed to be willing to pay civil penalties or acquire credits from another manufacturer, until paying civil penalties or purchasing credits becomes more cost-effective than increasing vehicle fuel economy. At this stage, the system assigns an incurred technology cost and updated fuel economy to each vehicle model, as well as any civil penalties incurred/credits purchased by each manufacturer. This compliance simulation process is repeated for each model year included in the study period (through model year 2050 in this analysis).

This point marks the system's transition between compliance simulation and effects calculations. At the conclusion of the compliance simulation for a given regulatory scenario, the system produces a full representation of the registered light-duty vehicle population in the United States. The CAFE Model then uses this fleet to generate estimates of the following (for each model year and calendar year included in the analysis): lifetime travel, fuel consumption, carbon dioxide and criteria pollutant emissions, the magnitude of various economic externalities related to vehicular travel (e.g., congestion and noise), and energy consumption (e.g., the economic costs of short-term increases in petroleum prices, or social damages associated with GHG emissions). The system then uses these estimates to measure the benefits and costs associated with each regulatory alternative (relative to the No-Action Alternative).

To perform this analysis, the CAFE Model uses millions of data points contained in several input files that have been populated by engineers, economists, and safety and environmental program analysts at both NHTSA and the DOT's Volpe National Transportations Systems Center (Volpe). In addition, some of the input data comes from modeling and simulation analysis performed by experts at Argonne National Laboratory using their Autonomie full vehicle simulation model and BatPaC battery cost model. Other inputs are derived from other models, such as the U.S. Energy Information Administration's (EIA's) National Energy Modeling System (NEMS), Argonne's "GREET" fuel-cycle emissions analysis model, and U.S. EPA's "MOVES" vehicle emissions analysis model. As NHTSA and Volpe are both organizations within DOT, we use DOT throughout these chapters to refer to the collaborative work performed for this analysis.

[45] Generally, the model considers a technology cost-effective if it pays for itself in fuel savings within 30 months. Depending on the settings applied, the model can continue to apply technologies that are *not* cost-effective rather than choosing other compliance options; if it does so, it will apply those additional technologies in order of cost-effectiveness (i.e., most cost-effective first).

This Chapter 2 and the following Chapter 3 describe the inputs that the compliance simulation requires, including an in-depth discussion of the technologies used in the analysis, how they are defined in the CAFE Model, how they are characterized on vehicles that already exist in the market, how they can be applied to realistically simulate manufacturer's decisions, their effectiveness, and their cost. The inputs and analyses for the effects calculations, including economic, safety, and environmental effects, are discussed later in Chapters 4 through 7, although the overview of inputs below provides a brief description of the information contained in the input files that supports those calculations.

2.1 Overview of Inputs to the Analysis

The CAFE Model input files defining the analysis fleet and the fuel-saving technologies to be included in the analysis span more than a million records, but deal with a relatively discrete range of subjects (e.g., what vehicles are in the fleet, what are the key characteristics of those vehicles, what fuel-saving technologies are expected to be available, and how might adding those technologies impact vehicles' fuel economy levels and costs). The CAFE Model makes use of a considerably wider range of other types of inputs, and most of these are contained in other model input files. The nature and function of many of these inputs remains unchanged relative to 2020 versions, although DOT staff have updated the values of many of these same inputs. The CAFE Model documentation accompanying today's final rule lists and describes all model inputs and explains how inputs are used by the model. Most input values are discussed below, in subsections discussing specific technical, economic, energy, safety, and environmental factors. The remainder of this subsection provides an overview of the scope of different model input files. The overview is organized based on CAFE Model file types, as in the model documentation.

2.1.1 Market Data File

The "Market Data" file contains the detailed description—discussed above—of the vehicle models and model configurations each manufacturer produces for sale in the United States. The file also contains a range of other inputs that, though not specific to individual vehicle models, may be specific to individual manufacturers.

The file contains a set of specific worksheets, as follows:

- **"Manufacturers" worksheet:** Lists specific manufacturers, indicates whether manufacturers are expected to prefer paying CAFE fines to applying technologies that would not be cost-effective, indicates what "payback period" defines buyers' willingness to pay for fuel economy improvements, enumerates CAFE and CO_2 credits banked from model years prior to those represented explicitly, and indicates how sales "multipliers" are to be applied when simulating compliance with CO_2 standards. DOT staff have updated this worksheet to include inputs used to account for aspects of each manufacturer's production relevant to compliance with ZEV mandates, as discussed further in Chapter 2.3, Simulating the Zero Emissions Vehicle Program.

- **"Credits and Adjustments" worksheet:** Enumerates estimates—specific to each manufacturer and fleet—of expected CO_2 and CAFE adjustments reflecting improved AC efficiency, reduced AC refrigerant leakage, improvements to “off cycle” efficiency, and production of flexible fuel vehicles (FFVs). The model applies AC refrigerant leakage adjustments only to CO_2 levels, and applies FFV adjustments only to CAFE levels.

- **“Vehicles” worksheet:** Lists vehicle models and model configurations each manufacturer produces for sale in the United States; identifies shared vehicle platforms; indicates which engine and transmission is present in each vehicle model configuration; specifies each vehicle model configuration’s fuel economy level, production volume, and average price; specifies several engineering characteristics (e.g., curb weight, footprint, and fuel tank volume); assigns each vehicle model configuration to a regulatory class, technology class, engine class, and safety class; specifies schedules on which specific vehicle models are expected to be redesigned and freshened; specifies how much U.S. labor is involved in producing each vehicle model/configuration; and indicates whether specific technologies are already present on specific vehicle model configurations, or, due to engineering or product planning considerations, should be skipped. DOT staff have updated this worksheet to include inputs used to indicate which models might reasonably treated as candidates to be replaces with vehicles earning credit toward compliance with ZEV mandates, as discussed in Chapter 2.3, Simulating the Zero Emissions Vehicle Program. DOT staff have also updated this worksheet to include inputs used to indicate which manufacturers are subject to the CARB’s “Framework Agreements,” as discussed in Chapter 1.

- **“Engines” worksheet:** Identifies specific engines used by each manufacturer and for each engine, lists a unique code (referenced by the engine code specified for each vehicle model configuration and identifies the fuel(s) with which the engine is compatible, the valvetrain design (e.g., dual overhead cam [DOHC]), the engine’s displacement, cylinder configuration and count, and the engine’s aspiration type (e.g., naturally aspirated, turbocharged). The worksheet also indicates whether specific technologies are already present on specific engines or, due to engineering or product planning considerations, should be skipped.

- **“Transmissions” worksheet:** Similar to the Engines worksheet, identifies specific transmissions used by each manufacturer and for each transmission, lists a unique code (referenced by the transmission code specified for each vehicle model configuration and identifies the type (e.g., automatic or CVT) and number of forward gears. Also, indicates whether specific technologies are already present or, due to engineering or product planning considerations, should be skipped.

2.1.2 Technologies File

The Technologies file identifies approximately six dozen technologies to be included in the analysis, indicates when and how widely each technology can be applied to specific types of vehicles, provides most of the inputs involved in estimating what costs will be incurred, and provides some of the inputs involved in estimating impacts on vehicle fuel consumption and weight.

The file contains the following types of worksheets:

- **"Parameters" worksheet:** Not to be confused with the "Parameters" file discussed below, this worksheet in the Technologies file indicates, for each technology class, the share of the vehicle's curb weight represented by the "glider" (the vehicle without the powertrain).

- **"Technologies" worksheet:** For each named technology, specifies the share of the entire fleet to which the technology may be additionally applied in each model year.

- **"Technology Class" worksheets:** In a separate worksheet for each of the 10 technology classes discussed above (and an additional 2—not used for this analysis—for heavy-duty pickup trucks and vans), identifies whether and how soon the technology is expected to be available for wide commercialization, specifies the percentage of miles a vehicle is expected to travel on a secondary fuel (if applicable, as for PHEVs), indicates a vehicle's expected electric power and all-electric range (AER) (if applicable), specifies expected impacts on vehicle weight, specifies estimates of costs for technologies in each model year (and factors by which electric battery costs are expected to be reduced in each model year), specifies any estimates of maintenance and repair cost impacts, and specifies any estimates of consumers' willingness to pay for the technology.

- **"Engine Type" worksheets:** In a separate worksheet for each of 28 initial engine types identified by cylinder count, number of cylinder banks, and configuration (DOHC, unless identified as OHV or single overhead cam [SOHC]), specifies estimates of costs in each model year, as well as any estimates of impacts on maintenance and repair costs.

2.1.3 Parameters File

The "Parameters" file contains inputs spanning a range of considerations, such as economic and labor utilization impacts, vehicle fleet characteristics, fuel prices, scrappage and safety model coefficients, fuel properties, and emission rates.

The file contains a set of specific worksheets, as follows:

- **"Economic Values" worksheet:** Specifies a variety of inputs, including social and consumer discount rates to be applied, the "base year" to which to discount social benefits and costs (i.e., the reference years for present value analysis), discount rates to be applied to the social cost of CO_2 emissions, the elasticity of highway travel with respect to per-mile fuel costs (also referred to as the rebound effect), the gap between test (for certification) and on-road (i.e., real world) fuel economy, the fixed amount of time involved in each refuel event, the share of the tank refueled during an average refueling event, the value of travel time (in dollars per hour per vehicle), the estimated average number of miles between mid-trip electric vehicle (EV) recharging events (separately for each BEV considered in the analysis), the rate (in miles of capacity per hour of charging) at which EV batteries are recharged during such events, the values (in dollars per vehicle-mile) of congestion and noise costs, costs of vehicle ownership and operation (e.g., sales tax), economic costs of oil imports, estimates of future macroeconomic measures (e.g., GDP), and rates of growth in overall highway travel (separately for low, reference, and high oil prices).

- **"Vehicle Age Data" worksheet:** Specifies nominal average survival rates and annual mileage accumulation for cars, vans and SUVs, and pickup trucks. These inputs are used only for displaying estimates of avoided fuel savings and CO_2 emissions while the model is operating. Calculations reported in model output files reflect, among other things, application of the scrappage model.

- **"Fuel Prices" worksheet:** Separately for gasoline, E85, diesel, electricity, hydrogen, and compressed natural gas (CNG), specifies historical and estimated future fuel prices (and average rates of taxation). Includes values reflecting low, reference, and high estimates of oil prices.

- **"DFS Model Values" worksheet:** Specifies coefficients used by the dynamic fleet share model, which estimates the relative proportions of passengers and light trucks in the total U.S. market for new vehicles.

- **"Scrappage Model Values" worksheet:** Specifies coefficients applied by the scrappage model, which the CAFE Model uses to estimate rates at which vehicles will be scrapped (removed from service) during the period covered by the analysis.

- **"Historic Fleet Data" worksheet:** For model years not simulated explicitly (here, model years through 2016), and separately for cars, vans and SUVs, and pickup trucks, specifies the initial size (i.e., number new vehicles produced for sale in the United States) of the fleet, the number still in service in the indicated calendar year (here, 2016), the relative shares of different fuel types, and the average fuel economy achieved by vehicles with different fuel types, and the averages of horsepower, curb weight, fuel capacity, and price (when new).

- **"Safety Values" worksheet:** Specifies coefficients used to estimate the extent to which changes in vehicle mass impact highway safety. Also, specifies statistical value of highway fatalities, the share of incremental risk (of any additional driving) internalized by drivers, rates relating the cost of damages from non-fatal losses to the cost of fatalities, and rates relating the occurrence of non-fatal injuries to the occurrence of fatalities. DOT staff have updated this worksheet to include inputs used to estimate the occurrence and monetized damages from crashes resulting in injuries or property damage, but not fatalities. Chapter 7 discusses these new estimation procedures.

- **"Fatality Rates" worksheet:** Separately for each model year from 1975-2050, and separately for each vehicle age (through 39 years) specifies the estimated nominal number of fatalities incurred per billion miles of travel by which to offset fatalities.

- **"Credit Trading Values" worksheet:** Specifies whether various provisions related to compliance credits are to be simulated (currently limited to credit carry-forward and transfers), and specifies the maximum number of years' credits may be carried forward to future model years. Also, specifies statutory (for CAFE only) limits on the quantity of credits that may be transferred between fleets, and specifies amounts of lifetime mileage accumulation to be assumed when adjusting the value of transferred credits. Also, accommodates a setting indicating the maximum number of model years to consider when using expiring credits.

- **"Employment Values" worksheet:** Specifies the estimated average revenue OEMs and suppliers earn per employee, the RPE factor applied in developing technology costs, the average quantity of annual labor (in hours) per employee, a multiplier to apply to U.S. final assembly labor utilization in order to obtain estimated direct automotive manufacturing labor, and a multiplier to be applied to all labor hours.

- **"Fuel Properties" worksheet:** Separately for gasoline, E85, diesel, electricity, hydrogen, and CNG, specifies energy density, mass density, carbon content, and tailpipe SO_2 emissions (grams per unit of energy).

- **"Fuel Import Assumptions" worksheet:** Separately for gasoline, E85, diesel, electricity, hydrogen, and CNG, specifies the extent to which (a) changes in fuel consumption lead to changes in net imports of finished fuel, (b) changes in fuel consumption lead to changes in domestic refining output, (c) changes in domestic refining output lead to changes in domestic crude oil production, and (d) changes in domestic refining output lead to changes in net imports of crude oil.

- **"Emissions Health Impacts" worksheet:** Separately for NO_X, SO_2 and $PM_{2.5}$ emissions, separately for upstream and vehicular emissions, and for each of calendar years 2020, 2025, and 2030, specifies estimates of various health impacts, such as premature deaths, acute bronchitis, and respiratory hospital admissions. Consulting with technical staff at EPA and Argonne National Laboratory, DOT staff have refined the structure of these inputs to account separately for refining, petroleum extraction, finished fuel distribution (i.e., transportation, storage, and distribution), and electricity generation, and to differentiate between gasoline and diesel vehicle emissions.

- **"Greenhouse Emission Costs" worksheet:** For each calendar year through 2080, specifies low, average, and high estimates of the social cost of CO_2 emissions, in dollars per metric ton. Accommodates analogous estimates for CH_4 and N_2O.

- **"Criteria Pollutant Emission Costs" worksheet:** Separately for NO_X, SO_2 and $PM_{2.5}$ emissions, separately for upstream and vehicular emissions, and for each of calendar years 2016, 2020, 2025, and 2030, specifies social costs on a per-ton basis.

- **"Upstream Emissions (UE)" worksheets:** Separately for gasoline, E85, diesel, electricity, hydrogen, and CNG, and separately for calendar years 2020, 2025, 2030, 2035, 2040, 2045, and 2050, and separately for various upstream processes (e.g., petroleum refining), specifies emission factors (in grams per million British thermal unit [BTU]) for each included criteria pollutant (e.g., NO_X) and toxic air contaminant (e.g., benzene).

- **"Tailpipe Emissions (TE)" worksheets:** Separately for gasoline and diesel, for each of model years 1975-2050, for each vehicle vintage through age 39, specifies vehicle tailpipe emission factors (in grams per mile) for CO, VOC, NO_X, $PM_{2.5}$, CH_4, N_2O, acetaldehyde, acrolein, benzene, butadiene, formaldehyde, and diesel particulate matter 10 microns or less in diameter (PM_{10}).

2.1.4 Scenarios File

The CAFE Model represents each regulatory alternative as a discrete scenario, identifying the first-listed scenario as the baseline relative to which impacts are calculated. Each scenario is described in a worksheet in the Scenarios input file, with standards and related provisions specified separately for each regulatory class (passenger car or light truck) and each model year. Inputs specify the standards' functional forms and defining coefficients in each model year. Multiplicative factors and additive offsets are used to convert fuel economy targets to CO_2 targets, the two being directly mathematically related by a linear transformation. Additional inputs specify minimum CAFE standards for domestic passenger car fleets, determine whether upstream emissions from electricity and hydrogen are to be included in CO_2 compliance calculations, specify the governing rates for CAFE civil penalties, specify estimates of the value of CAFE credits (for CAFE Model operating modes applying these values), specify how flexible fuel vehicles (FFVs) and PHEVs are to be accounted for in CAFE compliance calculations, specific caps on adjustments reflecting improvements to off-cycle and AC efficiency and emissions, specify any estimated amounts of average Federal tax credits earned by HEVs, PHEVs, BEVs, and FCVs. Consulting with CARB technical staff, DOT staff have added inputs to account for some manufacturers' commitment to CARB's "Framework Agreements," as discussed above in Chapters 1 and 2. DOT staff have also added inputs to identify specific model years for which new standards are being proposed or finalized. The worksheets also accommodate some other inputs, such those as involved in analyzing standards for heavy-duty pickups and vans, not used in today's analysis.

2.1.5 Run Time Settings

In addition to inputs contained in the above-mentioned files, the CAFE Model makes use of some settings selected when operating the model. These include which standards (CAFE or CO_2) are to be evaluated; what model years the analysis is to span; when technology application is to begin; whether use of compliance credits is to be simulated and, if so, until what model year; whether dynamic economic models are to be exercised and, if so, how many sales model iterations are to be undertaken and using what price elasticity; whether low, average, or high estimates are to be applied for fuel prices, SCC, and fatality rates; by how much to scale benefits to consumers; and whether to report an implicit opportunity cost. DOT staff have also added inputs that can be used to require technology application and vehicle sales under each regulatory alternative to remain unchanged from the No-Action Alternative (i.e., the baseline) until some future model year. For today's analysis, DOT staff have introduced new settings to the model, supporting the selection of alternative dynamic fleet share models to be applied, and supporting the direct specification of the portion of accumulated driving (in miles) to be included when calculating avoided fuel savings offsetting purchase costs when estimating impacts on new vehicle sales and used vehicle scrappage.

2.1.6 Simulation Inputs

As mentioned above, the CAFE Model makes use of databases of estimates of fuel consumption impacts and, as applicable, battery costs for different combinations of fuel saving technologies. For today's analysis, DOT developed these databases using a large set of full vehicle and accompanying battery cost model simulations developed by Argonne National Laboratory. To be used as files provided separately from the model and loaded every time the model is executed, these databases are prohibitively large, spanning more than a million records and more than half a gigabyte. To conserve memory and speed model operation, DOT has integrated the databases into the CAFE Model executable file. When the model is run, however, the databases are extracted and placed in an accessible location on the user's disk drive.

The databases, each of which is in the form of a simple (if large) text file, are as follows:

- **"FE1_Adjustments.csv":** This is the main database of fuel consumption estimates. Each record contains such estimates for a specific indexed (using a multidimensional "key") combination of technologies for each of the technology classes in the Market Data and Technologies files. Each estimate is specified as a percentage of the "base" technology combination for the indicated technology class.

- "**FE2_Adjustments.csv":** Specific to PHEVs, this is a database of fuel consumption estimates applicable to operation on electricity, specified in the same manner as those in the main database.

- **"Battery_Costs.csv":** Specific to technology combinations involving vehicle electrification (including 12V stop-start systems), this is a database of estimates of corresponding base costs (before learning effects) for batteries in these systems. As discussed below, for today's analysis, DOT staff have adjusted some of the estimates in this file in order to better represent batteries used in 12V stop-start systems.

2.1.7 Argonne National Laboratory Autonomie Simulation Databases

As discussed above, the technology effectiveness values used in the CAFE Model come from a set of full vehicle simulations developed by Argonne National Laboratory using the Autonomie model. While DOT adapts these prohibitively large simulation databases into the CAFE Model executable file, DOT provides a summary of simulation outputs for each vehicle technology class. Argonne also provides assumptions summary files to describe the assumptions used in building vehicle models and for the BatPaC battery cost modeling.

The workbooks Argonne provides for the full vehicle simulations are, as follows:

- "CompactNonPerfo_2101.csv; CompactPerfo_2101.csv; MidsizeNonPerfo_2101.csv; MidsizePerfo_2101.csv; MidsizeSUVNonPerfo_2101.csv; MidsizeSUVPerfo_2101.csv; PickupNonPerfo_2101.csv; PickupPerfo_2101.csv; SmallSUVNonPerfo_2101.csv; SmallSUVPerfo_2101.csv": These are the ten databases that contain the outputs of the Autonomie full vehicle simulations. These ten vehicle classes account for over one million simulations that have been considered for this analysis. These results are in raw absolute mpg form and then are converted to the appropriate incremental effectiveness value for use in the CAFE Model.

- **"ANL - All Assumptions_Summary_NPRM_022021.xlsx":** This summary workbook provides broad summaries of assumptions used for the Autonomie full vehicle simulations, such as component weights, cold start penalties, component specifications, etc.

- **"ANL - Data Dictionary_January 2021.xlsx":** This workbook contains descriptions of inputs and units for the Autonomie simulation results.

- **"ANL - Summary of Main Component Performance Assumptions_NPRM_022021.xlsx":** This workbook contains another set of characteristics data for transmission efficiencies, engine fueling rates, and electric motor efficiencies.

- **"ANL_BatPac_Lookup_tables_Feb2021v2.xlsx":** This contains the inputs, assumptions, and outputs of the battery pack modeling performed by Argonne for this analysis.

2.2 The Market Data File

The starting point for the evaluation of different stringency levels for future fuel economy standards is the analysis fleet, which is a snapshot of the recent light duty vehicle market. The analysis fleet provides a reference from which to project how manufacturers could apply additional technologies to vehicles to cost-effectively improve vehicle fuel economy, in response to regulatory action and market conditions.[46] As the scope of CAFE analysis has widened over successive rulemakings, the range of data that must be included for each vehicle in the analysis fleet has, in turn, widened, currently including nearly half a million pieces of information used and referenced in the CAFE Model analysis.

The Market Data file contains information about manufacturer credit banks, fine payment preferences, and whether a manufacturer has voluntary adopted the California Framework Agreements, committed to exceed the standards set in the 2020 final rule. Additionally, the Market Data file includes some information about the distribution of vehicle sales within the United States, recognizing the proportion of vehicles sold in California and Section 177 states, and in the rest of the United States. This information supports the representation of ZEV mandates, discussed in detail. Credit banks, fine payment preferences, and other information described in this paragraph appear on the "Manufacturers" tab of the Market Data file.

The "Credits and Adjustments" tab of the Market Data file summarizes additional credits previously claimed by manufacturer, by regulatory class. On this tab, the Market Data file includes historical data about claimed AC efficiency, AC leakage, off-cycle credits, and flex fuel

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[46] The CAFE Model does not generate compliance paths a manufacturer should, must, or will deploy. It is intended as a tool to demonstrate a compliance pathway a manufacturer *could* choose. It is almost certain all manufacturers will make compliance choices differing from those projected by the CAFE Model.

vehicle (FFV) credits, as well as forward looking projections about credits that DOT believes may be claimed in the future.[47]

The "Vehicles" tab of the Market Data file includes information about the vehicles sold in the United States in a given model year. In this tab, DOT staff catalogue the types of vehicles sold (including the number sold, the regulatory class, the footprint, and the fuel economy), and information about those vehicles that informs the baseline for the analysis (for instance, which fuel saving technologies already appear on production vehicles). The vehicles tab includes information necessary to link observed vehicles to effectiveness estimates for additional fuel saving technologies (with "technology class" assignments), and technology costs (with "technology class," and "engine class" assignments, needed to point to relevant cost information in the technologies input file). The Market Data file contains additional information about projected refresh and redesign cycles, and current part sharing of structural parts, engines, and transmissions (with "platforms," "engine code," and "transmission code") that the CAFE Model takes into account when applying additional fuel saving technologies. Estimates of manufacturer suggested retail price (MSRP), labor hours per vehicle, and percent U.S. content provide reference information used in other CAFE Model calculations.

The Market Data file "Engines" and "Transmissions" tabs characterize technology content of engine and transmission systems in use in the observed fleet and link these systems back to observed vehicles via the "engine code" and "transmission code."

A reasonable characterization of the analysis fleet is key to estimating costs and benefits resulting from the rulemaking action. The baseline sales volumes, fuel economies, and manufacturer fleet fuel economies when compared to future standards help DOT (via CAFE Model compliance simulations) evaluate how manufacturers may respond to any projected future standards (as future standards are outlined in the scenarios input file), in light of each manufacturer's product portfolio and projected market conditions (with market conditions including cost of fuel saving technologies as outlined in the technologies input file, and projected fuel prices as outlined in the parameters input file). The analysis fleet inputs, as characterized in the Market Data file, help DOT assess how and when technologies may be adopted in the future (considering refresh and redesign cycles and part sharing), help DOT account for technologies already applied to vehicles (reducing the likelihood of "double-counting" the effectiveness of technologies, which can occur if the analysis assumes already applied technologies are still available to improve a vehicle's fuel economy), and help DOT account for the idea that some fuel saving technologies may not meet functional requirements for all vehicle types, or performance applications. The Market Data file, and information outlined in this TSD, endeavors to make clear the baseline assumptions with respect to the fleet used in a rulemaking analysis.

The market for light-duty automotive equipment in the United States is highly heterogeneous, and even half a million data points may not be enough to characterize every potentially relevant nuance of the automotive marketplace. As for every CAFE rulemaking, today's analysis fleet

[47] DOT discusses the flexibilities and credits, as well as the basis for these projections, in Chapter 3.8 and preamble Section VII.

reflects a balance between the exigencies of the rulemaking and the availability of supporting data.

The following sections discuss the inputs included in the Market Data file, including vehicles and their technology content built in MY 2020 (i.e., the analysis fleet or baseline fleet), and baseline safety, economic, and manufacturer compliance positions.

2.2.1 Characterizing Vehicles and their Technology Content

Most of the information in the Market Data file is about specific vehicles, including sales, fuel economies, regulatory class, and the vehicle specifications (based on best information available at the time DOT staff assemble the Market Data file). Beyond specifications, information in the Market Data file links parts of the analysis. For instance, while the analysis fleet sets the baseline for fuel saving technology content already in use, by vehicle, the Market Data file also includes information linking individual vehicles to technology effectiveness estimates and technology costs (both of which may vary by the type of vehicle, and the configuration of equipment on the vehicle).

In the Market Data file, DOT staff assign each vehicle a “technology class.” The technology class is used to link the observed vehicle to effectiveness estimates and technology costs. The CAFE Model references the Argonne National Laboratory (Argonne) Autonomie simulations for many effectiveness estimates used in the compliance simulation. In these simulations, Argonne projects the fuel economies for ten different types of vehicles for many combinations of fuel saving technologies. The technology class in the Market Data file points the CAFE Model to the most relevant reference set of effectiveness estimates for each vehicle. Similarly, some costs for fuel saving technologies vary by the type of vehicle (for instance, a pound of weight saved on a small car may not cost the same as the cost of a pound of weight on a pickup truck, even if the two have adopted very little of the mass reduction technology considered in the analysis). The technology class in the Market Data file also points the CAFE Model to the most relevant reference costs in the “Technologies File,” with costs for vehicle technologies being listed on the technology class tab.

Just as some vehicle technology costs vary by type of vehicle (or technology class, as listed in the Market Data file and Technologies file), the cost of fuel saving engine technologies and some electrification systems vary by the engine architecture, or peak power output most closely associated with an engine architecture. For instance, the cost of adding cylinder deactivation to a naturally aspirated dual overhead cam (DOHC) inline four-cylinder engine is not projected to be the same as adding cylinder deactivation to a naturally aspirated overhead valve (OHV) V eight-cylinder engine. Similarly, some naturally aspirated inline four cylinder engines may retain four cylinders when turbocharged (“4C1B” engine technology class, meaning an engine with four cylinders and one bank), but lower power variants might go to three cylinders when turbocharged (“4C1B_L” engine technology class), and thereby have lower projected costs in comparison for the step to turbocharging. For a more detailed discussion of the mechanics of engine technology classes and engine costs, see Chapter 3.1.8. The engine technology class in the Market Data file points the CAFE Model to the most relevant engine technology costs.

For each type of vehicle (or row), the Market Data file lists a certification fuel economy, sales volume, regulatory class, and footprint. These are the bare minimum pieces of information needed to understand if a manufacturer is under or over complying with standards. The Market Data file often includes a few rows for vehicles that may have identical certification fuel economies, regulatory classes, and footprints (with compliance sales volumes divided out among rows), because other pieces of information used in the CAFE Model may be dissimilar.

For instance, in the reference materials used to create the Market Data file, for a nameplate curb weight may vary by trim level (with premium trim levels often weighing more on account of additional equipment on the vehicle), or a manufacturer may provide consumers the option to purchase a larger fuel tank size for their vehicle. These pieces of information may not impact the observed compliance position directly, but curb weight (in relation to other vehicle attributes) is important to assess mass reduction technology already used on the vehicle, and fuel tank size is directly relevant to saving time at the gas pump, which the CAFE Model uses when calculating the value of avoided time spent refueling.

The Market Data file also provides an inventory of fuel saving technologies already equipped on the observed vehicles. A reasonable characterization is important: underestimating the amount of fuel saving technology content on a vehicle would allow the CAFE Model to apply that technology again in the compliance simulation (likely at a low cost) and create a "phantom" projection of potential fuel economy savings. On the other hand, overestimating the amount of fuel saving technology content already on a vehicle would also remove the misapplied technologies from consideration, and confuse the cost accounting if that technology is replaced with another (for instance, if the assigned amount of engine technology content is higher than actually used, the projected incremental cost to switch to electrified technologies may be underestimated). The assignment process for each technology is described in detail in Chapter 3.1.5.

For some fuel saving technologies, manufacturers share parts or systems to get the most from economies of scale. The CAFE Model accounts for some relationships between vehicles that are important to consider. For instance, similar engines and transmissions often appear on many types of vehicles. Manufacturers often use platforms (with shared mass reduction technologies) on a family of vehicles. The CAFE Model includes measures to maintain complexity in compliance simulations as it evaluates cost-effective compliance pathways. DOT staff assign each vehicle in the Market Data file an "engine code," and "transmission code," and a "platform." With few exceptions, vehicles that share engine codes will adopt engine technologies together, and vehicles that share transmission codes will adopt transmission technologies together. Vehicles that share platforms will adopt mass reduction technologies together. Redesign cycles for all of the vehicles with shared components may not always be in sync, but vehicles in the family (with laggard redesigns and refreshes) inherit these shared systems at the first available opportunity.

In limited cases, the Market Data file includes information about technologies that the CAFE Model may *not* apply. For the row on the vehicle, engine, or transmission, and for the technology column listed in the Market Data file, "SKIP" appears in the spreadsheet cell. Generally, DOT staff have used data and logic to come up with these rules. For instance, secondary axle disconnect (SAX) may not be applied to vehicles that drive power through two wheels (because the SAX technology has a prerequisite of the vehicle driving all four wheels to be applied), so SKIP would appear in the Market Data file for vehicles to which the technology could not be applied (therefore acknowledging that manufacturers could not apply this particular fuel saving technology to achieve fuel economy improvements for a particular vehicle). Instances of SKIP logic includes SKIPs to high levels of aerodynamic improvements (taking into account form drag of some vehicle body styles), SKIPs to high levels of rolling resistance for performance vehicles (that have high needs for traction to meet handling objectives), and SKIPs to some engine packages (to account for low specific power output and torque requirements). If SKIP is applicable for a technology, the rules for restricting technology for a specific set of vehicles are described in Chapter 3.

The CAFE Model considers many types of fuel saving technologies, but some are very difficult to observe from public information available. For instance, the rolling resistance of a set of tires may not appear on a public specifications sheet, and the inner workings and efficiencies of a transmission may be hard for DOT staff to assess (without detailed study, or confidential business information). In these cases, DOT staff rely on best information available, and, occasionally, analyst judgement (or described analytical techniques, like in the case of mass reduction technology). When manufacturers or suppliers do provide confidential business information, NHTSA often verifies the information in due time, usually through contracted analysis at independent labs.

For today's analysis, for some technologies (like rolling resistance and aerodynamic improvements), DOT staff relied on confidential information provided by manufacturers about their MY 2016 fleet, and carried these values forward, by nameplate, for the MY 2020 fleet. With this approach, it is possible that DOT underestimates the extent to which manufacturers have added more hard-to-observe technologies in the MY 2020 fleet since MY 2016, increasing the risk of "double counting" effectiveness (especially for aerodynamics, rolling resistance, and improved accessory devices). While some technologies are difficult to observe, many technologies are straightforward to identify via specification sheets, marketing materials, or published technical papers, and to link with the most representative Argonne simulation, and equipment cost estimate. Whether a technology is easy to observe, or difficult to observe, DOT staff assign baseline technology content for each vehicle in the Market Data file.

The Market Data file catalogues DOT's understanding of technologies already equipped on vehicles, with many vehicles not yet exhausting all technologies that may improve internal combustion engine efficiency. The current technology assessment in the baseline fleet shows that many vehicles, even ones with advanced engine or transmission technologies, still may be marginally improved with the application of additional technologies. Often, recently released engines or transmissions may be reasonably characterized as early adopters of some technologies already considered in the analysis, in combination with a representation of a previous generation, widely adopted technology.

The following sections discuss the data sources used to populate the analysis fleet, and how DOT staff accurately characterize the starting point for the compliance simulation.

2.2.1.1 Data Sources Used to Populate the Analysis Fleet

The Market Data file integrates information from many sources, including manufacturer compliance submissions, publicly available information, and confidential business information. At times, information is still incomplete, and DOT staff use analyst judgement in populating the analysis fleet. When analyst judgement is used, DOT staff try to make clear the underlying data and logic informing the analysis.[48]

DOT staff make every effort to use current, credible sources with information that may be shared with the public or independently verified. DOT staff used mid-model year 2020 compliance data as the basis of the analysis fleet. Compliance data contain information about projected sales volumes, vehicle fuel economies, vehicle footprints, and often contains some information about engine architecture, transmission architecture, and vehicle drive configuration. For each vehicle nameplate, DOT staff identified and downloaded manufacturer specification sheets, usually from the manufacturer media website, or from online marketing brochures.[49] From specification sheets, DOT staff gathered information to identify engine technologies, engine families, transmission technologies, transmission families, and electrified drivetrain technologies. The team also recorded curb weights (often varying by powertrain, by drive configuration, and by trim level), peak horsepower, and occasionally a manufacturer reported the vehicle's aerodynamic drag coefficient, and occasionally some information useful in identifying hard-to-observe technologies, like improved accessory devices or SAX. For additional information in about how specification sheets informed the assignment of a technology to a vehicle in the MY 2020 fleet, see the technology specific "baseline assignment" sections in Chapter 3.

Often, one entry in the compliance record (typically including a nameplate, sales volume, fuel economy, footprint, drive configuration, and basic description of the engine and transmission) describes a range of vehicles with attributes that may vary meaningfully for the CAFE Model analysis. For instance, one compliance record may represent a range of trim levels, offered for sale at a range of prices, or spanning a range of curb weights. In these cases, DOT staff divide compliance record sales volume evenly among the vehicle types with different attributes, thereby increasing the number of rows in the Market Data file and atomizing the sales volume of each individual row. While this may seem superfluous from some perspectives, the atomization of sales in each row in the Market Data file plays an important role in the application of technology, especially the application of hybrid and electric vehicle technology, as the CAFE Model may add costly fuel saving technology only to the extent needed to comply with standards (reducing the likelihood of significant over compliance, after redesign cycles, and inheritance of shared engine, transmission, and mass reduction platform technology is taken into account).

One consequence of using historical compliance data to populate the Market Data file is that the analysis carries forward fleet composition, or at least iterates the fleet from an observation taken in the past. In other words, the Market Data file does not use forward looking information to project which nameplates may be introduced, or which nameplates will be retired, or evaluate

[48] Forward looking refresh/redesign cycles are one example of when analyst judgement is necessary.

[49] The catalogue of reference specification sheets (broken down by manufacturer, by nameplate) used to populate information in the Market Data file is available in the docket. BMW Data, FCA Data, Ford Data, Hyundai Data, Kia Data, Mercedes Data, Nissan Data, Toyota Data, Volvo Data, GM Data, Honda Data, Mitsubishi Data, VW Data, and JLR Data.

how competitive positions may evolve as manufacturers add fuel saving technologies and adjust product plans over time.[50] Similarly, manufacturers who submitted no compliance information in the baseline compliance year (perhaps because they had not yet commercialized products), are not included in the forward looking compliance simulation. The Market Data file does identify some vehicle model/configurations for which each manufacturer may adopt ZEV candidate technology (in today's case, battery electric vehicle technology), and more detail about how DOT staff selected these vehicles is described in Chapter 2.3.2, Calculation of ZEV Credits Per Manufacturer. As a result, it is reasonable to expect the composition of the fleet (in terms of nameplates offered, and manufacturer market shares) to look very different in the future years beyond the rulemaking time frame than the CAFE Model's projected compliance pathways.

2.2.1.1.1 Source and Vintage of Fleet Data

Using recent data for baseline assessments is more likely to reflect current market conditions than older data. Recent data will inherently include manufacturer's practical considerations about fuel saving technology characterization and efficiency, mix shifts in response to consumer preferences, and industry sales volumes that incorporate substantive macroeconomic events. Also, using recent data decreases the likelihood that the CAFE Model selects compliance pathways for future standards that affect vehicles already built in previous model years.[51]

While current data are highly desirable, real-time data to support fleet characterization in the Market Data file are extremely difficult to come by. There is a lag time for finalized model year compliance data and finalized compliance data for a given model year may not be available for a year or more after the last product for that model year rolls off the assembly line. Further complicating matters, once DOT staff identify a suitable set of compliance data, it takes significant effort to translate those compliance data into the Market Data file, augment that information with data from specification sheets and confidential business information, characterize fuel saving technology content on each vehicle, and produce a high-quality file that is suitable for use in the CAFE Model. DOT must balance the resources required to create the Market Data file (i.e., several staff for several months), with the availability of data and the timing of the rulemaking effort.

For today's analysis, DOT staff used mid-year compliance submissions from MY 2020 as the basis for the analysis fleet characterized in the Market Data file. While mid-year data are not "final" data, historically, manufacturers' mid-model year submissions change little between mid and final submissions. Most manufacturers had submitted mid-model year 2020 data as of August 2020, when DOT staff began building the Market Data file used in today's analysis. Moreover, by August of 2020, many manufacturers had shifted production to MY 2021 vehicles, so the "mid-year" vehicle volume data were stable, as production was mostly complete.

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[50] The sales model in the CAFE Model does, at an industry level, adjust overall sales volume up or down, and sales share between light trucks and passenger cars in response to technology costs, fuel economies, and fuel prices.

[51] For example, in this analysis the CAFE Model must apply technology to the MY 2020 fleet from MYs 2021-2023 for the compliance simulation that begins in MY 2024. While manufacturers have already built MY 2021 and later vehicles, the most current, complete dataset with regulatory fuel economy test results to build the analysis fleet at the time of writing remains MY 2020 data.

MY 2020 was an important year for the automotive marketplace. Light-duty sales dipped meaningfully in MY 2020 as compared to prior years, with the coronavirus pandemic and historically low gasoline prices causing an impact. Manufacturers reacted to supply chain factors as well, with notable events including transmission factories shutting down due to tornados, and assembly plants idling due to coronavirus. The MY 2020 Market Data file used in today's analysis reflects the market impacts of these events.

While MY 2020 may have been extraordinary, many long-term trends continued. Manufacturers continued to integrate more fuel saving technology in redesigned vehicles, likely in response to steady increases in fuel economy stringency and consumer preferences. Also, prices for new vehicles continued to rise, and many consumers continued to work with dealers and banks to finance or lease new cars and trucks. The compliance data from MY 2020 reflect the extent to which manufacturers successfully integrated additional fuel saving technology into their products, and the extent to which the market adopted the products offered.

While DOT staff used mid-MY 2020 compliance data as the basis for the Market Data file, the team often had to disaggregate compliance data to capture variation in curb weights, manufacturer suggested retail prices, and other market data fields that varied by trim level. As a result, the specific trim level sales volumes are estimates that reflect a mostly even distribution of sales volume as reported at the compliance level across sub-divisions. However, the combined compliance level reporting data are still reflected, exactly, in the Market Data file, when the atomized rows are aggregated. With respect to the luxury option content, and sales volumes of an individual trim level (to the extent that the Market Data file row volume reflects a disaggregated compliance row), the Market Data file can only go so far. However, the rows (and vehicle characteristics recorded) are well suited for use in the CAFE Model for projecting compliance pathways in response to regulatory alternatives.

2.2.1.1.2 Treatment of Confidential Business Information in Fleet Development

Some data in the Market Data file are informed by confidential business information. For instance, some mid-year manufacturer compliance submissions are marked as confidential. DOT staff occasionally considers confidential business information to assess vehicle engineering characteristics that, like rolling resistance and aerodynamic drag, are neither included in compliance data nor reliably available.

Prior to the 2018 NPRM, DOT staff gave manufacturers the opportunity to confidentially share rolling resistance values and drag coefficients. Manufacturers had commented extensively, in response to the Draft Technical Assessment Report (TAR), that their prior efforts to improve aerodynamics and tire rolling resistance had not been reasonably characterized in the Draft TAR Market Data file. Many manufacturers volunteered engineering data (aerodynamic drag coefficients, and tire rolling resistance values) to inform DOT staff, resulting in a more informed characterization of fuel saving technology already equipped on vehicles, and a more informed mapping of observed vehicles onto reference Argonne simulations and projected technology costs. However, this took place in 2017. The Market Data file for today's analysis still (in many cases) references previously submitted confidential business information, even though manufacturers may have integrated additional rolling resistance and aerodynamic technology over the past few years. DOT staff have supplemented the older confidential business information with recent studies and public information (as observed on specification sheets) when more recent, credible information is available. Generally, DOT recognizes benefits from referencing recent, credible information to inform the characterization of vehicles in the Market Data file and baseline fleet.

In addition, some transmission content, accessory efficiency improvements, and other vehicle technologies are difficult for DOT staff to objectively verify. As a practical matter, DOT cannot do a teardown study of every vehicle in the fleet every time staff produce a new analysis fleet. Agency staff use engineering judgement, and occasionally rely upon supplier, manufacturer, and Argonne's Advanced Mobility Technology Laboratory (AMTL)-presented information to inform the Market Data file.

2.2.1.2 Technology Classes in the Fleet

The Market Data file includes information the CAFE Model uses to connect each observed vehicle (per compliance data and DOT staff characterization of vehicle attributes, including fuel saving technologies), with estimates of the effectiveness of other possible combinations of fuel saving technologies, and prospective costs of those technologies. The "Technology Class" assigned in the Market Data file is the link the CAFE Model uses.

During the CAFE Model compliance simulations, the CAFE Model evaluates adding fuel saving technologies to each vehicle appearing in the Market Data file, at some projected fuel economy benefit. The CAFE Model references incremental effectiveness estimates, provided by Argonne with the Autonomie software, to project how the fuel efficiency of a vehicle may improve with the application of additional fuel saving technologies. For the CAFE Model to select the most relevant reference effectiveness estimate, informed by the catalogue of more-than-1-million Autonomie simulations, the Market Data file includes a reference "type" of vehicle (or "Technology class"), and the combination of fuel saving technologies already applied to that vehicle (technologies listed as "USED" on the vehicles, engines, and transmissions tabs of the Market Data file). With this information, the CAFE Model knows the reference point, and which effectiveness estimates to use, for vehicle as it progresses through the compliance simulations.

The CAFE Model considers costs of additional fuel saving technologies when forecasting which technologies manufacturers are likely to adopt in future scenarios. Costs of technologies can vary (sometimes significantly) by vehicle type. The "technologies" input file lists technology costs, and the CAFE Model uses the technology class (and engine class) in the Market Data file to lookup the most relevant technology costs for each vehicle, and fuel saving technology. The CAFE Model also references battery costs for electrification technologies (with battery costs derived from Argonne's BatPaC Model and Autonomie simulations), and these costs often vary significantly by technology class, and by combination of road load reducing technologies.

The algorithm by which each vehicle model/configuration is assigned to a technology class is a two-step process. First, a "size" of technology class is assigned to each nameplate; only the SmallCar, MedCar, SmallSUV, MedSUV, and Pickup classes are eligible to be assigned in this step. The algorithm then evaluates whether to assign the performance variant of the initial assignment to each vehicle within the nameplate. Performance variants include the SmallCarPerf, MedCarPerf, SmallSUVPerf, MedSUVPerf, and PickupHT classes.

The evaluations in both steps of the algorithm are conducted quantitatively using "fit scores," which are calculations that take into account key characteristics of vehicles in the fleet and compare those to the baseline characteristics of each technology class.[52] A vehicle receives a fit score for every technology class for which it is eligible. The lower the fit score, the more closely aligned a vehicle's characteristics are with the baseline characteristics for a given technology class. Therefore, the algorithm will assign the technology class with the lowest fit score to a given vehicle.

In the first step of the algorithm, the fit score used to assign the "size" of technology class evaluates each vehicle's footprint and curb weight according to Equation 2-1. (Both of these characteristics are recorded in the baseline fleet.) The difference in curb weight between the vehicle and the class baseline is divided by a "pounds per 1 second" quantity[53] that normalizes the equation such that curb weight and footprint are more equally weighted. Note that the equation is also weighted by the ratio of individual vehicle sales to total sales for the nameplate, so that the initial assignment favors higher-selling vehicle models. The MR0 curb weight is calculated as part of the mass reduction level assignment process.[54]

$$Size\ Fit\ Score = \frac{Vehicle\ Sales}{Nameplate\ Sales} \times \sqrt{\left(\frac{MR0\ Curb\ Weight}{Pounds\ per\ 1\ second} - \frac{Class\ Baseline\ Curb\ Weight}{Pounds\ per\ 1\ second}\right)^2 + (Vehicle\ footprint - Class\ Average\ Footprint)^2}$$

Equation 2-1 – Size Fit Score

In the second step, the fit score that evaluates the performance variant of the technology class as seen in Equation 2-2 takes a 0 to 60 miles per hour (mph) acceleration time into account.

$$Performance\ Fit\ Score = |\ (Vehicle\ estimated\ 0\ to\ 60\ mph\ acceleration\ time) - (Class\ Baseline\ 0\ to\ 60\ time)\ |$$

Equation 2-2 – Performance Fit Score

This characteristic is not consistently reported in publicly available data, so a 0 to 60 mph acceleration time for each vehicle is estimated based on its weight-to-horsepower ratio, calculated in Equation 2-3.

[52] Baseline 0 to 60 mph acceleration times are assumed for each technology class as part of the full vehicle simulations conducted in Autonomie. For more information, see Chapter 2.4 Technology Effectiveness Values. DOT staff calculated class baseline curb weights and footprints by averaging the curb weights and footprints of vehicles within each technology class as assigned in previous analyses.
[53] This quantity is calculated by multiplying the vehicle's horsepower by 2.744.
[54] For more information on how MR0 curb weight is calculated, see Chapter 3.4.2.

$$Vehicle\ estimated\ 0\ to\ 60\ time = \left(\frac{Vehicle\ curb\ weight\ [kg]}{Vehicle\ power\ [kW]} \times 0.5991\right) + 1.8514$$

Equation 2-3 – Vehicle Estimated 0 to 60 mph Acceleration Time

The Pickup and PickupHT classes are evaluated slightly differently. They use a different fit score calculation that considers the same vehicle characteristics as Equation 2-1, Equation 2-2, and Equation 2-3. The first step of the algorithm will initially assign the Pickup class if a vehicle has been assigned the "pickup" body style. The second step then assigns a fit score to Pickup and PickupHT that takes into account footprint, curb weight, and a 0 to 60 mph acceleration time, as seen in Equation 2-4.

$$Pickup\ Fit\ Score = \sqrt{\left(\frac{MR0\ Curb\ Weight}{Pounds\ per\ 1\ second} - \frac{Class\ Baseline\ Curb\ Weight}{Pounds\ per\ 1\ second}\right)^2 + (Vehicle\ footprint - Class\ Average\ Footprint)^2 + (Vehicle\ estimated\ 0\ to\ 60\ mph\ acceleration\ time - Class\ Baseline\ 0\ to\ 60\ mph\ acceleration\ time)^2}$$

Equation 2-4 – Pickup Fit Score

2.2.1.3 Fuel Saving Technology Content

The CAFE Model considers the application of many technologies to improve vehicle fuel economy. For each of these technologies, on each vehicle application, the CAFE Model needs reference cost and effectiveness values. Importantly, the CAFE Model must also consider which technologies are already equipped on vehicles in the baseline fleet, and the Market Data file includes this information.

The products offered in the U.S. automotive marketplace are highly heterogeneous, and manufacturers routinely update their products. Over time, some innovation efforts and investments in research and development can pay off, and manufacturers may bring to market new fuel saving technologies. The CAFE Model considers many technologies; some are nearly universally adopted in the MY 2020 fleet, some are used occasionally but show great future potential, and others have yet to be commercialized but are reasonable to include in the analysis based on reported activities in the supply chain and manufacturer interest. Similarly, costs of technologies in the future may be uncertain, but the analysis inputs assume that innovations will occur to lower the real costs of many fuel saving technologies over time. As manufacturers and suppliers bring technologies to market, intellectual property can significantly influence which manufacturers adopt technologies, and at what cost.[55] While every application of technology may have its own nuance, the CAFE Model effectiveness and cost assumptions attempt to represent a general characterization of fuel saving technologies that is a reasonable representation of the technology for any manufacturer.

[55] Ford. May 20, 2021. Ford News Media: *FORD COMMITS TO MANUFACTURING BATTERIES, TO FORM NEW JOINT VENTURE WITH SK INNOVATION TO SCALE NA BATTERY DELIVERIES.* https://media.ford.com/content/fordmedia/fna/us/en/news/2021/05/20/ford-commits-to-manufacturing-batteries.html. (Accessed: February 15, 2022).

If a technology is included in the analysis for possible application, the technology appears in the heading row of Market Data file, either on the vehicles tab, the engines tab, or the transmissions tab. The baseline fleet identifies which combination of modeled technologies most reasonably represents the fuel saving technologies on each vehicle in the compliance data. The fuel saving technologies considered in today's analysis are listed in Table 2-1.

Table 2-1 – Fuel Saving Technologies that the CAFE Model May Apply

Technology Name	Abbreviation	Market Data File Location	Technology Group
Electric Power Steering	EPS	Vehicles tab	Additional technologies
Improved Accessory Devices	IACC	Vehicles tab	Additional technologies
Start-Stop system	SS12V	Vehicles tab	Electrification
Belt Integrated Starter Generator	BISG	Vehicles tab	Electrification
Strong Hybrid Electric Vehicle, Parallel	SHEVP2	Vehicles tab	Electrification
Strong Hybrid Electric Vehicle, Power Split with Atkinson Engine	SHEVPS	Vehicles tab	Electrification
Strong Hybrid Electric Vehicle, Parallel with HCR0 Engine (Alternative path for Turbo Engine Vehicles)	P2HCR0	Vehicles tab	Electrification
Strong Hybrid Electric Vehicle, Parallel with HCR1 Engine (Alternative path for Turbo Engine Vehicles)	P2HCR1	Vehicles tab	Electrification
Strong Hybrid Electric Vehicle, Parallel with HCR1D Engine (Alternative path for Turbo Engine Vehicles)	P2HCR1D	Vehicles tab	Electrification
Strong Hybrid Electric Vehicle, Parallel with HCR2 Engine (Alternative path for Turbo Engine Vehicles)	P2HCR2	Vehicles tab	Electrification
Plug-in Hybrid Vehicle with Atkinson Engine and 20 miles of electric range	PHEV20	Vehicles tab	Electrification
Plug-in Hybrid Vehicle with Atkinson Engine and 50 miles of electric range	PHEV50	Vehicles tab	Electrification
Plug-in Hybrid Vehicle with TURBO1 Engine and 20 miles of electric range	PHEV20T	Vehicles tab	Electrification
Plug-in Hybrid Vehicle with TURBO1 Engine and 50 miles of electric range	PHEV50T	Vehicles tab	Electrification
Plug-in Hybrid Vehicle with Atkinson Engine and 20 miles of electric range (Alternative path for Turbo Engine Vehicles)	PHEV20H	Vehicles tab	Electrification
Plug-in Hybrid Vehicle with Atkinson Engine and 50 miles of electric range (Alternative path for Turbo Engine Vehicles)	PHEV50H	Vehicles tab	Electrification
Battery Electric Vehicle with 200 miles of range	BEV200	Vehicles tab	Electrification

Technology Name	Abbreviation	Market Data File Location	Technology Group
Battery Electric Vehicle with 300 miles of range	BEV300	Vehicles tab	Electrification
Battery Electric Vehicle with 400 miles of range	BEV400	Vehicles tab	Electrification
Battery Electric Vehicle with 500 miles of range	BEV500	Vehicles tab	Electrification
Fuel Cell Vehicle	FCV	Vehicles tab	Electrification
Low Drag Brakes	LDB	Vehicles tab	Additional technologies
Secondary Axle Disconnect	SAX	Vehicles tab	Additional technologies
Baseline Tire Rolling Resistance	ROLL0	Vehicles tab	Rolling Resistance
Tire Rolling Resistance, 10% Improvement	ROLL10	Vehicles tab	Rolling Resistance
Tire Rolling Resistance, 20% Improvement	ROLL20	Vehicles tab	Rolling Resistance
Baseline Aerodynamic Drag Technology	AERO0	Vehicles tab	Aerodynamic Drag
Aerodynamic Drag, 5% Drag Coefficient Reduction	AERO5	Vehicles tab	Aerodynamic Drag
Aerodynamic Drag, 10% Drag Coefficient Reduction	AERO10	Vehicles tab	Aerodynamic Drag
Aerodynamic Drag, 15% Drag Coefficient Reduction	AERO15	Vehicles tab	Aerodynamic Drag
Aerodynamic Drag, 20% Drag Coefficient Reduction	AERO20	Vehicles tab	Aerodynamic Drag
Baseline Mass Reduction Technology	MR0	Vehicles tab	Mass Reduction
Mass Reduction – 5.0% of Glider	MR1	Vehicles tab	Mass Reduction
Mass Reduction – 7.5% of Glider	MR2	Vehicles tab	Mass Reduction
Mass Reduction – 10.0% of Glider	MR3	Vehicles tab	Mass Reduction
Mass Reduction – 15.0% of Glider	MR4	Vehicles tab	Mass Reduction
Mass Reduction – 20.0% of Glider	MR5	Vehicles tab	Mass Reduction
Mass Reduction – 28.2% of Glider	MR6	Vehicles tab	Mass Reduction
Single Overhead Cam	SOHC	Engines tab	Basic Engines
Dual Overhead Cam	DOHC	Engines tab	Basic Engines
Engine Friction Reduction	EFR	Engines tab	Engine Improvements
Variable Valve Timing	VVT	Engines tab	Basic Engines
Variable Valve Lift	VVL	Engines tab	Basic Engines
Stoichiometric Gasoline Direct Injection	SGDI	Engines tab	Basic Engines
Cylinder Deactivation	DEAC	Engines tab	Basic Engines
Turbocharged Engine	TURBO1	Engines tab	Advanced Engines
Advanced Turbocharged Engine	TURBO2	Engines tab	Advanced Engines
Turbocharged Engine with Cooled Exhaust Gas Recirculation	CEGR1	Engines tab	Advanced Engines
Advanced Cylinder Deactivation	ADEAC	Engines tab	Advanced Engines
High Compression Ratio Engine (Atkinson Cycle)	HCR0	Engines tab	Advanced Engines
Advanced High Compression Ratio Engine (Atkinson Cycle)	HCR1	Engines tab	Advanced Engines

Technology Name	Abbreviation	Market Data File Location	Technology Group
Advanced High Compression Ratio Engine (Atkinson Cycle) with Cylinder Deactivation	HCR1D	Engines tab	Advanced Engines
High Compression Ratio Engine (Atkinson Cycle), with Cylinder Deactivation	HCR2	Engines tab	Advanced Engines
Variable Compression Ratio Engine	VCR	Engines tab	Advanced Engines
Variable Turbo Geometry Engine	VTG	Engines tab	Advanced Engines
Variable Turbo Geometry Engine with eBooster	VTGE	Engines tab	Advanced Engines
Turbocharged Engine with Cylinder Deactivation	TURBOD	Engines tab	Advanced Engines
Turbocharged Engine with Advanced Cylinder Deactivation	TURBOAD	Engines tab	Advanced Engines
Advanced Diesel Engine	ADSL	Engines tab	Advanced Engines
Advanced Diesel Engine with Improvements	DSLI	Engines tab	Advanced Engines
Advanced Diesel Engine with Improvements and Advanced Cylinder Deactivation	DSLIAD	Engines tab	Advanced Engines
Compressed Natural Gas Engine	CNG	Engines tab	Advanced Engines

Many of the technologies in the CAFE Model may be applied in combination. For instance, an engine and transmission may be selected independent of one another, and road load reducing technologies (mass reduction, aerodynamic drag, and rolling resistance) may be applied in any combination. Basic engine technologies may be applied in any combination. In the effectiveness estimates, some technologies have synergies, while others offer efficiency improvements from the same mechanism,[56] and therefore provide less benefit in combination than the sum of their efficiency improvements generated, independently.

Some technologies cannot appear together, on one vehicle (defined as a single row in the Market Data file), in the analysis. For instance, a vehicle may only have one advanced engine at a time. Similarly, battery electric vehicles do not have an internal combustion engine or a conventional transmission, and the costs projected for battery electric vehicles include the fixed drive gearbox that transmits the electric motor torque to the tires.

For additional information on the characterization of these technologies (including the cost, prevalence in the 2020 fleet, effectiveness estimates, and considerations for their adoption) see the appropriate technology section in Chapter 3.

2.2.1.4 AC and Off-Cycle Fuel Consumption Improvement Values

The Market Data file includes information about AC and off-cycle technologies, but the information is not currently broken out at a row level, vehicle by vehicle. Instead, historical data

[56] For example, SHEVP2 paired with advanced engine technologies. *See* Chapter 3.1.1 for further discussion.

(and forecast projections, which are used for analysis regardless of regulatory scenario) are listed by manufacturer, by fleet on the "Credits and Adjustments" tab of the Market Data file.

AC and off-cycle fuel consumption improvement values (FCIV), or credits,[57] significantly impact compliance pathways manufacturers choose. Chapter 3.8, Simulating Off-Cycle and AC Efficiency Technologies, shows model inputs specifying estimated adjustments (all in grams/mile) for improvements to air conditioner efficiency and other off-cycle energy consumption, and for reduced leakage of air conditioner refrigerants with high global warming potential. DOT estimated future values based on an expectation that manufacturers already relying heavily on these adjustments would continue do so, and that other manufacturers would, over time, also approach the limits on adjustments allowed for such improvements.

Regulatory provisions regarding off-cycle technologies are new, and manufacturers have only recently begun including related detailed information in compliance reporting data. For today's analysis, though, such information was not sufficiently complete to support a detailed representation of the application of off-cycle technology to specific vehicle model/configurations in the MY 2020 fleet.

2.2.1.5 Engine Configurations

Engine configurations may affect the cost of engine technologies. In that Market Data file, column "AE" on the vehicles tab lists the "Engine Technology Class," so the CAFE Model may reference the powertrain costs in the technologies file that most reasonably align with the observed vehicle (or row). DOT staff assign engine technology classes for all vehicles, including electric vehicles. If an electric powertrain replaces and internal combustion engine, the electric motor specifications may be different (and hence costs may be different) depending on the capabilities of the internal combustion engine it is replacing, and the costs in the technologies file (on the engine tab) account for the power output and capability of the gasoline or electric drivetrain.

2.2.1.6 Shared Engines, Transmissions, and Vehicle Platforms

Parts sharing across products is important, and common in the industry. Parts sharing helps manufacturers achieve economies of scale, deploy capital efficiently, and make the most of shared research and development expenses, while still presenting a wide array of consumer choices to the market. The CAFE Model takes part sharing into account, with shared engines, shared transmissions, and shared mass reduction platforms. Vehicles sharing a part (as recognized in the CAFE Model), will adopt fuel saving technologies affecting that part together.

In the Market Data file used as an input to the CAFE Model, vehicle model/configurations that share engines are assigned the same engine code,[58] vehicle model/configurations that share

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[57] Adjustments to a vehicle's fuel economy value based on off-cycle technologies are termed fuel consumption improvement values in NHTSA's program because they increase the rated fuel economy of a vehicle, whereas the off-cycle benefits are called credits in the EPA program.
[58] Engines (or transmissions) may not be exactly identical, as specifications or vehicle integration features may be different. However, the architectures are similar enough that it is likely the powertrain systems share R&D, tooling, and production resources in a meaningful way.

transmissions have the same transmission code, and vehicles that adopt mass reduction technologies together share the same platform. For more information about engine codes, transmission codes, and mass reduction platforms, see subsections in Chapter 3, Technology Pathways, Effectiveness, and Cost.

2.2.1.7 Product Design Cycles

Manufacturers often introduce fuel saving technologies at a major redesign of their product or adopt technologies at minor refreshes in between major product redesigns. In most cases, the CAFE Model may apply new fuel saving technologies to a vehicle only in redesign years. If a vehicle shares an engine or transmission, and the shared powertrain part has already incorporated additional fuel savings technology on other vehicle applications, the vehicle may inherit the upgraded shared engine or transmission at refresh or redesign.

To support the CAFE Model accounting for new fuel saving technology introduction as it relates to product lifecycle, the Market Data file includes a projection of redesign years (column "BN") and refresh years (column "BO") for each vehicle. DOT staff projected future redesign years and refresh years based on the historical cadence of that vehicle's product lifecycle. For new nameplates, DOT staff considered the manufacturer's treatment of product lifecycles for past products in similar market segments.

Table 2-2 – Sales Distribution by Age of Vehicle Engineering Design

Most Recent Engineering Redesign Model Year of the Observed MY 2020 Vehicle	% of MY 2020 Fleet (Unit Sales) by Engineering Design Age	Portion of the Analysis Fleet Observations MY 2020 Fleet by Engineering Design Age	Age of Vehicle Engineering Design	Portion of MY 2020 New Vehicle Sales with Engineering Designs as New or Newer than "Age of Vehicle Engineering Design"
2007	0.6%	0.7%	13	100.0%
2008	0.1%	0.4%	12	99.4%
2009	1.1%	5.1%	11	99.3%
2010	0.0%	0.0%	10	98.2%
2011	2.4%	1.0%	9	98.2%
2012	0.4%	0.6%	8	95.8%
2013	2.4%	2.3%	7	95.4%
2014	5.4%	6.0%	6	93.0%
2015	9.8%	16.7%	5	87.7%
2016	11.7%	9.3%	4	77.9%
2017	9.8%	11.6%	3	66.2%
2018	16.4%	12.2%	2	56.4%
2019	24.0%	25.3%	1	40.0%
2020	15.9%	8.8%	0	15.9%

Redesigns are major investments, and require coordination of product development, manufacturing, and marketing and sales. Many manufacturers have redesigned a large portion of products sold in MY 2020 recently, as shown in Table 2-2.

Manufacturers have different business strategies with respect to how frequently products are redesigned. Some manufacturers use shorter product cycles, and others use longer product cycles. Some manufacturers may use a shorter redesign cycle in one segment, and a longer redesign cycle in another. On average across the industry, manufacturers redesign vehicles every 6.5 years, as shown in Table 2-3. Note that many manufacturers do not compete in the marketplace in every vehicle segment.

Table 2-3 – Summary of Sales Weighted Average Time between Engineering Redesigns, by Manufacturer, by Vehicle Technology Class

Manufacturer	SmallCar	SmallCarPerf	MedCar	MedCarPerf	SmallSUV	SmallSUVPerf	MedSUV	MedSUVPerf	Pickup	PickupHT	All Classes
BMW	5.6	6.1	6.3	6.5	-	6.2	-	6.2	-	-	6.2
Daimler	-	5.8	6.3	6.4	10.0	6.9	6.9	8.2	-	-	7.1
FCA	7.0	6.8	-	8.2	8.1	8.2	8.8	8.9	9.0	10.0	9.0
Ford	-	-	6.2	6.6	7.6	6.6	6.0	6.9	5.5	6.0	6.6
GM	6.1	6.0	5.0	6.6	7.0	7.2	8.2	7.5	7.5	5.3	6.6
Honda	6.7	5.8	4.9	5.0	5.2	5.1	-	5.9	7.0	-	5.5
Hyundai Kia-H	5.5	4.9	5.0	6.1	5.4	5.1	-	6.0	-	-	5.3
Hyundai Kia-K	4.9	5.9	5.3	5.5	6.6	6.3	-	6.4	-	-	5.8
JLR	-	7.8	-	6.9	6.2	6.1	7.0	6.5	-	-	6.5
Mazda	8.0	6.2	4.8	-	5.2	5.0	7.0	-	-	-	5.5
Mitsubishi	9.7	-	-	-	6.0	6.0	-	-	-	-	6.6
Nissan	6.4	8.2	5.5	6.8	6.2	5.9	-	9.2	8.3	10.5	6.6
Subaru	4.9	5.3	6.0	6.0	5.0	5.0	-	5.0	-	-	5.0
Tesla	-	-	-	5.6	-	-	-	5.6	-	-	5.6
Toyota	5.1	5.3	6.1	5.9	6.2	5.7	6.0	6.7	10.3	9.4	6.5
Volvo	-	10.0	8.0	8.0	8.0	8.0	-	7.4	-	-	7.7
VWA	5.5	6.8	7.4	7.2	7.1	7.5	7.1	7.2	-	-	6.9
TOTAL	5.5	5.6	5.6	6.5	6.2	6.4	6.9	7.3	8.2	7.1	6.5

Even for manufacturers with similar times between redesigns, offering products in similar segments, the expected timing of product redesigns are often out of phase. When considering year-by-year analysis of standards, the timing of redesigns and the timing between redesigns often affect projected compliance pathways. As shown in Table 2-4, many manufacturers have very recently redesigned significant products, and will have some time before they are expected to redesign these products again. The timing of redesigns, and the duration between redesigns affect how quickly manufacturers may respond to standards.

Table 2-4 – Summary of Sales Weighted Average Age of Engineering Design in MY 2020 by Manufacturer, by Vehicle Technology Class

Manufacturer	SmallCar	SmallCarPerf	MedCar	MedCarPerf	SmallSUV	SmallSUVPerf	MedSUV	MedSUVPerf	Pickup	PickupHT	All Classes
BMW	0.8	1.4	4.3	4.4	-	3.9	-	2.4	-	-	3.2
Daimler	-	2.7	2.5	4.2	8.0	4.4	1.5	2.1	-	-	3.4
FCA	6.0	4.7	-	8.2	3.4	0.5	3.5	5.0	1.3	2.9	3.9
Ford	-	-	0.2	3.8	1.8	0.0	2.0	1.7	1.6	5.0	2.5
GM	5.2	2.6	3.9	2.5	2.9	1.9	1.9	2.7	3.4	1.1	2.5
Honda	4.3	4.1	2.3	2.9	3.2	1.0	-	3.6	3.0	-	3.2
Hyundai Kia-H	2.5	2.9	0.0	3.6	2.2	1.0	-	0.0	-	-	2.0
Hyundai Kia-K	1.3	2.8	1.0	1.8	5.7	6.0	-	0.1	-	-	2.6
JLR	-	6.0	-	3.2	3.0	1.6	6.0	4.1	-	-	3.6
Mazda	2.0	3.7	0.0	-	0.1	0.0	1.0	-	-	-	0.8
Mitsubishi	5.0	-	-	-	4.0	4.0	-	-	-	-	4.2
Nissan	0.1	5.0	1.0	4.4	4.7	4.1	-	6.5	6.0	4.0	3.5
Subaru	3.0	4.3	0.0	0.0	0.9	0.0	-	1.0	-	-	1.2
Tesla	-	-	-	1.0	-	-	-	1.0	-	-	1.0
Toyota	1.6	1.5	2.0	1.7	2.3	2.6	0.0	4.4	4.1	13.0	2.9
Volvo	-	9.0	1.0	1.4	1.0	1.0	-	2.7	-	-	2.1
VWA	1.2	3.5	0.7	1.9	1.8	4.0	1.4	1.6	-	-	2.1
TOTAL	1.8	3.2	1.7	3.4	2.7	2.4	1.5	3.1	3.2	3.4	2.8

Table 2-5 shows the resultant portion of each manufacturers MY 2020 total light-duty vehicle production volume (for the U.S. market) expected to be redesigned in each MY through 2029.

Table 2-5 – Portion of Production Redesigned in Each MY Through 2029

Name	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029
BMW	13%	25%	37%	13%	7%	14%	4%	39%	21%	7%
Daimler	0%	9%	19%	22%	17%	8%	23%	7%	13%	10%
Stellantis (FCA)	14%	6%	21%	7%	0%	0%	23%	13%	16%	2%
Ford	41%	27%	9%	12%	9%	2%	41%	27%	9%	8%
GM	2%	9%	12%	3%	30%	24%	20%	16%	7%	26%
Honda	0%	5%	63%	22%	7%	4%	2%	34%	52%	5%
Hyundai	22%	25%	16%	6%	32%	11%	35%	19%	2%	23%
Kia	35%	25%	0%	0%	60%	12%	5%	3%	39%	26%
Jaguar - Land Rover	7%	0%	13%	30%	35%	14%	7%	0%	0%	25%
Mazda	68%	3%	0%	13%	7%	63%	14%	0%	0%	16%
Mitsubishi	0%	0%	0%	0%	0%	100%	0%	0%	0%	0%
Nissan	14%	26%	24%	10%	22%	10%	1%	22%	21%	35%
Subaru	32%	5%	11%	16%	36%	27%	10%	11%	16%	36%
Tesla	0%	0%	0%	0%	100%	0%	0%	100%	0%	0%
Toyota	6%	5%	17%	8%	52%	2%	16%	6%	11%	36%
Volvo	0%	0%	0%	32%	0%	1%	2%	64%	0%	0%
VWA	13%	0%	10%	2%	31%	38%	10%	5%	8%	19%
Average	15%	12%	19%	10%	25%	12%	18%	18%	16%	20%

2.2.2 Characterizing Baseline Safety, Economic, and Compliance Positions

In addition to characterizing technologies, some information in the Market Data file supports economic calculations in the CAFE Model.

2.2.2.1 Safety Classes

The CAFE Model considers the potential safety effect of mass reduction technologies and crash compatibility of different vehicle types. Mass reduction technologies lower the vehicle's curb weight, which may change crash compatibility and safety, depending on the type of vehicle. DOT staff assign each vehicle in the Market Data file a "Safety class" (in column "AG" on the vehicles tab) that best aligns with the mass-size-safety analysis.

Baseline curb weight data, as recorded in the Market Data file, factor into the mass-size-safety analysis. In nearly all cases, DOT staff sourced curb weight data appearing in the Market Data file from manufacturer specification sheets. The curb weight data on the specification sheets may be generally representative of the weight of a vehicle row, but some deviation from that reported curb weight is expected depending on the option content of represented vehicles, and manufacturing variations.

2.2.2.2 Labor and Modeled Vehicles

The CAFE Model includes procedures to consider the direct labor impacts of manufacturer's response to CAFE regulations, considering the assembly location of vehicles, engines, and transmissions, the percent U.S. content (that reflects percent U.S. and Canada content),[59] and the dealership employment associated with new vehicle sales. Baseline labor information, by vehicle, is included in the Market Data input file. Sales volumes included in and adapted from the market data also influence total estimated direct labor projected in the analysis.

For the duration of the analysis, the percent U.S. content is held constant for each vehicle row. In practice, this may not be the case. Changes to trade policy and tariff policy may affect percent U.S. content in the future. Also, some technologies may be more or less likely to be produced in the United States, and if that is the case, their adoption could affect future U.S. content.

The labor hours projected in the Market Data file per unit transacted at dealerships, per unit produced for final assembly, per unit produced for engine assembly, and per unit produced for transmission assembly are projected to remain constant for the duration of the analysis, and the origin of these activities is projected to remain unchanged. In practice, it is reasonable to expect that plants could move locations, or engine and transmission technologies are replaced by another fuel saving technology (like electric motors and fixed gear boxes) that could require a meaningfully different amount of assembly labor hours.

Table 2-6 – Sales Weighted Percent U.S. Content by Manufacturer, by Regulatory Class

Manufacturer	PC	LT	Total MY 2020 Sales Weighted Percent U.S. Content	Portion of Vehicles Assembled in the U.S.	Portion of Engines Assembled in the U.S.	Portion of Transmissions Assembled in the U.S.
BMW	7.1%	29.3%	15.4%	42.4%	0.0%	0.0%
Daimler	19.1%	36.2%	28.1%	41.2%	39.8%	0.0%
FCA	47.7%	52.9%	52.2%	68.0%	41.3%	45.7%
Ford	35.2%	47.5%	44.2%	83.4%	32.9%	88.5%
GM	39.8%	47.0%	44.7%	68.3%	69.8%	86.1%
Honda	55.8%	61.7%	58.3%	74.9%	85.9%	58.6%
Hyundai Kia-H	21.8%	0.0%	19.4%	46.0%	46.0%	34.3%
Hyundai Kia-K	12.8%	33.3%	20.7%	38.4%	17.2%	37.8%
JLR	2.6%	6.3%	6.2%	0.0%	0.0%	31.7%
Mazda	1.1%	1.1%	1.1%	0.0%	0.0%	0.0%
Mitsubishi	0.0%	0.3%	0.2%	0.0%	0.0%	0.0%
Nissan	29.0%	32.6%	30.1%	49.9%	47.5%	0.0%
Subaru	35.5%	22.9%	25.6%	53.2%	0.0%	0.0%

[59] Percent U.S. content was informed by the 2020 Part 583 American Automobile Labeling Act Reports, appearing on NHTSA's website.

Tesla[60]	50.6%	50.0%	50.6%	100.0%	100.0%	100.0%
Toyota	35.2%	42.7%	38.7%	42.4%	46.0%	19.4%
Volvo	10.2%	1.1%	3.4%	12.4%	0.0%	0.0%
VWA	10.3%	8.8%	9.4%	13.5%	0.0%	0.0%
TOTAL	32.4%	41.2%	37.4%	57.1%	44.1%	44.1%

As observed from Table 2-6, manufacturers employ U.S. labor with varying intensity. In many cases, vehicles certifying in the light truck (LT) regulatory class have a larger percent U.S. content than vehicles certifying in the passenger car (PC) regulatory class.

2.2.2.3 Credit Banks

Manufacturers may over-comply with CAFE standards and bank so-called over compliance credits. As discussed further in preamble Section III.C.7, manufacturers may use these credits later, sell them to other manufacturers, or let them expire. The CAFE Model does not explicitly trade credits between and among manufacturers, but analysts have adjusted starting credit banks to reflect trades that are likely to happen when the simulation begins (in MY 2020). Considering information manufacturers have reported regarding compliance credits, and considering recent manufacturers' compliance positions, DOT staff have estimated manufacturers' potential use of compliance credits in earlier model years. This aligns to an extent that represents how manufacturers could deplete their credit banks rather than producing high volume vehicles with fuel saving technologies in earlier model years. This also avoids unrealistic application of technologies for manufacturers in early analysis years that typically rely on credits. These assumptions are included in the Market Data input file.

To estimate the size and potential disposition of manufacturer's CAFE compliance credit banks, staff make use of data in NHTSA's CAFE Public Information Center (PIC), which provides public access to a range of information regarding the CAFE program,[61] including manufacturers' credit balances. However, there is a data lag in the information presented on the CAFE PIC that may not capture credit actions across the industry for as much as several months. To address the limitations of the publicly available data, DOT staff examined preliminary compliance data for each manufacturer's fleets in MYs 2018 and 2019, as well as verified credit transactions between manufacturers that have been reported to NHTSA. From these sources, staff estimated compliance deficits or surpluses for each fleet based on fuel economy performance, then combined those estimates with credits either acquired from another manufacturer or traded from a model year fleet's surplus.

CAFE credits that are traded between manufacturers are adjusted to preserve the gallons saved that each credit represents.[62,63] The adjustment occurs at the time of application rather than at

[60] Tesla does not have internal combustion engines, or multi-speed transmissions, even though they are identified as producing engine and transmission systems in the United States in the Market Data file.
[61] CAFE Public Information Center, https://one.nhtsa.gov/cafe_pic/home. (Accessed: February 15, 2022).
[62] *See* 49 U.S.C. 32903(f), which requires the credit trading program preserve total oil savings.
[63] CO_2 credits for EPA's program are denominated in metric tons of CO_2 rather than gram/mile compliance credits and require no adjustment when traded between manufacturers or fleets.

the time the credits are traded. This means that a manufacturer that has acquired credits through trade, but has not yet applied them, may show a credit balance that is either considerably higher or lower than the real value of the credits when they are applied. For example, a manufacturer that buys 40 million credits from Tesla may show a credit balance in excess of 40 million. However, when those credits are applied, they may be worth only 1/10 as much—making that manufacturer's true credit balance closer to 4 million than 40 million.

In order to accurately determine each manufacturer's current credit position – inclusive of earned credits (or deficits), acquired credits that have not yet been applied, or transferred credits that have not yet been applied – DOT adjusted each credit transaction to reflect the true value of the credit in the current model year and fleet where it resides.[64] Staff reevaluated existing compliance positions for MYs 2017-2019 after adjusting credit values and used analyst judgment to resolve deficits in those years. The CAFE program allows manufacturers to pay civil penalties for non-compliance; however, manufacturers cannot comply with the minimum domestic passenger car standard with transferred credits,[65] so a manufacturer must pay civil penalties if it fails to meet that standard. Credits can then be applied to any remaining deficit between the domestic car fleet CAFE and the calculated standard. However, in most other instances, manufacturers have preferred to apply credits when possible. Credits expire five years after they are earned, so in MY 2018 (for example) expiring credits would have been earned in MY 2013. Manufacturers typically find trading partners for expiring credits, and we let no expiring credits go unused if there were opportunities to resolve deficits in MYs 2018 and 2019.

Some manufacturers faced deficits in the MYs prior to 2020 that had not yet been resolved, despite holding positive credit balances (of mostly traded credits). These credits were also applied, where appropriate to resolve compliance deficits – including transfers between fleets and credit carry-forward from older model years. In a small number of cases, we assume some small amount of fine payment (aside from the minimum domestic standard) would be required to resolve deficits. All of these actions were required to estimate credit banks in MYs 2015-2019 across the industry because all of those credits can be carried forward into the analysis – beginning with MY 2015 credits that expire in MY 2020 and can be used to offset compliance deficits in the first year of the simulation.

Staff reviewed credit balances, estimated the potential that some manufacturers could trade credits based on their projected compliance positions in the No-Action Alternative, and developed inputs that make carried-forward credits available in each of MYs 2020-2024, after subtracting credits assumed to be traded to other manufacturers, adding credits assumed to be acquired from other manufacturers through such trades, and adjusting any traded credits (up or down) to reflect their true value for the fleet and model year into which they were traded.[66] When identifying trading partners for credit transactions, staff examined hundreds of individual credit transactions that have occurred over the last decade and attempted to avoid trading credits

[64] Because compliance credits are specific to the model year and fleet in which they are earned, even if they are traded between manufacturers, traded credits must be traded *into* a specific model year and fleet.
[65] 49 U.S.C. 32903(g)(4).
[66] The adjustments, which are based upon the CAFE standard and model year of both the party originally earning the credits and the party applying them, were implemented assuming the credits would be applied to the model year in which they were set to expire. For example, credits traded into a domestic passenger car fleet for MY 2017 were adjusted assuming they would be applied in the domestic passenger car fleet for MY 2022.

between manufacturers that have not previously traded. While the specific transactions are considered confidential business information, manufacturers report to NHTSA the fleet and model year in which the credits were earned, the fleet and model year into which they are traded, and the (unadjusted) quantity of traded credits. DOT staff took a conservative approach, preserving credits in a manufacturer's bank for future use if it was forced to take aggressive compliance actions (defined as applying technologies that did not "pay back" for new car buyers in the first three years of ownership). This ensures that the CAFE Model has the maximal ability to balance the need for technology application against the need to minimize compliance costs in the early years of the program for manufacturers who have accumulated compliance credits.

Manufacturers' estimated credit banks for the domestic car, imported car, and light truck fleets are shown below. While the CAFE Model will transfer expiring credits into another fleet (e.g., moving expiring credits from the domestic car credit bank into the light truck fleet), staff moved some of these credits into the initial banks to improve the efficiency of application and both to reflect better the projected shortfalls of each manufacturer's regulated fleets and to represent observed behavior. For context, a manufacturer that produces one million vehicles in a given fleet, and experiences a shortfall of 2 mpg, would need 20 million credits, adjusted for fuel savings, to offset the shortfall completely.

Table 2-7 – Estimated Domestic Car CAFE Credit Banks

	MY 2015	MY 2016	MY 2017	MY 2018	MY 2019
BMW	-	-	-	-	
Daimler	-	-	-	-	
FCA	-	3,808,660	7,463,700	6,904,300	6,710,380
Ford	7,089,840	-	-	-	-
GM	-	-	20,648,600	10,107,600	9,624,540
Honda	-	-	-	-	-
Hyundai Kia-H	-	-	-	-	
Hyundai Kia-K	-	-	-	-	-
JLR	-	-	-	-	-
Mazda	-	-	-	-	-
Mitsubishi	-	-	-	-	-
Nissan	62,285,000	29,295,800	20,845,700	-	-
Subaru	-	-	-	-	-
Tesla	-	-	-	-	-
Toyota	2,328,440	875,292	-	1,237,920	16,900,300
Volvo	-	-	-	-	-
VWA	2,769,080	2,953,040	2,198,680	2,621,610	2,843,660

Table 2-8 – Estimated Imported Car CAFE Credit Banks

	MY 2015	MY 2016	MY 2017	MY 2018	MY 2019
BMW	9,084,950	2,418,490	-	-	-
Daimler	5,080,630	698,678	-	7,799,040	-
FCA	11,545,600	11,685,400	5,504,460	5,416,840	5,368,870
Ford	-	-	6,163,920	519,456	-
GM	1,304,200	-	5,970,840	-	-

	MY 2015	MY 2016	MY 2017	MY 2018	MY 2019
Honda	-	-	2,073,250	1,527,830	-
Hyundai Kia-H	-	8,901,780	-	-	-
Hyundai Kia-K	3,565,710	3,940,200	3,093,680	4,362,850	389,371
JLR	3,701,660	3,587,060	4,117,450	4,460,500	-
Mazda	-	14,670,500	1,825,340	2,873,730	-
Mitsubishi	640,530	-	1,781,950	1,518,710	-
Nissan	3,522,070	473,522	-	-	-
Subaru	8,874,730	10,618,700	10,388,800	10,861,200	-
Tesla	-	-	-	-	-
Toyota	-	-	3,458,500	159,407	5,336,410
Volvo	219,505	-	-	48,354	-
VWA	-	8,880,780	-	-	-

Table 2-9 – Estimated Light Truck CAFE Credit Banks

	MY 2015	MY 2016	MY 2017	MY 2018	MY 2019
BMW	480,144	-	-	-	-
Daimler	-	-	-	-	
FCA	-	-	7,266,830	13,540,000	6,019,540
Ford	-	-	-	-	11,227,400
GM	-	107,249	1,338,560	-	-
Honda	-	-	-	-	-
Hyundai Kia-H	-	-	883,431	-	101,044
Hyundai Kia-K	-	-	-	-	-
JLR	3,535,400	3,533,360	1,871,660	4,318,390	-
Mazda	1,260,690	4,289,380	1,116,210	1,150,140	640,075
Mitsubishi	232,985	470,352	640,211	136,052	-
Nissan	3,851,010	-	-	-	-
Subaru	2,068,050	1,082,840	4,412,450	2,524,660	8,440,450
Tesla	-	-	-	-	-
Toyota	9,198,200	9,891,330	10,286,800	6,173,270	-
Volvo	-	-	943,100	1,981,480	1,158,000
VWA	2,790,830	3,588,920	4,038,400	-	-

The CAFE Model includes a similar representation of existing credit banks in EPA's CO_2 program. As discussed in Chapter 1, today's analysis accounts for the combined effects of CAFE standards, federal CO_2 standards, ZEV mandates, and the CARB/OEM "Framework Agreements" that specifies *de facto* federal CO_2 standards for participating manufacturers. While the life of a CO_2 credit, denominated in metric tons of CO_2, has a five-year life, matching the lifespan of CAFE credits, such credits earned in the early MY 2009-2011 years of the EPA program, may be used through MY 2021.[67] As inputs to today's analysis, staff developed the CO_2 compliance credit banks presented below for manufacturers' passenger car (unlike EPCA,

[67] In the 2010 rule, EPA placed limits on credits earned in MY 2009, which expired prior to this rule. However, credits generated in MYs 2010-2011 may be carried forward, or traded, and applied to deficits generated through MY 2021.

the CAA does not require EPA to differentiate between domestic and imported cars) and light truck fleets.

Table 2-10 – Estimated Passenger Car CO_2 Credit Banks (metric tons)

	MY 2015	MY 2016	MY 2017	MY 2018	MY 2019
BMW	1,300,000	835,000	1200000	940,000	1,200,000
Daimler	1,950,000	1,300,000	1,300,000	1,500,000	1,300,000
FCA	3,200,000	1,800,000	2,000,000	2,000,000	1,500,000
Ford	3,000,000	6,300,000	-	-	-
GM	3,600,000	3,800,000	2,100,000	3,500,000	-
Honda	4,000,000	3,000,000	2,500,000	2,200,000	2,300,000
Hyundai Kia-H	3,700,000	3,200,000	2,000,000	1,900,000	100,000
Hyundai Kia-K	1,200,000	-	-	-	-
JLR	50,000	50,000	70,000	50,000	50,000
Mazda	1,500,000	2,500,000	170,000	165,000	-
Mitsubishi	330,000	300,000	171,000	200,000	53,000
Nissan	2,300,000	2,000,000	650,000	-	-
Subaru	1,500,000	1,500,000	500,000	100,000	2,000,000
Tesla	-	-	-	-	-
Toyota	-	-	-	-	-
Volvo	225,000	225,000	330000	270000	300,000
VWA	1,250,000	1,350,000	2,000,000	2,050,000	2,100,000

Table 2-11 – Estimated Light Truck CO_2 Credit Banks (metric tons)

	MY 2015	MY 2016	MY 2017	MY 2018	MY 2019
BMW	-	-	-	-	-
Daimler	1,150,000	950,000	1,050,000	580,000	650,000
FCA	5,950,000	7,900,000	2,700,000	8,000,000	9,500,000
Ford	-	-	-	-	-
GM	5,050,000	550,000	-	2,000,000	-
Honda	4,000,000	3,000,000		2,000,000	
Hyundai Kia-H	600,000	1,000,000	850,000	600,000	700,000
Hyundai Kia-K	1,300,000	-	-	-	-
JLR	950,000	900,000	700,000	450,000	480,000
Mazda	500,000	2,000,000	170,000	-	-
Mitsubishi	105,000	170,000	-	-	-
Nissan	2,000,000	2,000,000	-	-	-
Subaru	500,000	2,500,000	-	-	500,000
Tesla	-	-	-	-	-
Toyota	5,000,000	5,000,000	1,900,000	2,100,000	1,600,000
Volvo	-	-	943,100	1,981,480	1,158,000
VWA	2,790,830	3,588,920	4,038,400	-	-

While the CAFE Model does not simulate the ability to trade credits between manufacturers, it does simulate the strategic accumulation and application of compliance credits, as well as the ability to transfer credits between fleets to improve the compliance position of a less efficient fleet by leveraging credits earned by a more efficient fleet. The model prefers to hold on to earned compliance credits within a given fleet, carrying them forward into the future to offset potential future deficits. This assumption is consistent with observed strategic manufacturer behavior dating back to 2009.

From 2009 to present, no manufacturer has transferred CAFE credits into a fleet to offset a deficit in the same year in which they were earned. This has occurred with credits acquired from other manufacturers via trade but not with a manufacturer's own credits. Therefore, the current representation of credit transfers between fleets—where the model prefers to transfer expiring, or soon-to-be-expiring credits rather than newly earned credits—is both appropriate and consistent with observed industry behavior.

This may not be the case for CO_2 standards, though it is difficult to be certain at this point. The CO_2 program seeded the industry with a large quantity of early compliance credits (earned in MYs 2009-2011[68]) prior to the existence formal CO_2 standards. Early credits from MYs 2010 and 2011, however, do not expire until 2021. Thus, for manufacturers looking to offset deficits, it is more sensible to exhaust credits that were generated during later model years (which are set to expire within the next five years), rather than relying on the initial bank of credits from MYs 2010 and 2011. Considering that under the CO_2 program manufacturers simultaneously comply with passenger car and light truck fleets, to more accurately represent the CO_2 credit system the CAFE Model simulates (and, in effect, encourages) intra-year transfers between regulated fleets for the purpose of simulating compliance with the CO_2 standards.

2.2.2.4 Civil Penalty Payment Preferences

EPCA requires that if a manufacturer does not achieve compliance with a CAFE standard in a given model year and cannot apply credits sufficient to cover the compliance shortfall, the manufacturer must pay civil penalties (i.e., fines) to the federal government. Some manufacturers have sometimes elected to pay civil penalties rather than achieving compliance with CAFE standards. Until recently, such penalties were assessed at $5.50 per 0.1 mpg of residual shortfall (i.e., after applying compliance credits) per vehicle in the noncompliance fleet with the penalty rate being adjusted to $14 for model years 2019 through 2021 and to $15 beginning in model year 2022. Additional adjustments to the rate will be assessed annually as required by law and otherwise as appropriate. If inputs indicate that a manufacturer treats civil penalty payment as an economic choice (i.e., one to be taken if doing so would be economically preferable to applying further technology toward compliance), the CAFE Model, when evaluating the manufacturer's response to CAFE standards in a given model year, will apply fuel-saving technology only up to the point beyond which doing so would be more expensive (after subtracting the value of avoided fuel outlays) than paying civil penalties.

For today's analysis, DOT has exercised the CAFE Model with inputs treating all manufacturers as treating civil penalty payment as an economic choice through model year 2023. While DOT expects that only manufacturers with some history of paying civil penalties would actually treat penalty payment as an acceptable option, the CAFE Model does not currently simulate

[68] In response to public comment, EPA eliminated the possible use of credits earned in MY 2009 for future model years. However, credits earned in MY 2010 and MY 2011 remain available for use.

compliance credit trading between manufacturers, and DOT expects that this treatment of penalty payment will serve as a reasonable proxy for compliance credit purchases some manufacturers might actually make through model year 2023. These input assumptions for model years through 2023 reduce the potential that the model will overestimate technology application in the model years leading up to those for which the agency is finalizing new standards. As in past CAFE rulemaking analyses (except that supporting the 2020 final rule), DOT has treated manufacturers with some history of fine payment (i.e., BMW, Daimler, FCA, Jaguar-Land Rover, Volvo, and Volkswagen) as continuing to treat civil penalty payment as an acceptable option beyond model year 2023, but has treated all other manufacturers as unwilling to do so beyond model year 2023.

2.2.2.5 Payback

The CAFE Model uses an "effective cost" metric to evaluate options to apply specific technologies to specific engines, transmissions, and vehicle model configurations. Expressed on a $/gallon basis, this metric is computed by subtracting the estimated values of avoided fuel outlays and civil penalties from the corresponding technology costs and dividing the result by the quantity of avoided fuel consumption. The value of fuel outlays is computed over a "payback period" representing the manufacturer's expectation that the market will be willing to pay for some portion of fuel savings achieved through higher fuel economy. Once the model has applied enough technology to a manufacturer's fleet to achieve compliance with CAFE standards (and CO_2 standards and ZEV mandates) in a given model year, the model will apply any further fuel economy improvements estimated to produce a negative effective cost (i.e., any technology applications for which avoided fuel outlays during the payback period are larger than the corresponding technology costs). As discussed above in Chapter 1 and below in Chapter 3, DOT staff anticipate that manufacturers are likely to act as if the market is willing to pay for avoided fuel outlays expected during the first 30 months of vehicle operation.

2.2.2.6 Zero Emissions Vehicles

When considering other standards that may affect fuel economy compliance pathways, DOT included projected ZEVs that would be required for manufacturers to meet standards in California and Section 177 states, per the waiver granted under the Clean Air Act.

To support the inclusion of the ZEV program in the analysis, DOT staff identified specific vehicle model/configurations that could adopt BEV technology in response to the ZEV program, independent of CAFE standards, at the first redesign. These ZEVs are identified in the Market Data file as future BEV200s, BEV300s, or BEV400s. Not all announced BEV nameplates appear in the MY 2020 Market Data file; in these cases, in consultation with NHTSA and CARB, DOT staff used the volume from a comparable vehicle in the manufacturer's Market Data file portfolio as a proxy.[69] The Market Data file also includes information about the portion of each manufacturer's sales that occur in California and Section 177 states, which is helpful for determining how many ZEV credits each manufacturer will need to generate in the future to

[69] While manufacturers may introduce BEVs that are entirely new designs, staff anticipate that simulating BEVs as new versions of existing vehicle model/configurations should represent these designs reasonably for purposes of this analysis, given that CAFE Model inputs should account reasonably for electric powertrains supplanting conventional powertrains.

comply with the ZEV program with their own portfolio in the 2025 timeframe. These new procedures are described in more detail in Chapter 2.3.

2.2.2.7 California Agreements

In 2020, five vehicle manufacturers reached a voluntary commitment with the State of California to lower GHG emissions of their future nationwide fleets above and levels required by the 2020 final rule. For this analysis, compliance with this agreement is in the baseline case for designated manufacturers. The Market Data input file contains inputs indicating whether each manufacturer has committed to exceed federal requirements per this agreement.

2.3 Simulating the Zero Emissions Vehicle Program

California's ZEV program is one part of a program of coordinated standards that the California Air Resources Board (CARB) has enacted to control emissions of criteria pollutants and greenhouse gas emissions from vehicles. The program began in 1990, within the low-emission vehicle (LEV) regulation,[70] and has since expanded to include eleven other states.[71] [72] These states are usually referred to as Section 177 states, in reference to Section 177 of the Clean Air Act,[73] but it is important to note that not all Section 177 states have adopted the ZEV program component.[74] In the following discussion of the incorporation of the ZEV program into the CAFE Model, any reference to the Section 177 states refers to those states that have also adopted California's ZEV program requirements.

To account for the ZEV program, and particularly as other states have recently adopted California's ZEV standards, DOT staff have included the main provisions of the ZEV program in the CAFE Model's analysis of compliance pathways. As explained below, incorporating the ZEV program into the model includes converting vehicles that have been identified as potential ZEV candidates into battery-electric vehicles (BEVs) at the first redesign opportunity, so that a

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[70] California Air Resource Board (CARB), Zero-Emission Vehicle Program. California Air Resources Board. https://ww2.arb.ca.gov/our-work/programs/zero-emission-vehicle-program/about. (Accessed: February 15, 2022).

[71] Through 2020, the Section 177 states that had adopted the ZEV program included Colorado, Connecticut, Maine, Maryland, Massachusetts, New Jersey, New York, Oregon, Rhode Island, Vermont, and Washington. *See* Vermont Department of Environmental Conservation, Zero Emission Vehicles. Accessed April 12, 2021. https://dec.vermont.gov/air-quality/mobile-sources/zev#:~:text=To%20date%2C%2012%20states%20have,ZEVs%20over%20the%20next%20decade. (Accessed: February 15, 2022).

[72] The states of Minnesota, Nevada, and Virginia have recently adopted ZEV standards, which will go into effect for model year 2025. As discussed in Section III.C of today's *Federal Register* notice, reflecting these three states' adoption of ZEV mandates would have only negligibly impacted the agency's national-scale analysis. *See* Green Car Reports, Minnesota adopts California EV mandate. https://www.greencarreports.com/news/1133027_minnesota-adopts-california-ev-mandate-makes-it-tougher-for-plug-in-compliance-cars (Accessed February 15, 2022); State of Nevada Climate Initiative, Adopt Low-and Zero-Emissions Passenger Vehicle Standards. https://climateaction.nv.gov/policies/lev-zev/ (Accessed February 15, 2022); Green Car Reports, Virginia becomes 15th Clean Cars State. https://www.greencarcongress.com/2021/03/20210330-virginia.html#:~:text=30%20March%202021,become%20a%20Clean%20Cars%20state. (Accessed: February 15, 2022).

[73] Section 177 of the Clean Air Act allows other states to adopt California's air quality standards.

[74] At the time of writing, Delaware and Pennsylvania are the two states that have adopted the LEV standards, but not the ZEV portion.

manufacturer's fleet meets calculated ZEV credit requirements. Since ZEV program compliance pathways happen independently from the adoption of fuel saving technology in response to increasing CAFE standards, the ZEV program is considered in the baseline of the CAFE Model, and in all other regulatory alternatives for CAFE standards.

2.3.1 Overview of the ZEV Program

Through its zero-emissions vehicle program, California requires that all manufacturers that sell cars within the state meet the ZEV credit standards. The current credit requirements are calculated based on manufacturers' California sales volumes. Manufacturers primarily earn ZEV credits through the production of battery electric vehicles (BEVs), fuel cell electric vehicles (FCEVs), and transitional zero-emissions vehicles (TZEVs), which are vehicles with partial electrification, namely plug-in hybrids (PHEVs). Total credits are calculated by multiplying the credit value each ZEV receives by the vehicle's volume.

The ZEV credit value per vehicle is calculated based on the vehicle's range, according to the formula in Equation 2-5. ZEVs may earn up to 4 credits each.

$$ZEV\ credit\ value\ =\ (0.01 * UDDS\ range)\ + 0.5$$

Equation 2-5 – ZEV Credits per Vehicle

The TZEV (PHEV) credit formula also depends on the vehicle's range, as seen in Equation 2-6.

$$TZEV\ credit\ value\ =\ (0.01 * All - electric\ range)\ +\ 0.03$$

Equation 2-6 – TZEV Credits per Vehicle

PHEVs with a US06 AER capability of 10 mi or higher receive an additional 0.2 credits.[75] The maximum PHEV credit amount available per vehicle is 1.10.[76]

2.3.2 Calculation of ZEV Credits per Manufacturer

For the purposes of simulating the ZEV program, DOT staff calculated approximate ZEV credit targets as a first step in adding ZEV compliance to the baseline. We built these credit targets based on examination of the ZEV regulation updates from 2018, estimation of national sales volumes by manufacturer, analysis of manufacturers' market share in Section 177 states, and application of CARB's credit requirement formulas.

2.3.2.1 Characterizing the Market

The CAFE Model is designed to present outcomes at a national scale, so the ZEV analysis considers the Section 177 states as a group as opposed to estimating each state's ZEV credit requirements individually. To capture the appropriate volumes subject to the ZEV requirement,

[75] US06 is one of the drive cycles used to test fuel economy and AER, specifically for the simulation of aggressive driving. *See* https://www.epa.gov/vehicle-and-fuel-emissions-testing/dynamometer-drive-schedules for more information, as well as Chapter 2.4 Technology Effectiveness Values and Chapter 3.3.4 in this document.
[76] 13 CCR § 1962.2(c)(3).

we calculate each manufacturer's total market share in Section 177 states. We also calculate the market share of ZEVs in Section 177 states, in order to estimate as closely as possible the number of predicted ZEVs expected to be sold in those states. These shares are later used to scale down national-level information in the CAFE Model to ensure that only Section 177 states are represented in the final calculation of ZEV credits projected to be earned by each manufacturer in future years.

DOT staff used Polk's National Vehicle Population Profile (NVPP) from January 2020, to calculate these percentages.[77] These data include vehicle characteristics such as powertrain, fuel type, manufacturer, nameplate, and trim level, as well as the state in which vehicles were sold, which allows staff to identify the different types of ZEVs sold in the Section 177 state group. At that time, model year 2019 data from the NVPP contained the most current estimate of new vehicle market shares by manufacturer, and best represented the registered vehicle population on January 1, 2020.

Table 2-12 illustrates the estimated total and ZEV-only market shares of manufacturers in Section 177 states, using the 2019 model year data.

Table 2-12 – Total and ZEV-only Market Shares in Section 177 States

	Percent of Total Vehicle Sales in Section 177 States	Percent of ZEVs sold in Section 177 States
BMW	50.6%	76.3%
Daimler	50.1%	85.5%
FCA	24.4%	60.9%
Ford	22.5%	50.0%
General Motors	22.2%	72.1%
Honda	41.0%	98.0%
Hyundai	30.6%	90.8%
Kia	29.8%	79.4%
JLR	43.5%	57.8%
Mazda	42.9%	N/A[78]
Mitsubishi	27.6%	71.2%
Nissan	27.2%	72.0%
Subaru	45.8%	91.1%
Tesla	61.8%	61.8%
Toyota	36.3%	84.8%
Volvo	43.6%	64.4%
VWA	39.4%	71.7%

[77] National Vehicle Population Profile (NVPP) 2020, IHS Markit – Polk.
[78] In the dataset used in the calculation of these percentages, Mazda was shown to have produced no ZEV-qualifying vehicles. However, as discussed in Chapter 2.2, Mazda has indicated its intention to build electric vehicles in the future. In the absence of ZEV market share data for Mazda, DOT staff assumed that 100 percent of future ZEVs would be sold in Section 177 states.

2.3.2.2 Estimating ZEV Credit Targets

Volumes used for the ZEV credit requirement calculation are based on each manufacturer's future assumed market share in Section 177 states. The market shares shown in Table 2-12, calculated using NVPP data from model year 2019 as discussed in the previous section, are carried forward to future years. The assumption to carry these data forward was made after examination of past market share data from model year 2016, from the 2017 version of the NVPP.[79] Comparison of these data to the 2020 version showed that manufacturers' market shares remain fairly constant in terms of geographic distribution. Therefore, we determined that it was reasonable to carry forward the recently calculated market shares to future years.

Table 2-13 – ZEV Credit Percentage Requirement Schedule[80]

Year	ZEV credit percentage requirement
2020	9.5%
2021	12%
2022	14.5%
2023	17%
2024	19.5%
2025 onward	22%

We calculate total credits required for ZEV compliance by multiplying the percentages from CARB's ZEV requirement schedule by the Section 177 state volumes, as seen in Equation 2-7. Table 2-13 shows CARB's ZEV credit percentage requirements for each future year. Note that CARB's ZEV percentage requirements do not currently change after 2025.[81]

$$ReqCredits = SalesVol_M * Mktshare_M * ZEVPercent$$

Equation 2-7 – Required ZEV Credits Formula

Where:

ReqCredits = Required credits

Sales Vol = National sales volumes

Mktshare = Share of sales in Section 177 states with ZEV standards

ZEVPercent = ZEV credit percentage requirement

M = Manufacturer

[79] National Vehicle Population Profile (NVPP) 2017, IHS Markit – Polk.
[80] 13 CCR § 1962.2(b).
[81] 13 CCR § 1962.2(b).

We generate national sales volume predictions for future years using CAFE Model outputs reporting sales by manufacturer, fleet, and model year.[82] The compliance report used corresponds to the baseline scenario of 1.5 percent per year increases in standards for both passenger car and light truck fleets.

The resulting national sales volume predictions by manufacturer are then multiplied by each manufacturer's total market share in the Section 177 states to capture the appropriate volumes in the ZEV credits calculation (See Table 2-14). Required credits by manufacturer, per year, are determined by multiplying the Section 177 state volumes by CARB's ZEV credit percentage requirement. These required credits are subsequently added to the CAFE Model inputs as targets for manufacturer compliance with ZEV standards in the CAFE baseline.

Table 2-14 – Estimated Sales Volumes in Section 177 States

Manufacturer	Estimated Sales Volumes in Section 177 States					
	2020	2021	2022	2023	2024	2025
BMW	149,829	165,849	190,765	201,795	202,216	199,651
Daimler	182,364	198,540	224,488	235,597	234,106	229,816
FCA	366,807	390,980	432,127	448,646	440,582	429,043
Ford	379,909	406,993	452,309	470,838	463,732	452,487
GM	514,095	550,411	611,293	636,138	626,317	610,988
Honda	530,745	581,491	661,838	696,726	694,599	683,396
Hyundai	226,679	247,912	281,648	296,241	295,064	290,123
Kia	177,618	195,613	223,839	236,221	236,119	232,722
JLR	60,142	63,939	70,465	73,057	71,634	69,683
Mazda	111,752	120,557	134,995	141,032	139,448	136,432
Mitsubishi	31,086	33,331	37,078	38,615	38,052	37,144
Nissan	280,583	306,345	347,417	365,121	363,353	357,058
Subaru	344,272	370,757	414,381	432,524	427,250	417,736
Tesla	121,113	137,263	161,629	172,779	175,058	174,092
Toyota	643,330	702,964	797,883	838,869	835,161	820,928
Volvo	45,299	48,840	54,653	57,082	56,414	55,186
VWA	168,255	183,847	208,666	219,377	218,404	214,678

2.3.3 Identifying ZEV Candidates in the Analysis Fleet

The ZEV credit requirements estimated in the previous section serve as a target for simulating ZEV compliance in the baseline. To achieve this, we determined a modeling philosophy for ZEV pathways, reviewed various sources for information regarding upcoming ZEV programs, and inserted those programs into the analysis fleet inputs. The following sections elaborate on these components.

[82] These model outputs are available at https://www.nhtsa.gov/file-downloads?p=nhtsa/downloads/CAFE/2021-NPRM-LD-2024-2026/Central%20Analysis/. (Accessed: February 15, 2022).

2.3.3.1 Modeling Philosophy on ZEV Pathways

As manufacturers can meet ZEV standards in a variety of different ways, using various technology combinations, DOT staff made certain simplifying assumptions in choosing ZEV pathways. These assumptions were made in conjunction with guidance from CARB staff.

First, we target 2025 compliance, as opposed to assuming manufacturers would perfectly comply with their credit requirements in each year prior to 2025. This simplifying assumption was made upon review of past history of ZEV credit transfers, existing ZEV credit banks, and redesign schedules. We focus on integrating ZEV technology throughout that timeline with the target of meeting 2025 obligations; thus, some manufacturers are estimated to over-comply or under-comply, depending on their individual situations, in the years 2021-2024.

Second, we determined that the most reasonable way to model ZEV compliance would be to allow under-compliance in certain cases and assume that some manufacturers would not meet their ZEV obligation on their own in 2025. Instead, these manufacturers are assumed to prefer to purchase credits from another manufacturer with a credit surplus. Reviews of past ZEV credit transfers between manufacturers informed the decision to make this simplifying assumption.[83] CARB staff advised that for these manufacturers, the CAFE Model should still project that each manufacturer meet approximately 80 percent of their ZEV requirements with technology included in their own portfolio. Manufacturers that are observed to have generated many ZEV credits in the past or had announced major upcoming BEV initiatives are projected to meet 100 percent of their ZEV requirements on their own, without purchasing ZEV credits from other manufacturers.[84]

Third, we assume that manufacturers will meet their ZEV credit requirements in 2025 though the production of battery electric vehicles (BEVs). As discussed in Chapter 2.3.1, manufacturers may choose to build PHEVs or fuel cell vehicles to earn some portion of their required ZEV credits. However, we project that manufacturers will rely on BEVs to meet their credit requirements, based on reviews of press releases and industry news, as well as discussion with CARB staff. Since nearly all manufacturers have announced some plans to produce BEVs at a scale meaningful to future ZEV requirements, we consider this to be a reasonable assumption.[85] Furthermore, as CARB only allows intermediate-volume manufacturers to meet their ZEV credit requirements through the production of PHEVs, and the volume status of these few manufacturers might change over the years, assuming BEV production for ZEV compliance is the most straightforward path.

Fourth, to account for the new BEV programs announced by some manufacturers, we identify vehicles in the 2020 fleet that closely match the upcoming BEVs, by regulatory class, market segment, and redesign schedule. We made an effort to distribute ZEV candidate vehicles by CAFE regulatory class (light truck, passenger car), by manufacturer, in a manner consistent with

[83] *See* https://ww2.arb.ca.gov/our-work/programs/advanced-clean-cars-program/zev-program/zero-emission-vehicle-credit-balances for past credit balances and transfer information. (Accessed: February 15, 2022).

[84] The following manufacturers were assumed to meet 100 percent ZEV compliance: Ford, General Motors, Hyundai, Kia, Jaguar Land Rover, and Volkswagen Automotive. Tesla was also assumed to meet 100 percent of its required standards, but we did not need to add additional ZEV substitutes to the baseline for this manufacturer.

[85] *See* Table 2-15 for a list of potential BEV programs recently announced by manufacturers.

the 2020 manufacturer fleet mix. Since passenger car and light truck mixes by manufacturer could change in response to the CAFE policy alternative under consideration, this effort was deemed necessary in order to avoid redistributing the fleet mix in an unrealistic manner. However, there are some exceptions to this assumption, as some manufacturers are already a long way to meeting their ZEV obligation through 2025 with BEVs currently produced, and some manufacturers underperform their compliance targets more so in one fleet than another. In these cases, we deviate from keeping the LT/PC mix of BEVs evenly distributed across the manufacturer's portfolio.[86] See Table 2-16 for examples of the regulatory class distribution across manufacturers.

2.3.3.2 Manufacturer ZEV Efforts

DOT staff identified future ZEV programs by manufacturer that could plausibly contribute towards the ZEV requirements for each manufacturer by 2025. To obtain this information, staff examined various sources, including trade press releases, industry announcements, and investor reports. In many cases, these BEV programs are in addition to programs already in production.[87] Some manufacturers have not yet released details of future electric vehicle programs at the time of writing, but have indicated goals of reaching certain percentages of electric vehicles in their portfolios by a specified year. In these cases, we reviewed the manufacturer's current fleet characteristics as well as the aspirational information in press releases and other news in order to make reasonable assumptions about the vehicle segment and range of those future EVs.[88]

Table 2-15 lists the potential upcoming ZEV programs that we consider. Overall, we assume that manufacturers will lean towards producing BEV300s rather than BEV200s, based on the information reviewed and an initial conversation with CARB staff.[89] Phase-in caps are also considered, especially for BEV200, with the understanding that the CAFE Model will always pick BEV200 before BEV300 or BEV400, until the quantity of BEV200s is exhausted. See Chapter 3.3.3 for details regarding phase-in caps in the CAFE Model.

BEVs with smaller battery packs and less range, are less likely to meet all the performance needs of traditional pickup truck owners, such as long-range towing. However, longer-range BEV pickups are being introduced, and may be joined by new markets in the form of electric delivery trucks and some light-duty electric truck applications in state and local government. The extent to which BEVs will be used in these and other new markets is difficult to project. We do identify certain trucks as upcoming BEVs for ZEV compliance, and these BEVs are expected to have higher ranges, due to the specific performance needs associated with these vehicles. Outside of the ZEV inputs described here, the CAFE Model does not handle the application of BEV technology with any special considerations as to whether the vehicle is a pickup truck or not. See Chapter 3.3 for more information regarding BEV application in the CAFE Model.

[86] The GM light truck and passenger car distribution is one such example.
[87] Examples of BEV programs already in production include the Nissan Leaf and the Chevrolet Bolt.
[88] For example, see the entries under FCA and Mitsubishi in Table 2-15.
[89] BEV300s are battery-electric vehicles with 300-mile range. *See* Chapter 3.3.2 for further information regarding electrification fleet assignments.

Table 2-15 – Potential Upcoming ZEV Programs[90]

Manufacturer	Nameplate	Technology	First Model Year	Likely Fleet
BMW	i4	BEV300	2022	IC
BMW	iX3	BEV300	2022	LT
BMW	iNext	BEV300	2024	LT
Daimler	Mercedes-Benz EQA SUV	BEV200	2022	PC
Daimler	Mercedes-Benz EQE Sedan	BEV200	2022	PC
Daimler	Mercedes-Benz EQS Sedan	BEV400	2022	PC
Daimler	Mercedes-Benz EQB SUV	BEV200	2023	LT
Daimler	Mercedes-Benz EQE SUV	BEV200	2023	LT
Daimler	Mercedes-Benz G-Class Electric	BEV300	2023	LT
Daimler	Mercedes-Benz EQS SUV	BEV400	2023	LT
Daimler	Mercedes-Benz EQC SUV	BEV200	2024	LT
FCA	Jeep Wrangler EV	BEV300	2023	LT
FCA	Car EV	BEV300	2024	PC
FCA	SUV EV	BEV300	2024	LT
Ford	Mustang Mach-e	BEV200	2021	PC
Ford	Mustang Mach-e	BEV300	2021	PC
Ford	F-150 Electric Pickup	BEV300	2022	LT
Ford	E-Transit	BEV200	2023	LT
Ford	Lincoln SUV	BEV200	2024	LT
Ford	Lincoln SUV	BEV300	2025	LT
GM	Cadillac Lyriq	BEV300	2022	LT
GM	Bolt EUV	BEV300	2022	PC
GM	GMC Hummer	BEV400	2022	LT
GM	Cadillac Celestiq	BEV300	2024	LT
GM	Chevrolet Electric Pickup	BEV300	2025	LT
Honda	SUV EV	BEV200	2025	LT
Honda	SUV EV	BEV300	2025	LT

[90] *See* Car and Driver, Every Electric Vehicle that's expected in the Next Five Years. Car and Driver (Jan 12, 2021), https://www.caranddriver.com/news/g29994375/future-electric-cars-trucks/ (Accessed: February 15, 2022); Preston, B., Hot New Electric Cars Are Coming Soon. Consumer Reports (Feb 4, 2021), https://www.consumerreports.org/hybrids-evs/hot-new-electric-cars-are-coming-soon/ (Accessed: February 15, 2022); Docket No. NHTSA-2021-0053-0006, Press Releases for ZEV Candidate Vehicles.

Manufacturer	Nameplate	Technology	First Model Year	Likely Fleet
Honda	PC EV	BEV300	2025	PC
Hyundai	Ioniq 5 (Midsize SUV)	BEV300	2023	LT
Hyundai	Ioniq 6 Sedan	BEV300	2023	PC
Hyundai	Genesis Essentia	BEV300	2024	PC
Hyundai	Ioniq 7 SUV	BEV300	2024	LT
JLR	Jaguar XJ Electric	BEV200	2022	IC
JLR	Range Rover EV	BEV300	2024	LT
Kia	7 dedicated EVs by 2026	BEV200	2023	PC
Kia	7 dedicated EVs by 2026	BEV300	2024	PC
Kia	7 dedicated EVs by 2026	BEV400	2025	PC
Mazda	MX-30	BEV200	2023	LT
Mitsubishi	Unknown	BEV200	2022	LT
Mitsubishi	Unknown	BEV300	2022	LT
Nissan	Ariya	BEV300	2022	PC
Nissan	Ariya	BEV300	2022	LT
Subaru	Electric SUV / Joint venture with Toyota	BEV200	2022	LT
Subaru	Electric SUV / Joint venture with Toyota	BEV300	2022	LT
Toyota	Electric SUV / Joint venture with Subaru	BEV200	2022	LT
Toyota	Lexus EV SUC	BEV300	2023	LT
Volvo	Polestar 2	BEV200	2021	PC
Volvo	XC40 Recharge	BEV200	2022	LT
Volvo	XC40 Recharge	BEV300	2023	LT
VWA	Audi E-Tron Sportback	BEV200	2021	LT
VWA	ID.4	BEV300	2021	PC
VWA	Audi E-Tron GT	BEV200	2022	PC
VWA	ID.4	BEV200	2022	LT
VWA	Audi Q4 e-tron	BEV300	2022	LT
VWA	Porsche Taycan Cross Turismo	BEV300	2022	PC
VWA	I.D. Buzz	BEV300	2023	LT
VWA	I.D. Space Vizzion	BEV300	2023	PC
VWA	Porsche Macan EV	BEV300	2024	LT

2.3.3.3 Inserting ZEV Programs into the CAFE Model Analysis Fleet

The CAFE analysis fleet summarizes the roughly 13.6 million light-duty vehicles produced and sold in the United States in the 2020 model year with more than 3,500 rows, each reflecting information for one vehicle type observed. Each row includes the vehicle's nameplate and trim level, the sales volume, engine, transmission, drive configuration, regulatory class, projected redesign schedule, and fuel saving technologies, among other attributes. For a comprehensive discussion of how we built the analysis fleet, see Chapter 2.1.

In order to simulate manufacturers' compliance with their particular ZEV credits target, 142 rows in the analysis fleet are identified as substitutes for future ZEV programs (See

Table 2-15). As the goal of the ZEV analysis is to simulate compliance with the ZEV program in the baseline, and the analysis fleet only contains vehicles produced during model year 2020, we identify existing models in the analysis fleet that share certain characteristics with upcoming BEVs. We also focus on identifying substitute vehicles with redesign years similar to the future BEV's introduction year. The sales volumes of those existing models, as predicted for 2025, are then used to simulate production of the upcoming BEVs. We were able to identify a combination of rows that would meet the ZEV target, could contribute productively towards CAFE program obligations (by manufacturer and by fleet), and would introduce BEVs in each manufacturer's portfolio in a way that reasonably aligned with projections and announcements. We tag each of these rows with information in the Market Data file,[91] instructing the CAFE Model to apply the specified BEV technology to the row at the first redesign year, regardless of the scenario or type of CAFE or GHG simulation.

The CAFE Model does not optimize compliance with the ZEV mandate; it relies upon the inputs described in this chapter in order to estimate each manufacturer's resulting ZEV credits. The resulting amount of ZEV credits earned by manufacturer for each model year can be found in the CAFE Model's output files.

Not all ZEV-qualifying vehicles in the United States earn ZEV credits, as they are not all sold in states that have adopted ZEV regulations. In order to reflect this in the CAFE Model, which only estimates sales volumes at the national level, we use the percentages calculated in Chapter 2.3.2.1 to scale down the national-level volumes. These percentages (representing the share of ZEVs sold in Section 177 states) may be found in Table 2-12. Multiplying national-level ZEV sales volumes by these percentages ensures that only the ZEVs sold in Section 177 states count towards the ZEV credit targets of each manufacturer.[92] See Chapter 5.8 of the CAFE Model Documentation for a detailed description of how the model applies these ZEV technologies and any changes made to the model's programming for the incorporation of the ZEV program into the baseline.

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[91] *See* Chapter 2.2 for further information on the Market Data file.

[92] The single exception to this assumption is Mazda, as Mazda has not yet produced any ZEV-qualifying vehicles at the time of writing. Thus, the percentage of ZEVs sold in Section 177 states cannot be calculated from existing data. However, Mazda has indicated its intention to produce ZEV-qualifying vehicles in the future, so DOT staff assumed that 100 percent of future ZEVs would be sold in Section 177 states for the purposes of estimating ZEV credits in the CAFE Model.

As discussed in Chapter 2.3.3.1, DOT staff made an effort to distribute the newly identified ZEV candidates between CAFE regulatory classes (light truck and passenger car) in a manner consistent with the proportions seen in the 2020 analysis fleet, by manufacturer. The resulting distribution of the ZEV candidates compared to the observed fleet mix distribution in the 2020 analysis fleet is shown in Table 2-16. As mentioned previously, there are a few exceptions to this assumption in cases where manufacturers' regulatory class distribution of current or planned ZEV programs clearly differed from their regulatory class distribution as a whole.

Table 2-16 – Regulatory Class Distributions

Manufacturer	2020 LT sales (percent)	LT ZEV candidates (percent)	2020 PC sales (percent)	PC ZEV candidates (percent)
BMW	37.2%	52.0%	62.8%	48.0%
Daimler	52.9%	46.1%	47.1%	53.9%
FCA	86.2%	87.1%	13.8%	12.9%
Ford	73.5%	75.0%	26.5%	25.0%
GM	67.5%	0.0%	32.5%	100.0%
Honda	42.3%	45.9%	57.7%	54.1%
Hyundai	10.7%	31.9%	89.3%	68.1%
Kia	38.5%	43.9%	61.5%	56.1%
JLR	95.8%	88.6%	4.2%	11.4%
Mazda	51.7%	0.0%	48.3%	100.0%
Mitsubishi	54.3%	0.0%	45.7%	100.0%
Nissan	30.9%	68.3%	69.1%	31.7%
Subaru	79.0%	77.5%	21.0%	22.5%
Tesla[93]	3.1%	N/A	96.9%	N/A
Toyota	46.9%	59.1%	53.1%	40.9%
Volvo	74.7%	86.1%	25.3%	13.9%
VWA	58.0%	86.1%	42.0%	13.9%

In some instances, the regulatory distribution of flagged ZEV candidates leans towards a higher portion of PCs. The reasoning behind this differs in each case, but there is an observed pattern in the 2020 analysis fleet of fewer BEVs being light trucks, especially pickups. The 2020 analysis fleet contains no BEV pickups in the light truck segment. The slow emergence of electric pickups could be linked to the specific performance needs associated with pickup trucks. However, the market for BEVs may emerge in unexpected ways that are difficult to project. Examples of this include anticipated electric delivery trucks and light-duty electric trucks used by state and local governments. Due to these considerations, we tagged some trucks as BEVs for ZEV, and expected that these would generally be of higher ranges.

93 No ZEV candidates were flagged for Tesla, as Tesla is already compliant with the ZEV program and its vehicles in the 2020 fleet are already EVs.

Table 2-17 shows the portion of BEVs observed in the analysis fleet, by manufacturer and by regulatory class, and compares those percentages to the regulatory class distribution in the 2020 analysis fleet overall.

Table 2-17 – Portion of Battery Electric Vehicles Observed in the Analysis Fleet

Manufacturer	2020 LT Sales (percent)	2020 PC Sales (percent)	2020 BEVs Observed (percent)	Portion of LT BEVs Observed in 2020 (percent)	Portion of PC BEVs Observed in 2020 (percent)
BMW	37.2%	62.8%	0.67%	0%	100%
Daimler	52.9%	47.1%	0.07%	0%	100%
FCA	86.2%	13.8%	0.00%	N/A	N/A
Ford	73.5%	26.5%	0.00%	N/A	N/A
GM	67.5%	32.5%	1.22%	0%	100%
Honda	42.3%	57.7%	0.00%	N/A	N/A
Hyundai Kia-H	10.7%	89.3%	0.81%	0%	100%
Hyundai Kia-K	38.5%	61.5%	0.16%	0%	100%
JLR	95.8%	4.2%	1.34%	100%	0%
Mazda	51.7%	48.3%	0.00%	N/A	N/A
Mitsubishi	54.3%	45.7%	0.00%	N/A	N/A
Nissan	30.9%	69.1%	1.12%	0%	100%
Subaru	79.0%	21.0%	0.00%	N/A	N/A
Tesla	3.1%	96.9%	100.00%	3%	97%
Toyota	46.9%	53.1%	0.00%	N/A	N/A
Volvo	74.7%	25.3%	0.00%	N/A	N/A
VWA	58.0%	42.0%	1.21%	15%	85%

Table 2-18 shows the scope of the fleet affected, including the penetration rates of BEVs observed in the 2020 fleet prior to and after the simulation of the ZEV program in the baseline. The penetration rate of BEVs in 2025 is also shown. These rates are all based on 2020 baseline volumes and 2025 projected sales volumes in the baseline scenario. For further discussion of the effects of increased BEV penetration rates in the baseline fleet, see FRIA Chapter 6.3.1.

Table 2-18 – Penetration of BEVs due to Simulation of the ZEV Program

Manufacturer	Penetration Rate of BEVs Observed in 2020 fleet	2020 Observed BEV Volume	Penetration Rate of BEVs (Observed and Added) in 2020	2025 ZEV Candidate Volume	Penetration Rate of ZEV Candidates in 2025
BMW	0.67%	1997	2.58%	7396	1.90%
Daimler	0.07%	258	3.48%	14108	3.07%
FCA	0%	0	1.08%	18957	1.08%
Ford	0%	0	1.24%	25534	1.28%
GM	1.22%	28197	2.24%	26798	0.98%
Honda	0%	0	1.78%	30675	1.83%

Manufacturer	Penetration Rate of BEVs Observed in 2020 fleet	2020 Observed BEV Volume	Penetration Rate of BEVs (Observed and Added) in 2020	2025 ZEV Candidate Volume	Penetration Rate of ZEV Candidates in 2025
Hyundai	0.81%	6003	2.13%	13567	1.42%
Kia	0.16%	965	2.40%	17882	2.27%
JLR	1.34%	1858	2.98%	2655	1.67%
Mazda	0%	0	3.09%	9135	2.88%
Mitsubishi	0%	0	1.73%	2217	1.65%
Nissan	1.12%	11558	1.66%	6280	0.48%
Subaru	0%	0	2.27%	20779	2.28%
Tesla	100.00%	196000	100%	0	0.00%
Toyota	0%	0	1.96%	39540	1.74%
Volvo	0%	0	2.96%	3653	2.89%
VWA	1.21%	5187	2.70%	7525	1.38%

2.4 Technology Effectiveness Values

The next inputs required to simulate manufacturers' decision-making processes for the year-by-year application of technologies to specific vehicles are estimates of how effective each technology would be at reducing fuel consumption. For this analysis, we use full-vehicle modeling and simulation to estimate the fuel economy improvements manufacturers could make to a fleet of vehicles, considering the vehicles' technical specifications and how combinations of technologies interact. Full-vehicle modeling and simulation uses physics-based models to predict how combinations of technologies perform as a full system under defined conditions.

A model is a mathematical representation of a system, and simulation is the behavior of that mathematical representation over time. In this analysis, the model is a mathematical representation of an entire vehicle,[94] including its individual components such as the engine and transmission, overall vehicle characteristics such as mass and aerodynamic drag, and the environmental conditions, such as ambient temperature and barometric pressure. We simulate the model's behavior over test cycles, including the 2-cycle laboratory compliance tests (or 2-cycle tests),[95] to determine how the individual components interact. The 2-cycle tests are test cycles used to measure fuel economy and emissions for CAFE compliance, and therefore are the relevant test cycles for determining technology effectiveness when establishing CAFE standards. In the laboratory, 2-cycle testing involves sophisticated test and measurement equipment, carefully controlled environmental conditions, and precise procedures to provide the most

[94] Each full vehicle model in this analysis is composed of sub-models, which is why the full vehicle model could also be referred to as a full system model, composed of sub-system models.

[95] EPA's compliance test cycles are used to measure the fuel economy of a vehicle. For readers unfamiliar with this process, it is like running a car on a treadmill following a program—or more specifically, two programs. The "programs" are the "urban cycle," or Federal Test Procedure (abbreviated as "FTP"), and the "highway cycle," or Highway Fuel Economy Test (abbreviated as "HFET"), and they have not changed substantively since 1975. Each cycle is a designated speed trace (of vehicle speed versus time) that all certified vehicles must follow during testing. The FTP is meant roughly to simulate stop and go city driving, and the HFET is meant roughly to simulate steady flowing highway driving at about 50 mph.

repeatable results possible with human drivers. These structured procedures serve as a uniform assessment for fuel economy measurements.

Full-vehicle modeling and simulation was initially developed to avoid the costs of designing and testing prototype parts for every new type of technology. For example, if a truck manufacturer has a concept for a light-weight tailgate and wants to determine the fuel economy impact for the weight reduction, the manufacturer can use physics-based computer modeling to estimate the impact. The vehicle, modeled with the proposed change, can be simulated on a defined test route and under defined test conditions, such as city or highway driving in warm ambient temperature conditions, and compared against the baseline vehicle without the change. Full-vehicle modeling and simulation allows the consideration and evaluation of different designs and concepts before building a single prototype. In addition, full vehicle modeling and simulation is beneficial when considering technologies that provide small incremental improvements. These improvements are difficult to measure in laboratory tests due to variations in how vehicles are driven over the test cycle by human drivers, variations in emissions measurement equipment, and variations in environmental conditions.[96]

Full-vehicle modeling and simulation requires detailed data describing individual vehicle technologies and performance-related characteristics. Those data generally come from design specifications, laboratory measurements, and other subsystem simulations or modeling. One example of data used as an input to the full vehicle simulation are engine maps for each engine technology that define how much fuel is consumed by the engine technology across its operating range.

Using full-vehicle modeling and simulation to estimate technology efficiency improvements has two primary advantages over using single or limited point estimates. An analysis using single or limited point estimates may assume that, for example, one fuel economy improving technology with an effectiveness value of 5 percent by itself and another technology with an effectiveness value of 10 percent by itself, when applied together achieve an additive improvement of 15 percent. Single point estimates generally do not provide accurate effectiveness values because they do not capture complex relationships among technologies. Technology effectiveness often differs significantly depending on the vehicle type (e.g., sedan versus pickup truck) and the way in which the technology interacts with other technologies on the vehicle, as different technologies may provide different incremental levels of fuel economy improvement if implemented alone or in combination with other technologies. Any oversimplification of these complex interactions leads to less accurate and often overestimated effectiveness estimates.

In addition, because manufacturers often add several fuel-saving technologies simultaneously when redesigning a vehicle, it is difficult to isolate the effect of individual technologies using laboratory measurement of production vehicles alone. Modeling and simulation offer the opportunity to isolate the effects of individual technologies by using a single or small number of baseline vehicle configurations and incrementally adding technologies to those baseline configurations. This provides a consistent reference point for the incremental effectiveness

[96] Difficulty in controlling for such variability is reflected, for example, in 40 CFR 1065.210, Work input and output sensors, which describes complicated instructions and recommendations to help control for variability in real world (non-simulated) test instrumentation set up.

estimates for each technology and for combinations of technologies for each vehicle type. Vehicle modeling also reduces the potential for overcounting or undercounting technology effectiveness.

An important feature of this analysis is that the incremental effectiveness of each technology and combinations of technologies should be accurate and relative to a consistent baseline vehicle. We use the absolute fuel economy values from the full vehicle simulations only to determine incremental effectiveness, but not to assign an absolute fuel economy value to any vehicle model or configuration.

For this analysis, the baseline absolute fuel economy value for each vehicle in the analysis fleet is based on CAFE compliance data.[97] For subsequent technology changes, we apply the incremental effectiveness values of one or more technologies to the baseline fuel economy value to determine the absolute fuel economy achieved for applying the technology change. We determine the effectiveness values using full vehicle simulations performed in Autonomie, a physics-based full-vehicle modeling and simulation software developed and maintained by the U.S. Department of Energy's Argonne National Laboratory.

As an example, if a Ford F-150 2-wheel drive crew cab and short bed in the analysis fleet has a fuel economy value of 30 mpg for CAFE compliance, we consider 30 mpg the reference absolute fuel economy value. A similar full vehicle model node in the Autonomie simulation may begin with an average fuel economy value of 32 mpg, and with the incremental addition of a specific technology X its fuel economy improves to 35 mpg, a 9.3 percent improvement. In this example, the incremental fuel economy improvement (9.3 percent) from technology X is applied to the F-150's 30 mpg absolute value.

We determine the incremental effectiveness of technologies as applied to the thousands of unique vehicle and technology combinations in the analysis fleet. Although, as mentioned above, full-vehicle modeling and simulation reduces the work and time required to assess the impact of moving a vehicle from one technology state to another, it would be impractical—if not impossible—to build a unique vehicle model for every individual vehicle in the analysis fleet. Therefore, as discussed in the following chapters, the Autonomie analysis relies on ten vehicle technology class models that are representative of large portions of the analysis fleet vehicles. The vehicle technology classes ensure that we reasonably represent key vehicle characteristics in the full vehicle models. The next sections discuss the details of the technology effectiveness analysis input specifications and assumptions.

2.4.1 Full-Vehicle Modeling, Simulation Inputs, and Data Assumptions

This analysis uses Argonne's full vehicle modeling tool, Autonomie, to build vehicle models with different technology combinations to determine the effectiveness of those technologies over simulated regulatory test cycles. We consider over 50 technologies as inputs to the Autonomie

[97] *See* Chapter 2.2.1 Characterizing Vehicles and their Technology Content for further discussion of CAFE compliance data.

modeling.[98] These inputs consist of engine technologies, transmission technologies, powertrain electrification, light-weighting, aerodynamic improvements, and tire rolling resistance improvements. Chapter 3 broadly discusses each of the technology groupings definitions, inputs, and assumptions. We include a deeper discussion of the Autonomie modeled subsystems, and how inputs feed the sub models resulting in outputs, in the Argonne Autonomie documentation that accompanies this analysis.

We develop Autonomie model inputs considering real-world and compliance test cycle constraints, to the extent the modeling tool allows. Examples include using an engine knock model in engine map development, noise-vibration-harshness (NVH) constraints on cylinder deactivation, and NVH constraints on the number of engine on/off events (e.g., from start/stop 12V micro hybrid systems).

One of the important inputs to the Autonomie model is the set of engine fuel map models. The engine map models define the fuel consumption rate for an engine equipped with specific technologies when operating over a variety of engine load (torque) and engine speed conditions. We developed the engine map models by creating a base, or root, engine map and then modifying that root map, incrementally, to isolate the effects of the added technologies. These engine maps, developed by IAV using their GT-Power modeling tool, are based on real-world engine designs. One important feature of the IAV's GT Power modeling tool is the embedded IAV knock model, which was also developed using real-world engine data.[99,100] This ensures that the engine maps appropriately include real-world constraints as the Autonomie built vehicles are simulated on the test cycles.

Although the same engine map models are used for all vehicle technology classes, the effectiveness varies based on the characteristics of each class. For example, a compact car with a turbocharged engine will have a different effectiveness value than a pickup truck with the same engine technology type. The engine map models development and specifications are discussed further in TSD Chapter 3.1.

Other key Autonomie inputs and assumptions are default values and recommendations from Argonne's technical teams, based on test data and technical publication review.[101] For other Autonomie model inputs, such as, for example, throttle time response and shifting strategies for different transmission technologies, assumptions are based on the latest test data and current

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[98] Islam, E. S., A. Moawad, N. Kim, R. Vijayagopal, and A. Rousseau. *A Detailed Vehicle Simulation Process to Support CAFE Standards for the MY 2024-2026 Analysis*. ANL/ESD-21/9 [hereinafter Autonomie model documentation]. ANL - All Assumptions_Summary_NPRM_022021.xlsx, ANL - Data Dictionary_January 2021.xlsx, ANL - Summary of Main Component Performance Assumptions_NPRM_022021.xlsx, and ANL_BatPac_Lookup_tables_Feb2021v2.xlsx.

[99] Engine knock in spark ignition engines occurs when combustion of some of the air/fuel mixture in the cylinder does not result from propagation of the flame front ignited by the spark plug, but one or more pockets of air/fuel mixture explodes outside of the envelope of the normal combustion front.

[100] *See* IAV material submitted to the docket; IAV_20190430_Eng 22-26 Updated_Docket.pdf, IAV_Engine_tech_study_Sept_2016_Docket.pdf, IAV_Study for 4 Cylinder Gas Engines_Docket.pdf.

[101] An example of a default assumption is the cylinder deactivation methodology within Autonomie. The controller within Autonomie has been developed, using test data, to consider NVH and cold start operation when to enable cylinder deactivation.

market information.[102] The Autonomie modeling tool did not simulate vehicle attributes determined to have minimal impacts on fuel economy, like whether a vehicle had a sunroof or leather seats, as those attributes would have trivial impact in the overall analysis.

Because this analysis models ten different vehicle types (i.e., vehicle classes) to represent the thousands of vehicles in the analysis fleet, improper assumptions about an advanced technology could lead to errors in estimating effectiveness. Autonomie is a sophisticated full-vehicle modeling tool that requires extensive technology characteristics based on both physical and intangible data, like proprietary software (e.g., control strategies for cylinder deactivation). For a few technologies, we did not have publicly available data but had received confidential business information confirming the potential availability of the technology in the market during the rulemaking timeframe. For some advanced technologies, such as advanced cylinder deactivation (ADEAC), we adopt a method in the CAFE Model to represent the effectiveness of the technology and did not explicitly simulate the technologies in the Autonomie model. For this limited set of technologies, we determined that effectiveness could reasonably be represented as a fixed value.[103] Effectiveness values for technologies not explicitly simulated in Autonomie are discussed further in the individual technology sections of this TSD.

2.4.2 Defining Vehicle Classes in Autonomie

Argonne builds full-vehicle models and runs simulations for many combinations of technologies, but it does not simulate literally every single vehicle model/configuration in the analysis fleet. Not only would it be impractical to assemble the requisite detailed information specific to each vehicle/model configuration, much of which would likely only be provided on a confidential basis, but doing so would increase the scale of the simulation effort by orders of magnitude. Instead, Argonne simulates ten different vehicle types, corresponding to the five "technology classes" generally used in CAFE analysis over the past several rulemakings, each with two performance levels and corresponding vehicle technical specifications (e.g., small car, small performance car, pickup truck, performance pickup truck, and so on).

Technology classes are a means of specifying common technology input assumptions for vehicles that share similar characteristics. Because each vehicle technology class has unique characteristics, the effectiveness of technologies and combinations of technologies is different for each technology class. Conducting Autonomie simulations uniquely for each technology class provides a specific set of simulations and effectiveness data for each technology class. In this analysis the technology classes are compact cars, midsize cars, small SUVs, large SUVs, and pickup trucks. In addition, for each vehicle class there are two levels of performance attributes (for a total of 10 technology classes). The high performance and low performance vehicles classifications allow for better diversity in estimating technology effectiveness across the fleet.

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[102] *See* further details in Chapter 2.2 and in Chapter 3's individual technology pathway sections.

[103] For this analysis, 12 out of 50 plus technologies use fixed offset effectiveness values. The total effectiveness of these technologies cannot be captured on the 2-cycle test or, like ADEAC, they are a new technology where robust data that could be used as an input to the technology effectiveness modeling does not yet exist. Specifically, these technologies are LDB, SAX, EPS, IACC, EFR, HCR1D, BEV400, BEV500, ADEAC, DSLI, DSLIAD and TURBOAD.

Argonne developed a vehicle characteristics database to capture baseline vehicle attributes that are used to build the full vehicle models. Representative vehicle attributes and characteristics are identified from publicly available information and automotive benchmarking databases such as A2Mac1,[104] Argonne's Downloadable Dynamometer Database (D^3),[105] EPA compliance and fuel economy data,[106] and EPA's guidance on the cold start penalty on 2-cycle tests.[107] The resulting vehicle technology class baseline characteristics assumptions database consists of over 100 different attributes like vehicle frontal area, drag coefficient, fuel tank weight, transmission housing weight, transmission clutch weight, hybrid vehicle component weights, weights for components that comprise engines and electric machines, tire rolling resistance, transmission gear ratios and final drive ratios.

Argonne then assigns each of the ten vehicle types a set of baseline attributes based on representative values determined from the compiled vehicle databases. For example, the characteristics of a MY 2020 Honda Civic are considered along with a wide range of other compact cars to identify representative characteristics for the base compact car technology class models. These vehicle technology class attributes coupled with technology attributes are compiled as inputs for the full-vehicle Autonomie simulations. The simulations then determine the fuel economy improvement from applying each combination of technologies to the baseline technology set.

For each vehicle technology class and for each vehicle attribute, Argonne estimates the attribute value using statistical distribution analysis of publicly available data and data obtained from the A2Mac1 benchmarking database. Some vehicle attributes are based on test data and vehicle benchmarking, like the cold-start penalty for the FTP test cycle and vehicle electrical accessories load. Table 2-19 shows some key attributes that are assigned to the baseline reference vehicles. The Autonomie model documentation includes more detail about vehicle attributes used in this analysis,[108] and values for each vehicle technology class are provided with the Argonne Input and Assumptions files.[109]

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[104] A2Mac1: Automotive Benchmarking. (Proprietary data). Retrieved from https://www.a2mac1.com. A2Mac1 is subscription-based benchmarking service that conducts vehicle and component teardown analyses. Annually, A2Mac1 removes individual components from production vehicles such as oil pans, electric machines, engines, transmissions, among the many other components. These components are weighed and documented for key specifications which is then available to their subscribers.

[105] Downloadable Dynamometer Database (D^3). Argonne National Laboratory, Energy Systems Division. https://www.anl.gov/es/downloadable-dynamometer-database. (Accessed: February 15, 2022).

[106] Data on Cars used for Testing Fuel Economy. EPA Compliance and Fuel Economy Data. https://www.epa.gov/compliance-and-fuel-economy-data/data-cars-used-testing-fuel-economy. (Accessed: February 15, 2022).

[107] EPA PD TSD at 2-265-2-266.

[108] Autonomie model documentation, Chapter 5.

[109] ANL - All Assumptions_Summary_NPRM_022021.xlsx, ANL - Data Dictionary_January 2021.xlsx, ANL - Summary of Main Component Performance Assumptions_NPRM_022021.xlsx, and ANL_BatPac_Lookup_tables_Feb2021v2.xlsx.

Table 2-19 – Reference Autonomie

Vehicle Class	Performance Category	0-60 MPH Time (s)	Towing (kg)	Drag Coefficient	Tire Rolling Resistance	Frontal Area (m^2)	Estimated Curb Weight (kg)	Base Elec Acc Load (w)	Cold Start Penalty (bag_1/bag_2 %) NA*:TC
Compact Car	Low	10	N/A	0.3	0.009	2.3	1337	250	14.6/2.3:13.8/1.7
Midsize Car	Low	9	N/A	0.3	0.009	2.35	1431	250	14.6/2.3:13.8/1.7
Small SUV	Low	9	N/A	0.36	0.009	2.65	1633	250	14.6/2.3:13.8/1.7
Midsize SUV	Low	9	N/A	0.38	0.009	2.85	1746	300	14.6/2.3:13.8/1.7
Pickup	Low	10	3000	0.42	0.009	3.25	1675	300	14.6/2.3:13.8/1.7
Compact Car	High	8	N/A	0.3	0.009	2.3	1835	300	14.6/2.3:13.8/1.7
Midsize Car	High	6	N/A	0.3	0.009	2.35	1801	300	14.6/2.3:13.8/1.7
Small SUV	High	7	N/A	0.36	0.009	2.65	2103	300	14.6/2.3:13.8/1.7
Midsize SUV	High	7	N/A	0.38	0.009	2.85	2011	300	14.6/2.3:13.8/1.7
Pickup	High	7	4350	0.42	0.009	3.25	2481	300	14.6/2.3:13.8/1.7

These are the reference points for the baseline vehicles.
* NA = Naturally Aspirated.

One notable vehicle attribute is engine mass. We did not believe it appropriate to assign a single engine mass for each vehicle technology class. To account for the difference in weight for different engine types, Argonne performed a regression analysis of engine peak power versus weight, based on attribute data taken from the A2Mac1 benchmarking database. For example, to account for the weight of different engine sizes, like 4-cylinder versus 8-cylinder or turbocharged versus naturally aspirated engines, Argonne developed a relationship curve between peak power and engine weight based on the A2Mac1 benchmarking data. Argonne uses the developed relationship to estimate mass for all engines. The analysis applies secondary weight reduction associated with changes in engine technology by using this linear relationship between engine power and engine weight.

For example, when a vehicle in the analysis fleet with an 8-cylinder engine adopts a more fuel-efficient 6-cylinder engine, the total vehicle weight reflects the updated engine weight with two fewer cylinders based on the peak power versus engine weight relationship. The Autonomie simulation data accounts for the impact of engine mass reduction on effectiveness directly in the Autonomie simulation data through the application of the above relationship. Engine mass reduction through downsizing is, therefore, appropriately not included as part of vehicle mass reduction technology that is discussed in Chapter 3.4, because doing so would result in double counting the impacts. We use two separate curves, one for naturally aspirated engines and the other for turbocharged engines, to improve the precision of the engine weight estimates.

In addition, we hold some attributes at constant levels within each technology class to maintain vehicle functionality, performance, and utility, including NVH, safety, and other utilities important for customer satisfaction. For example, in addition to the vehicle performance constraints discussed in Chapter 2.4.5, the analysis does not allow the frontal area of the vehicle to change in order to maintain utility like ground clearance, head-room space, and cargo space. Another example is the cold-start penalty used to account for fuel economy degradation for heater performance and emissions system catalyst light-off.[110] This allows the analysis to capture discrete improvements in technology effectiveness while maintaining vehicle attributes that are important like vehicle utility, consumer acceptance and compliance with criteria emission standards. These constraints are considered as manufacturers consider them in the real world.

2.4.3 Building Representative Vehicles and Vehicle Optimization

Before any simulation is initiated in Autonomie, Argonne must "build" a vehicle by assigning reference technologies and initial attributes to the components of the vehicle model representing each technology class.[111] The reference technologies are baseline technologies that represent the first step on each technology pathway used in the analysis. For example, a compact car is built by assigning it a baseline engine (DOHC, VVT, PFI), a baseline transmission (5-speed automatic transmission (AT5)), a baseline level of aerodynamic improvement (AERO0), a baseline level of rolling resistance improvement (ROLL0), a baseline level of mass reduction technology (MR0), and corresponding attributes from the Argonne vehicle assumptions database like individual

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[110] The catalyst light-off is the temperature necessary to initiate the catalytic reaction and this energy is generated from the engine.

[111] Further discussion of this process is in Chapter 5 of the Autonomie model documentation.

component weights.[112] A baseline vehicle will have a unique starting point for the simulation and a unique set of assigned inputs and attributes, based on its technology class.

The next step in the process is to run a powertrain sizing algorithm that ensures the built vehicle meets or exceeds defined performance metrics, including low-speed acceleration (time required to accelerate from 0-60 mph), high-speed passing acceleration (time required to accelerate from 50-80 mph), gradeability (the ability of the vehicle to maintain constant 65 miles per hour speed on a six percent upgrade), and towing capacity. Together, these performance criteria are widely used by the automotive industry as metrics to quantify vehicle performance attributes that consumers observe and that are important for vehicle utility and customer satisfaction.

In the compact car example used above, we assign an initial specific engine design and engine power, transmission, AERO, ROLL, and MR technologies, and other attributes like vehicle weight. If the built vehicle does not meet all the performance criteria as the vehicle is simulated over the defined test cycles in the first iteration, then the engine power is increased to meet the performance requirement. The increase in power achieved by increasing engine displacement, which might involve an increase in number of cylinders, may lead to an increase in the engine weight. This iterative process then determines if the compact car with increased engine power and corresponding updated engine weight meets the required performance metrics. The iterative process stops once all the performance requirements are met for the baseline vehicle, and it is at this point the compact car technology class vehicle model is ready for simulation. For further discussion of the vehicle performance metrics, see Chapter 2.4.5.

Autonomie then adopts a single fuel saving technology to the baseline vehicle model, keeping everything else the same except for that one technology and the attributes associated with it. For example, the model applies an 8-speed automatic transmission in place of the baseline 6-speed automatic transmission (AT6), which would lead either to an increase or decrease in the total weight of the vehicle based on the technology class assumptions. Autonomie then confirms whether performance metrics are met for this new vehicle model through the previously discussed sizing algorithm and iterations. Once a technology is assigned to the vehicle model and the resulting vehicle meets its performance metrics, the vehicle model is used as an input to the full vehicle simulation. As an example, for just the 6-speed to 8-speed automatic transmission technology update, the initial ten vehicle models (one for each technology class) are created, plus the ten new vehicle models with the updated 8-speed automatic transmission, for a total of 20 different vehicle models for simulation. This permutation process is repeated for each of the over 50 technologies considered, which results in more than one million optimized vehicle models. Figure 2-1 shows a flow chart of the process for building vehicle models in Autonomie for simulation.

[112] Further discussion of this setup is in Chapter 5.2 of the Autonomie model documentation.

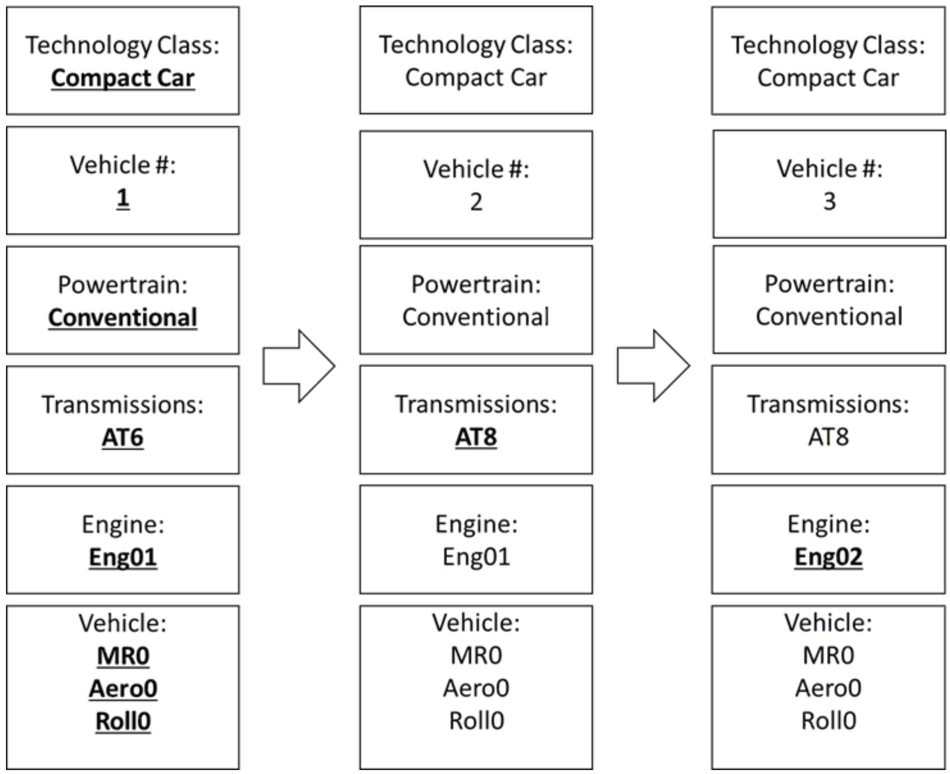

Figure 2-1 – Autonomie Technology Adoption Process for Vehicle Building with Compact Car Technology Class as an Example

Some technologies require extra steps for optimization before the vehicle models are built for simulation. For example, the sizing and optimization process is more complex for the electrified vehicles (e.g., HEVs, PHEVs) compared to vehicles with only internal combustion engines, as discussed further below. During the vehicle building process, the following items are considered for optimization:

- Vehicle weight is adjusted in response to switching from one type of engine or transmission technology to another.

- Vehicle performance is decreased or increased in response to the addition of mass reduction technologies.

- Vehicle performance is decreased or increased in response to the addition of a new technology like AERO or ROLL for the same hybrid electric machine.

- Electric vehicle battery size is decreased or increased in response to the addition of MASS, AERO and/or ROLL technologies.

Every time a vehicle adopts a new technology, the vehicle weight is updated to reflect the new component weight. For some technologies, the direct weight change is easy to assess. For example, when a vehicle is updated to a higher geared transmission the weight of the original transmission is replaced with the corresponding transmission weight (e.g., the weight of a vehicle moving from a AT6 to an 8-speed automatic transmission is updated based on the 8-speed transmission weight).

For other technologies, like engine technologies, assessing the updated vehicle weight is more complex. As discussed earlier, modeling a change in engine technology involves both the new technology adoption and a change in power (because the reduction in vehicle weight leads to lower engine loads, and a resized engine). When a vehicle adopts new engine technology, the associated weight change to the vehicle is accounted for based on the earlier discussed regression analysis of weight versus power. The engine weight regression analysis includes mass data for 19 different engine technologies that consist of unique components to achieve fuel economy improvements. This regression analysis is technology agnostic by taking the approach of using engine peak power versus engine weight because it removed biases to any specific engine technology in the analysis. Although using the regression does not estimate the specific weight for each individual engine technology, such as variable valve timing (VVT) or stoichiometric gasoline direct injection (SGDI), this process provides a reasonable estimate of the weight differences among engine technologies.

Figure 2-2 shows an example of the engine mass regression for the naturally aspirated, forced air induction, and diesel engines. Argonne updated the regression for this analysis to reflect the latest data from A2Mac1, which resulted in two changes. First, small naturally aspirated 4-cylinder engines that adopt turbocharging technology reflect the increased weight of associated components like ducting, clamps, the turbocharger itself, a charged air cooler, wiring, fasteners, and a modified exhaust manifold. Second, larger cylinder count engines like naturally aspirated 8-cylinder and 6-cylinder engines that adopt turbocharging and downsized technologies have less weight due to having fewer engine cylinders. For example, a naturally aspirated 8-cylinder engine that adopts turbocharging technology when downsized to a 6-cylinder turbocharged engine appropriately reflects the added weight of turbocharging components, and the lower weight of fewer cylinders.

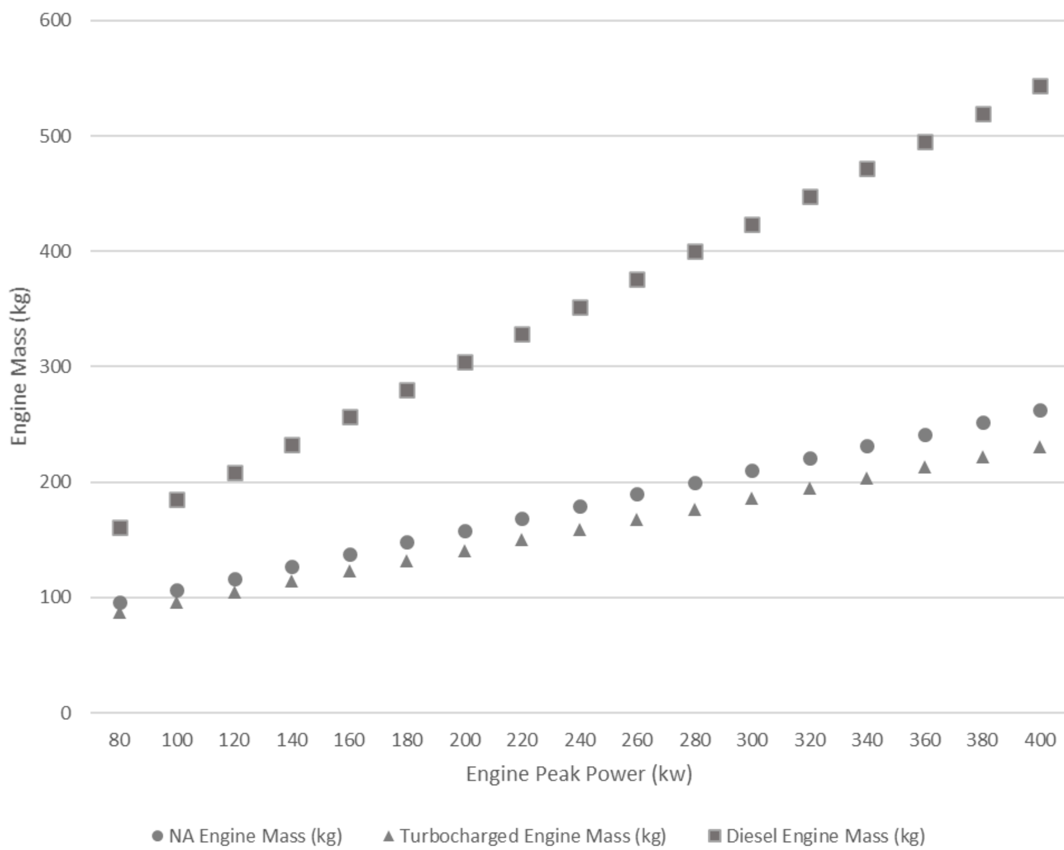

Figure 2-2 – Engine Mass Determination as a Function of Power and Type of Air Induction and Engine Type

As with conventional vehicle models, Autonomie also builds electrified vehicle models from the ground up. To capture improvements for electrified vehicles for this analysis, Argonne applies the same mass regression analysis process that considers electric motor weight versus electric motor power for vehicle models that adopt electric motors. Argonne analyzed benchmarking data for hybrid and electric vehicles from the A2Mac1 database to develop a regression curve of electric motor peak power versus electric motor weight.[113] Figure 2-3 below shows the electric motor mass regression as a function of peak power.

[113] Autonomie model documentation, Chapter 5.2.10 Electric Machines System Weight.

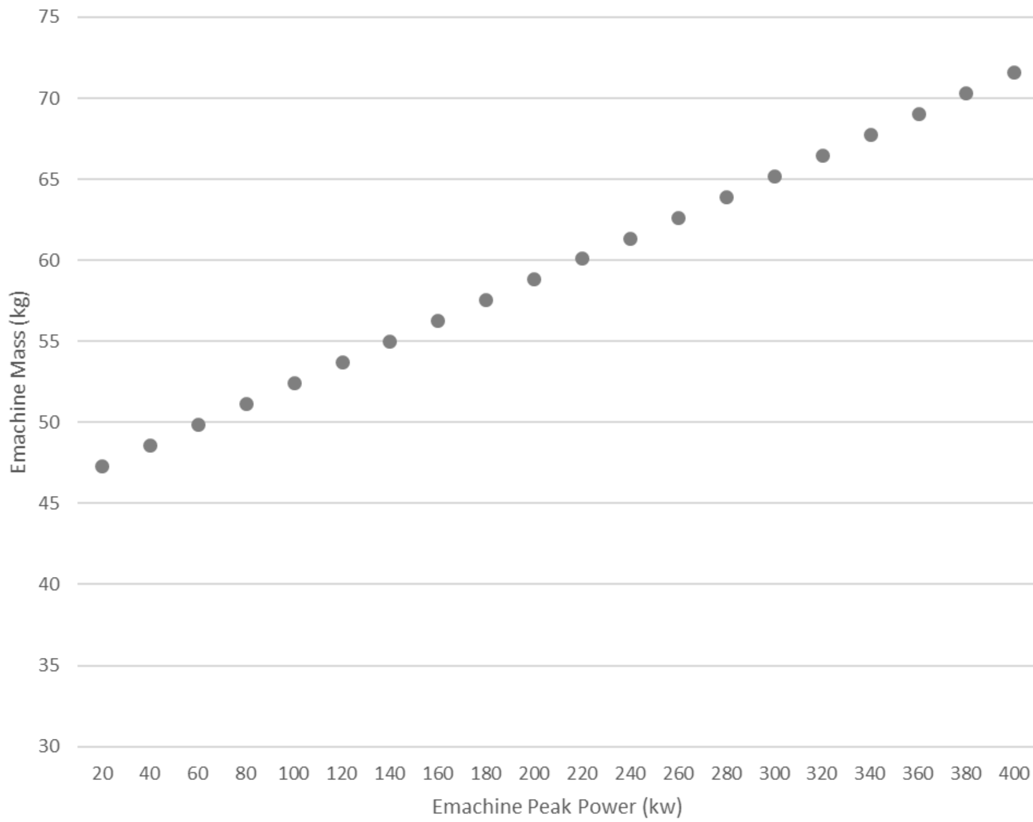

Figure 2-3 – Electric Motor Mass Determination as Function of Peak Power

2.4.4 Sizing Powertrains

We maintain performance neutrality in the full vehicle simulations by resizing engines, electric machines, and hybrid electric vehicle battery packs at specific incremental technology steps. To address product complexity and economies of scale, engine resizing is limited to specific incremental technology changes that would typically be associated with a major vehicle or engine redesign. This is intended to reflect manufacturers' comments to DOT on how they consider engine resizing and product complexity, and DOT's observations on industry product complexity.

When a powertrain does need to be resized, Autonomie attempts to mimic manufacturers' practices to the greatest extent possible. As discussed earlier, the Autonomie vehicle building process is initiated by building a baseline vehicle model with a baseline engine, transmission, and other baseline vehicle technologies. This baseline vehicle model (for each technology class) is sized to meet a specific set of performance criteria, including acceleration and gradeability.

The modeling also accounts for the industry practice of platform, engine, and transmission sharing to manage component complexity and the associated costs.[114] At a vehicle refresh cycle, a vehicle may inherit an already resized powertrain from another vehicle within the same engine-

[114] For example, Ford EcoBoost Engines are shared across ten different models in MY 2019. https://www.ford.com/powertrains/ecoboost/. (Accessed: February 15, 2022).

sharing platform that adopted the powertrain in an earlier model year. In the Autonomie modeling, when a new vehicle adopts fuel saving technologies that are inherited, the engine is not resized (the properties from the baseline reference vehicle are used directly and unchanged) and there may be a small change in vehicle performance. For example, in Figure 2-1 above, Vehicle 2 inherits Eng01 from Vehicle 1 while updating the transmission. Inheritance of the engine with the new transmission may change performance. This example illustrates how manufacturers generally manage manufacturing complexity for engines, transmissions, and electrification technologies.

Autonomie implements different powertrain sizing algorithms depending on the type of powertrain being considered because different types of powertrains contain different components that must be optimized.[115] For example, Autonomie's conventional powertrain resizing algorithm considers only the reference power of the conventional engine (e.g., Eng01, a basic VVT engine, is rated at 108 kilowatts and this is the starting reference power for all technology classes), versus the power-split hybrid (SHEVPS) resizing algorithm that must separately optimize engine power, battery size (energy and power), and electric motor power. An engine's reference power rating can either increase or decrease depending on the architecture, vehicle technology class, and whether it includes other advanced technologies.

Performance requirements also differ depending on the type of powertrain because vehicles with different powertrain types may need to meet different criteria. For example, a PHEV) powertrain that can travel a certain number of miles on its battery energy alone (referred to as AER, or as performing in electric-only mode) is also sized to ensure that it can meet the performance requirements of a US06 drive cycle in electric-only mode.

The powertrain sizing algorithm is an iterative process that attempts to optimize individual powertrain components at each step. For example, the sizing algorithm for conventional powertrains estimates required power to meet gradeability and acceleration performance and compares it to the reference engine power for the technology class. If the power required to meet gradeability and acceleration performance exceeds the reference engine power, the engine power is updated to the new value. Similarly, if the reference engine power exceeds the gradeability and acceleration performance power, it is decreased to the lower power rating. If the change in power requires a change in the engine design, like increasing displacement (e.g., going from a 1.8-liter to 2.4-liter engine) or increasing cylinder count (e.g., going from an I4 to a V6), the engine weight will also change. The new engine power is used to update the weight of the engine.

Next, the conventional powertrain sizing algorithm enters an acceleration algorithm loop to verify low-speed acceleration performance (the time it takes to go from 0 mph to 60 mph). In this step, Autonomie adjusts engine power to maintain a performance attribute for the given technology class and updates engine weight accordingly. Once this performance criteria are met, Autonomie ends the low-speed acceleration performance algorithm loop and enters a high-speed acceleration (the time it takes to go from 50 mph to 80 mph) algorithm loop. Again, Autonomie

[115] Autonomie model documentation, Chapter 8.3.1 Conventional-Vehicle Sizing Algorithm; Chapter 8.3.2 Split-HEV Sizing Algorithm; Chapter 8.3.3 Parallel HEV Sizing Algorithm; 8.3.4 Parallel PHEV sizing Algorithm; 8.3.5 Split PHEV (Vehicle Sizing Algorithm; Chapter 8.3.6 Voltec PHEV Vehicle Sizing Algorithm; Chapter 8.3.7 BEV Sizing Algorithm.

might need to adjust engine power to maintain a performance attribute for the given technology, and it exits this loop once the performance criteria are met. At this point, the sizing algorithm is complete for the conventional powertrain based on the designation for engine type, transmission type, aerodynamic improvement type, mass reduction technology, and low rolling resistance technology. Figure 2-4 below shows the sizing algorithm for conventional powertrains. Each circle in the flow chart is a closed loop system and the loop must be completed to move to the next loop; e.g., the acceleration performance loop must be complete before the model sizes components to meet the passing acceleration performance loop. This allows us to avoid under- or oversizing components, engines, and electric motors to minimize over and under compliance in the analysis.

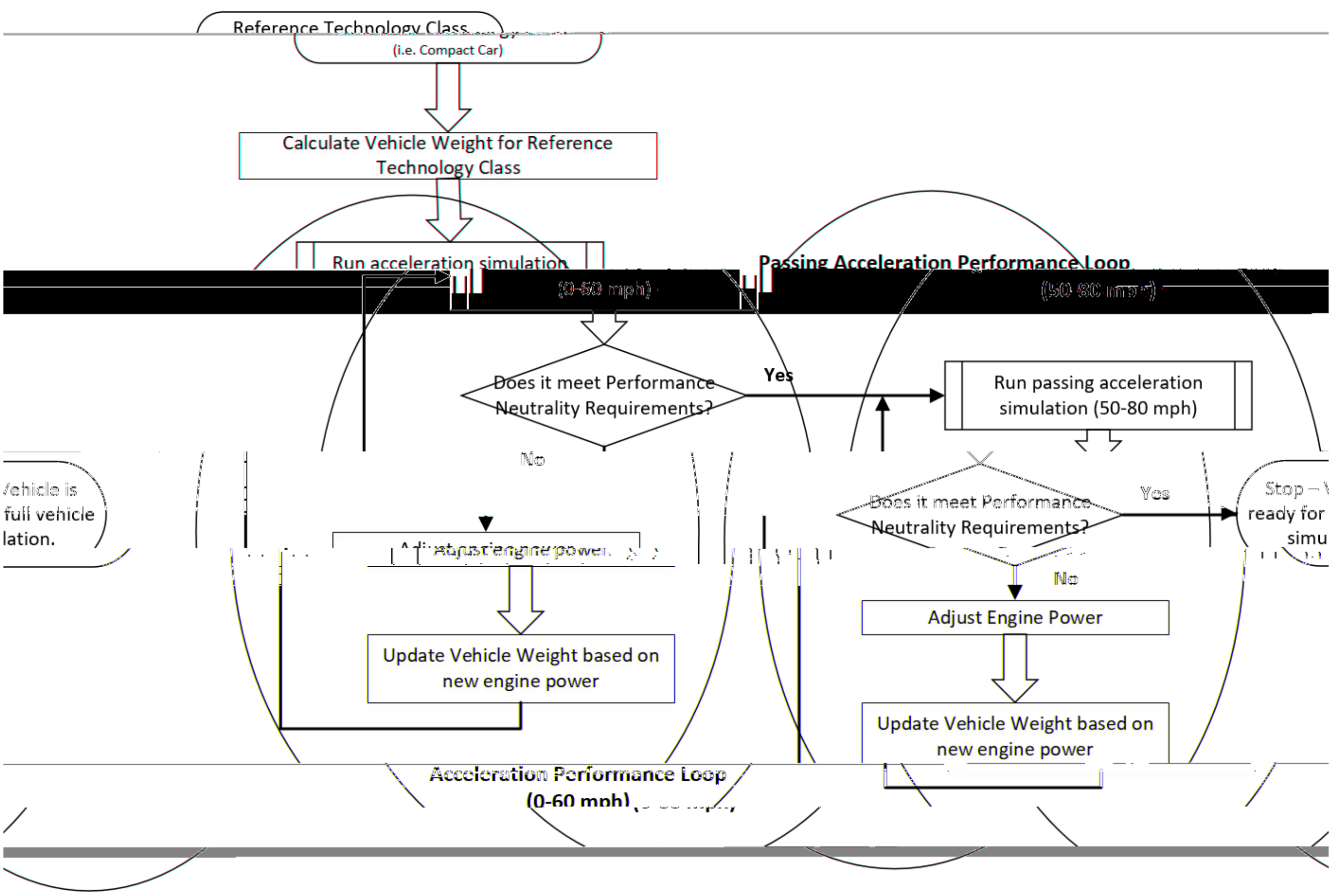

Figure 2-4 – Conventional Powertrain Sizing Algorithm

Depending on the type of powertrain considered, the sizing algorithms may size to meet the different performance criteria in a different order. For example, the electrified powertrain sizing algorithm considers different requirements, including range, and battery power in addition to performance. The powertrain sizing algorithms for electrified vehicles are considerably more complex and are discussed in further detail in Autonomie model documentation.[116]

2.4.5 Performance Neutrality

The purpose of this analysis is to examine the impact of technology application that can improve fuel economy. A fuel economy improvement can be realized by improving the powertrain that propels the vehicle (e.g., by replacing a 6-cylinder engine with a smaller, turbocharged 4-cylinder engine), or by reducing the vehicle's loads or burdens (e.g., by lowering aerodynamic drag, reducing vehicle mass and/or rolling resistance). Either way, these changes reduce energy consumption and create a range of choices for vehicle manufacturers. At the two ends of the range, the manufacturer can choose to either:

A) Design a vehicle that does same the amount of work as before but uses less fuel.

For example, a redesigned pickup truck would receive a turbocharged V6 engine in place of the outgoing naturally aspirated V8. The pickup would offer no additional towing capacity, acceleration, larger wheels and tires, expanded infotainment packages, or customer convenience features, but would achieve a higher fuel economy rating.

Or:

B) Design a vehicle that does more work and uses the same amount of fuel as before.

For example, a redesigned pickup truck would receive a turbocharged V6 engine in place of the outgoing naturally aspirated V8, but with engine efficiency improvements that allow the same amount of fuel to do more work. The pickup would offer increased towing capacity, faster acceleration, larger wheels and tires, an expanded (heavier) infotainment package, and more convenience features, while maintaining (not improving) the fuel economy rating of the previous year's model.

In other words, automakers weigh the trade-offs between vehicle performance/utility and fuel economy, and they choose a blend of these attributes to balance meeting fuel economy and emissions standards and meeting utility requirements during research and development.

Historically, vehicle performance has improved over the years. The average horsepower is the highest that it has ever been; all vehicle types have improved horsepower by at least 43 percent compared to the 1978 model year, and pickup trucks have improved by 49 percent.[117] Since 1978, vehicles' 0-60 acceleration time has improved by 40-49 percent depending on vehicle type.[118] Fuel economy has also improved, but the horsepower and acceleration trends show that not 100 percent of technological improvements have been applied to fuel savings. While future

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[116] Autonomie model documentation, Chapter 8.3.1 Conventional-Vehicle Sizing Algorithm; Chapter 8.3.2 Split-HEV Sizing Algorithm; Chapter 8.3.3 Parallel HEV Sizing Algorithm; 8.3.4 Parallel PHEV sizing Algorithm; 8.3.5 Split PHEV (Vehicle Sizing Algorithm; Chapter 8.3.6 Voltec PHEV Vehicle Sizing Algorithm; Chapter 8.3.7 BEV Sizing Algorithm.

[117] "The 2021 EPA Automotive Trends Report, Greenhouse Gas Emissions, Fuel Economy, and Technology since 1975," EPA-420-R-21-023, November 2021, at pp. 20-7 [hereinafter 2021 EPA Automotive Trends Report].

[118] 2021 EPA Automotive Trends Report, at pp. 26-7.

trends are uncertain, the past trends suggest vehicle performance is unlikely to *decrease*, as it seems reasonable to assume that customers will, at a minimum, demand vehicles that offer the same utility as today's fleet.

For this rulemaking analysis, we analyze technology pathways manufacturers could use for compliance that attempt to maintain vehicle attributes, utility, and performance. Using this approach allows us to assess the costs and benefits of potential standards under a scenario where consumers continue to get the similar vehicle attributes and features, other than changes in fuel economy. The purpose of constraining vehicle attributes is to simplify the analysis and reduce variance in other attributes that consumers may value across the analyzed regulatory alternatives. This allows for a streamlined accounting of costs and benefits by not requiring the values of other vehicle attributes that trade off with fuel economy. The CAFE Model maintains the initial performance and utility levels of the analysis fleet, while considering real world constraints faced by manufacturers.

To maintain performance neutrality when applying fuel economy technologies, it is first necessary to characterize the performance levels of each of the vehicle models in the baseline fleet. As discussed in Chapter 2.4.2, above, we assign each individual vehicle model in the analysis fleet to one of ten vehicle "technology classes"— the class that is most similar to the vehicle model. The technology classes include five standard class vehicles (compact car, midsize car, small SUV, midsize SUV, pickup) plus five "performance" versions of these same body styles.[119] Each vehicle class has a unique set of attributes and characteristics, including vehicle performance metrics, that describe the typical characteristics of the vehicles in that class.

The analysis uses four criteria to characterize vehicle performance attributes and utility:

- Low-speed acceleration (time required to accelerate from 0-60 mph)
- High-speed acceleration (time required to accelerate from 50-80 mph)
- Gradeability (the ability of the vehicle to maintain constant 65 miles per hour speed on a six percent upgrade); and
- Towing capacity

Low-speed and high-speed acceleration target times are typical of current production vehicles and range from 6 to 10 seconds depending on the vehicle class; for example, the midsize SUV performance class has a low- and high-speed acceleration target of 7 seconds.[120] The gradeability criterion requires that the vehicle, given its attributes of weight, engine power, and transmission gearing, be capable of maintaining a minimum of 65 mph while going up a six percent grade. The towing criterion, which is applicable only to the pickup truck and performance pickup truck vehicle technology classes, is the same as the gradeability requirement but adds an additional payload/towing mass (3,000 lbs. for pickups, or 4,350 lbs. for performance pickups) to the vehicle, essentially making the vehicle heavier.

[119] Separate technology classes better account for performance diversity across the fleet.
[120] Note, for all vehicle classes, the low and high-speed acceleration targets use the same value. *See* Chapter 2.2.

In addition, to maintain the capabilities of certain electrified vehicles, the analysis requires that those vehicles be capable of achieving the accelerations and speeds of certain standard driving cycles. Autonomie uses the US06 “aggressive driving” cycle and the Urban Dynamometer Driving Schedule (UDDS) “city driving” cycle to ensure that core capabilities of BEVs and PHEVs, such as driving certain speeds and/or distances in electric-only mode, are maintained. In addition to the four criteria discussed above, the following performance criteria are applied to these electrified vehicles:

- Battery electric vehicles (BEV) are sized to be capable of completing the US06 “aggressive driving” cycle.
- Plug-in hybrid vehicles with 50-mile AER (PHEV50) are sized to be capable of completing the US06 “aggressive driving” cycle in electric-only mode.
- Plug-in hybrid vehicles with 20-mile AER (PHEV20) are sized to be capable of completing the UDDS “city driving” cycle in electric-only (charge depleting) mode.[121]

Together, these performance criteria are widely used by the automotive industry as metrics to quantify vehicle performance attributes that consumers observe and that are important for vehicle utility and customer satisfaction.[122]

When fuel-saving technologies are applied that significantly affect vehicle performance, such as replacing a pickup truck’s V8 engine with a turbocharged V6 engine, Autonomie iteratively resizes the vehicle powertrain (engine, electric motors, and/or battery) such that the above performance criteria are maintained. For example, if the aforementioned engine replacement causes an improvement in acceleration, the engine may be iteratively resized until vehicle acceleration performance is shifted back to the initial target time for that vehicle technology class. For the low and high-speed acceleration criteria, engine resizing iterations continue until the acceleration time is within plus or minus 0.2 seconds of the target time,[123,124] which reasonably balances the precision of engine resizing with the number of simulation iterations needed to achieve performance within the 0.2 second window, and the associated computer resources and time required to perform the iterative simulations.

[121] PHEV20s are blended-type plug-in hybrid vehicles, which are capable of completing the UDDS cycle in charge depleting mode without assistance from the engine. However, under higher loads, this charge depleting mode may use supplemental power from the engine.

[122] Conlon, B., Blohm, T., Harpster, M., Holmes, A. et al., “The Next Generation “Voltec” Extended Range EV Propulsion System,” SAE Int. J. Alt. Power. 4(2):2015, doi:10.4271/2015-01-1152. Kapadia, J., Kok, D., Jennings, M., Kuang, M., et al., "Powersplit or Parallel - Selecting the Right Hybrid Architecture," SAE Int. J. Alt. Power. 6(1):2017, doi:10.4271/2017-01-1154. Islam, E., A. Moawad, N. Kim, and A. Rousseau, 2018a, An Extensive Study on Vehicle Sizing, Energy Consumption and Cost of Advance Vehicle Technologies, Report No. ANL/ESD-17/17, Argonne National Laboratory, Lemont, Ill., Oct 2018.

[123] For example, if a vehicle has a target 0-60 acceleration time of 6 seconds, a time within 5.8-6.2 seconds is accepted.

[124] With the exception of a few performance electrified vehicle types which, based on observations in the marketplace, use different criteria to maintain vehicle performance without battery assist. Performance PHEV20, and Performance PHEV50 resize to the performance of a conventional six-speed automatic (CONV 6AU). Performance SHEVP2, engines/electric-motors are resized if the 0-60 acceleration time is worse than the target, but not if the acceleration time is better than the target time.

The Autonomie simulation resizes until the least capable of the performance criteria is met, to ensure the pathways do not degrade any of the vehicle performance metrics. It is possible that as one criterion target is reached after the application of a specific technology or technology package, other criteria may be better than their target values. For example, if the engine size is decreased until the low-speed acceleration target is just met, it is possible that the resulting engine size would cause high speed acceleration performance to be better than its target. Or, a PHEV50 may have an electric motor and battery appropriately sized to operate in all electric mode through the repeated accelerations and high speeds in the US06 driving cycle, but the resulting motor and battery size enables the PHEV50 to slightly over-perform in 0-60 acceleration, which utilizes the power of both the electric motor and combustion engine.

To address product complexity and economies of scale, we limit engine resizing to specific incremental technology changes that would typically be associated with a major vehicle or engine redesign. Manufacturers have repeatedly and consistently told NHTSA that the high costs for redesign and the increased manufacturing complexity that would result from resizing engines for small technology changes preclude them from doing so. It would be unreasonable and unaffordable to resize powertrains for every unique combination of technologies. Engine displacements are further described in Chapter 3.1.

To address this issue, the Autonomie simulations allow engine resizing when mass reduction is applied at several different levels,[125] and when one powertrain architecture is replaced with another architecture during a redesign cycle.[126] At its refresh cycle, a vehicle may also inherit an already resized powertrain from another vehicle within the same engine-sharing platform. The analysis does not resize the engine in response to adding technologies that have smaller effects on vehicle performance. For instance, if MR1 is applied to a vehicle, causing the 0-60 mile per hour time to improve slightly, the model would not resize the engine. This criterion better reflects what is feasible for manufacturers to do.[127]

Because the regulatory analysis compares differences in impacts among the alternatives, we believe that having consistent performance across the alternatives is an important aspect of performance neutrality. If the vehicle fleet had performance gains which varied significantly depending on the alternative, performance differences would impact the comparability of the simulations.

In order to confirm that there are minimal differences in performance metrics across regulatory alternatives, we analyzed the sales-weighted average 0-60 mph acceleration performance of the entire simulated vehicle fleet for MYs 2020 and 2029. The analysis compared performance under the baseline standards and Preferred Alternative. Two inputs are required for this

[125] For more detail on glider mass calculations, see Chapter 3.4.
[126] Some engine and accessory technologies may be added to an engine without an engine architecture change. For instance, manufacturers may adapt, but not replace engine architectures to include cylinder deactivation, VVL, belt-integrated starter generators, and other basic technologies. However, switching from a naturally aspirated engine to a turbo-downsized engine is an engine architecture change typically associated with a major redesign and radical change in engine displacement.
[127] For instance, a vehicle would not get a modestly bigger engine if the vehicle comes with floor mats, nor would the vehicle gets a modestly smaller engine without floor mats. This example demonstrates small levels of mass reduction. If manufacturers resized engines for small changes, manufacturers would have dramatically more part complexity, potentially losing economies of scale.

performance neutrality analysis. The first input required is the CAFE Model's Vehicles Report, which lists the MY 2020 sales volumes and the resulting "tech key" for every vehicle in the analysis fleet for every simulated model year. The tech key is a string of characters that summarizes the technologies applied to that vehicle, as deemed necessary by the CAFE Model simulations of manufacturers' responses to different potential standards. The second input is the full set of Autonomie simulation databases, which include the 0-60 and 50-80 mph acceleration times related to every tech key.

Using a spreadsheet program, each vehicle in the Vehicles Report is matched, via tech key, with the appropriate acceleration time in the Autonomie simulation databases. This process effectively assigned a 0-60 mph time to every vehicle in the fleet for four scenarios: 1) MY 2020 under the no action scenario (i.e., No-Action Alternative), 2) MY 2020 under the Preferred Alternative, 3) MY 2029 under the no action scenario, and 4) MY 2029 under the Preferred Alternative.[128] Using the MY 2020 sales volumes as weights, we calculated the weighted average 0-60 mph acceleration time for the analysis fleet in each of the four above scenarios. This analysis identified that the analysis fleet under no action standards in MY 2029 had a 0.0.0615 percent better 0-60 mph acceleration time than under the Preferred Alternative, indicating there is minimal difference in performance between the alternatives. Figure 2-5 shows the spread of 0-60 mph acceleration times between the No-Action Alternative and Preferred Alternative. This assessment shows that for this analysis, the performance difference is minimal across regulatory alternatives and across the simulated model years, which allows for fair, direct comparison among the alternatives.

[128] The baseline reference for both the No-Action Alternative and the Preferred Alternative is MY 2020 fleet performance.

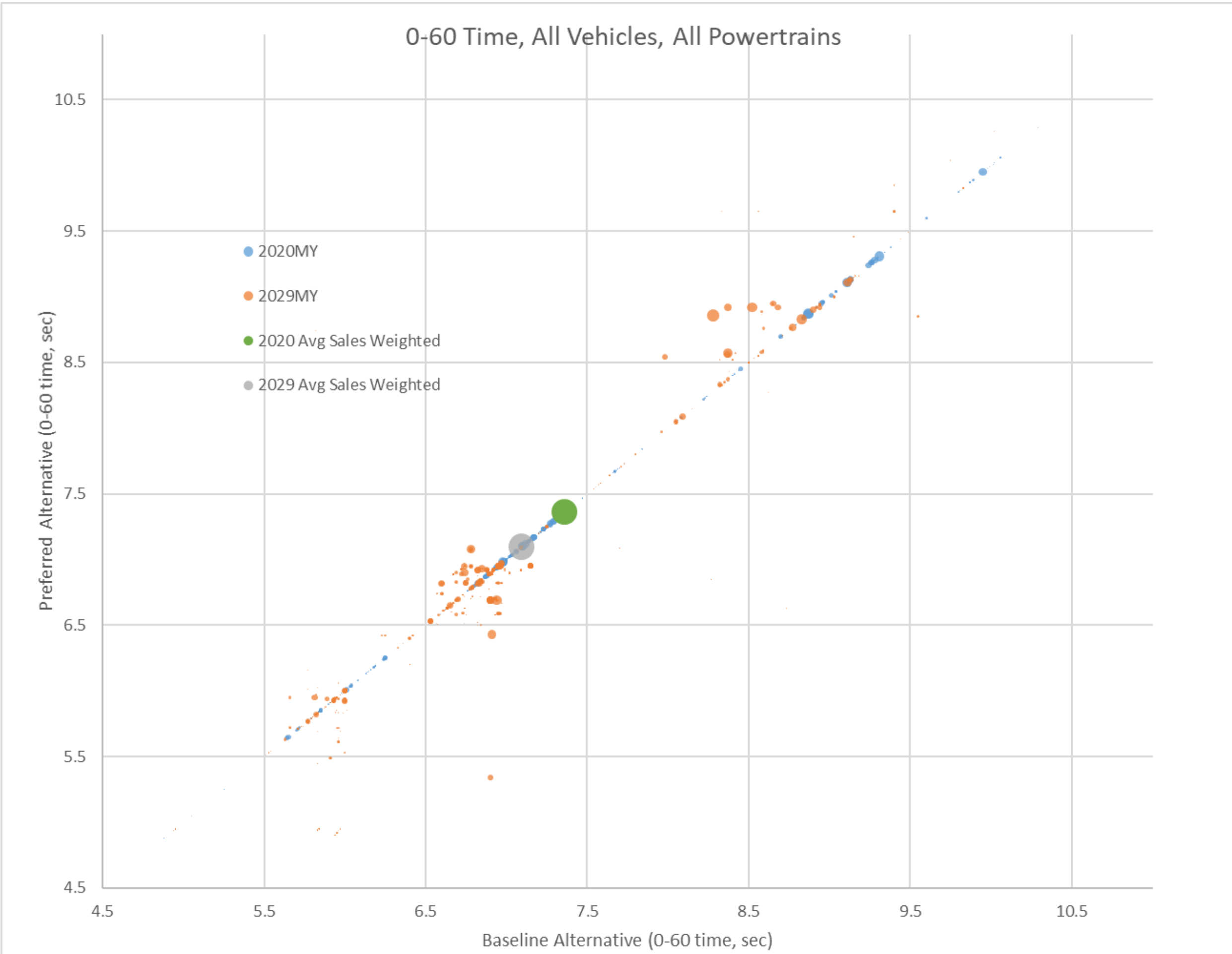

Figure 2-5 – 0-60 mph Acceleration Times for Analysis Fleet, No-Action Alternative Standard and Preferred Alternative Standard[129]

As we attempt to minimize the performance shift occurring over the relevant analysis years, it must be noted that a small increase in performance is expected and would be reasonable. This increase is attributed to the analysis recognizing the practical constraints on the number of unique engine displacements manufacturers can implement, and therefore not resizing powertrains for every individual technology and every combination of technologies when the performance impacts are small. Perfectly equal performance with zero percent change would not be achievable while accounting for these real-world resizing constraints. The performance analysis in the 2011 NAS report shared a similar view on performance changes, stating that

[129] The sales weighted average in MY 2020 is 7.36 seconds. The change in sales weighted average performance for the No-Action Alternative and Preferred Alternative are 7.09 seconds and 7.10 seconds, respectively, in 2029. This equates to 0.0615 percent difference in performance between the two alternatives. In the 2020 final rule, this difference was 4 percent, which demonstrates that successive Autonomie analyses are improving performance neutrality across alternatives.

"truly equal performance involves nearly equal values… within 5 percent."[130] We determined that the change in performance seen for this analysis is reasonable and is well within the 5 percent bound discussed by the NAS in its 2011 report.

2.4.6 Simulating the Built Vehicles on Test Cycles

After Autonomie builds vehicle models for every combination of technologies and vehicle classes represented in the analysis, Autonomie simulates the vehicles' performance on test cycles to calculate the effectiveness improvement of adding fuel-economy-improving technologies to the vehicle. Simulating vehicles' performance using tests and procedures specified by federal law and regulations minimizes the potential variation in determining technology effectiveness.

Autonomie simulates vehicles in a very similar process as the test procedures and energy consumption calculations that manufacturers must use for CAFE compliance.[131,132,133] Argonne simulates each vehicle model across several test cycles to evaluate technology effectiveness. For vehicles with conventional powertrains and micro hybrids, Autonomie simulates the vehicles per EPA 2-cycle test procedures and guidelines.[134] For mild and full hybrid electric vehicles and FCVs, Autonomie simulates the vehicles using the same EPA 2-cycle test procedure and guidelines, and the drive cycles repeat until the initial and final state of charge (SOC) are within a SAE J1711 tolerance. For PHEVs, Autonomie simulates vehicles per similar procedures and guidelines as prescribed in SAE J1711.[135] For BEVs Autonomie simulates vehicles per similar procedures and guidelines as prescribed in SAE J1634.[136]

2.4.7 Implementation in the CAFE Model

While the Autonomie model produces a large amount of information about each simulation run—for a single technology combination, in a single technology class—the CAFE Model only uses two elements of that information: battery costs and fuel consumption on the city and highway cycles. We combine the fuel economy information from the two cycles to produce a composite fuel economy for each vehicle, and on each fuel for dual fuel vehicles. Plug-in hybrids are the only dual-fuel vehicles in the Autonomie simulation, and require efficiency estimates for operation on both gasoline and electricity, as well as an estimate of the utility factor, or the number of miles driven on each fuel. The fuel economy information for each technology combination, for each technology class, is converted into a single number for use in the CAFE Model.

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[130] National Research Council. 2011. Assessment of Fuel Economy Technologies for Light-Duty Vehicles. Washington, DC – The National Academies Press, at 62. http://nap.edu/12924. (Accessed: February 15, 2022).
[131] EPA, "How Vehicles are Tested." https://www.fueleconomy.gov/feg/how_tested.shtml. (Accessed: February 15, 2022).
[132] Autonomie model documentation, Chapter 6 Test Procedures and Energy Consumption Calculations.
[133] EPA Guidance Letter. "EPA Test Procedures for Electric Vehicles and Plug-in Hybrids." Nov. 14, 2017. https://www.fueleconomy.gov/feg/pdfs/EPA%20test%20procedure%20for%20EVs-PHEVs-11-14-2017.pdf. (Accessed: February 15, 2022).
[134] 40 CFR part 600.
[135] PHEV testing is broken into several phases based on SAE J1711: charge-sustaining on the city cycle, charge-sustaining on the HWFET cycle, charge-depleting on the city and HWFET cycles.
[136] SAE J1634. "Battery Electric Vehicle Energy Consumption and Range Test Procedure." July 12, 2017.

As described in greater detail below, each Autonomie simulation record represents a unique combination of technologies, and we create a technology "key" or technology state vector that describes all the technology content associated with a record. The 2-cycle fuel economy of each combination is converted into fuel consumption (gallons per mile) and then normalized relative to the starting point for the simulations. In each technology class, the combination with the lowest technology content is the VVT (only) engine, with a 5-speed transmission, no electrification, and no body-level improvements (mass reduction, aerodynamic improvements, or low rolling resistance tires). This is the reference point (for each technology class) for all of the effectiveness estimates in the CAFE Model. The improvement factors that the model uses are a given combination's fuel consumption improvement relative to the reference vehicle in its technology class.

For the majority of the technologies analyzed within the CAFE Model, the fuel economy improvements are derived from the database of Autonomie's detailed full-vehicle modeling and simulation results. In addition to the technologies found in the Autonomie simulation database, the CAFE modeling system also incorporates a handful of technologies that are included for CAFE modeling but are not explicitly simulated in Autonomie. The total effectiveness of these technologies either could not be captured on the 2-cycle test, or there are no robust data usable as an input to the full-vehicle modeling and simulation, like with emerging technologies such as ADEAC. These additional technologies are discussed further in Chapter 3's individual technologies sections. For calculating fuel economy improvements attributable to these additional technologies, the model uses defined fuel consumption improvement factors that are constant across all technology combinations in the database and scale multiplicatively when applied together. The Autonomie-simulated and additional technologies are then externally combined, forming a single dataset of simulation results (referred to as the vehicle simulation database, or simply, database), which may then be utilized by the CAFE modeling system.

To incorporate the results of the combined database of Autonomie-simulated and additional technologies, while still preserving the basic structure of the CAFE Model's technology subsystem, it is necessary to translate the points in this database into corresponding locations defined by the technology pathways. By recognizing that most of the pathways are unrelated and are only logically linked to designate the direction in which technologies are allowed to progress, it is possible to condense the paths into a smaller number of groups based on the specific technology. In addition, to allow for technologies present on the Basic Engine and Dynamic Road Load (DLR, i.e., MASS, AERO, and ROLL) paths to be evaluated and applied in any given combination, we established a unique group for each of these technologies.

As such, the following technology groups are defined within the modeling system: engine cam configuration (CONFIG), VVT engine technology (VVT), VVL engine technology (VVL), SGDI engine technology (SGDI), DEAC engine technology (DEAC), non-basic engine technologies (ADVENG), transmission technologies (TRANS), electrification and hybridization (ELEC), low rolling resistance tires (ROLL), aerodynamic improvements (AERO), mass reduction levels (MR), EFR engine technology (EFR), electric accessory improvement technologies (ELECACC), LDB technology (LDB), and SAX technology (SAX). The combination of technologies along each of these groups forms a unique technology state vector and defines a unique technology combination that corresponds to a single point in the database for each technology class evaluated within the modeling system. This technology state vector is commonly referred to as a 'technology key' or 'tech key' in this analysis.

As an example, a technology state vector describing a vehicle with a SOHC engine, variable VVT (only), a AT6, a belt-integrated starter generator, rolling resistance (level 1), aerodynamic improvements (level 2), mass reduction (level 1), electric power steering, and low drag brakes, is specified as "SOHC; VVT; ; ; ; ; AT6; BISG; ROLL10; [aero drag reduction, level 4] AERO20; MR1; ; EPS; LDB ; ."[137] By assigning each unique technology combination a tech key such as the one in the example, the CAFE Model can identify the initial technology state of each vehicle in the analysis fleet and map it to a point (unique technology combination) in the database.

Once a vehicle is assigned (or mapped) to an appropriate technology state vector (from one of approximately three million unique combinations, which are defined in the vehicle simulation database as CONFIG; VVT; VVL; SGDI; DEAC; ADVENG; TRANS; ELEC; ROLL; AERO; MR; EFR; ELECACC; LDB; SAX), adding a new technology to the vehicle simply represents progress from a previous state vector to a new state vector. The previous state vector simply refers to the technologies that are currently in use on a vehicle. The new state vector, however, is computed within the modeling system by adding a new technology to the combination of technologies represented by the previous state vector, while simultaneously removing any other technologies that are superseded by the newly added one.

For example, consider the vehicle with the state vector described as: SOHC; VVT; AT6; BISG; ROLL10; AERO20; MR1; EPS; LDB. Assume the system is evaluating PHEV20 as a candidate technology for application on this vehicle. The new tech state vector for this vehicle is computed by removing SOHC, VVT, AT6, and BISG technologies from the previous state vector,[138] while also adding PHEV20, resulting in the following: PHEV20; ROLL10; AERO20; MR1; EPS; LDB.

From here, it is relatively simple to obtain a fuel economy improvement factor for any new combination of technologies and apply that factor to the fuel economy of a vehicle in the analysis fleet. The formula for calculating a vehicle's fuel economy after application of each successive technology represented within the database is defined as the ratio of the fuel economy improvement factor associated with the technology state vector before application of a candidate technology and after the application of a candidate technology.[139] The resulting improvement is applied to the original compliance fuel economy value for a discrete vehicle in the analysis fleet, as discussed previously in this chapter.

[137] In the example technology state vector, the series of semicolons between VVT and AT6 correspond to the engine technologies which are not included as part of the combination, while the gap between MR1 and EPS corresponds to EFR and the omitted technology after LDB is SAX. The extra semicolons for omitted technologies are preserved in this example for clarity and emphasis, and will not be included in future examples.

[138] For more discussion of how the CAFE Model handles technology supersession, see S4.5 of the CAFE Model Documentation.

[139] For more discussion of how the CAFE Model calculates a vehicle's fuel economy where the vehicle switches from one type of fuel to another, for example, from gasoline operation to diesel operation or from gasoline operation to plug-in hybrid/electric vehicle operation, see S4.6 of the CAFE Model Documentation.

2.4.8 Compliance and Real-World Fuel Economy "Gap"

The statutorily mandated vehicle fuel economy test cycles for NHTSA CAFE and EPA GHG program compliance consist of two separate test cycles, the "city" and "highway" cycles, commonly referred to as the 2-cycle tests. In 2008, EPA introduced three additional test cycles to bring "label" values from two-cycle testing in line with efficiency values consumers were experiencing in the real world, particularly for hybrids. This is known as 5-cycle testing.

Generally, the revised 5-cycle testing values have proven to be a good approximation of what consumers will experience during vehicle operation, significantly better than the previous 2-cycle test values.

The CAFE regulatory analysis utilizes "on-road" fuel economy values, which are the ratio of 5-cycle to 2-cycle testing values, i.e., the CAFE compliance values to the "label" values.

For this analysis, DOT applied a certain percent difference between the 2-cycle test and 5-cycle test to represent the gap in compliance fuel economy and real-world fuel economy.[140] This percent difference, or "gap", is calculated as shown in Equation 2-8.

$$\frac{2cycleFE - 5cycleFE}{2cycleFE} * 100 = "fuel\ economy\ gap"\ (\%)$$

Equation 2-8 – Percent Difference Between 2-cycle and 5-cycle Tests

Table 2-20 below shows a summary of the inputs used for the fuel economy gap for different fuel types.[141] The underlying data for this was from EPA test data.[142] These data are average fleet-wide values; in reality the true fuel economy gap will be lower for some vehicles and higher for other vehicles.

Table 2-20 – 2-Cycle to 5-Cycle "Gap" Used for this Analysis, by Fuel Type

	Cars	Vans/SUVs	Pickups
Gasoline	24%	24%	24%
Ethanol-85	24%	24%	24%
Diesel	24%	24%	24%
Electricity	29%	29%	29%
Hydrogen	29%	29%	29%
Compressed Natural Gas	24%	24%	24%

2.5 Defining Technology Adoption in the Rulemaking Timeframe

As discussed in Chapter 2.2, starting with a fixed analysis fleet, the CAFE Model estimates ways each manufacturer could potentially apply specific fuel-saving technologies to specific vehicle model/configurations in response to, among other things (such as fuel prices), CAFE standards,

140 For more details see the CAFE Model Documentation.
141 This input is specific in the CAFE Model Parameters file.
142 Download Fuel Economy Data. EPA. https://www.fueleconomy.gov/feg/download.shtml. (Accessed: February 15, 2022).

CO_2 standards, commitments some manufacturers have made to CARB's Framework Agreements, and ZEV mandates imposed by California and several other states. The CAFE Model follows a year-by-year approach to simulating manufacturers' potential decisions to apply technology, accounting for multiyear planning within the context of estimated schedules for future vehicle redesigns and refreshes during which significant technology changes may most practicably be implemented.

The modeled technology adoption for each manufacturer under each regulatory alternative depends on this representation of multiyear planning, and on a range of other factors represented by other model characteristics and inputs, such as the logical progression of technologies defined by the model's technology pathways; the technologies already present in the analysis fleet; inputs directing the model to "skip" specific technologies for specific vehicle model/configurations in the analysis fleet (e.g., because SAX cannot be applied to 2-wheel-drive vehicles, and because manufacturers already heavily invested in engine turbocharging and downsizing are unlikely to abandon this approach in favor of using high compression ratios); inputs defining the sharing of engines, transmissions, and vehicle platforms in the analysis fleet; the model's logical approach to preserving this sharing; inputs defining each regulatory alternative's specific requirements; inputs defining expected future fuel prices, annual mileage accumulation, and valuation of avoided fuel consumption; and inputs defining the estimated efficacy and future cost (accounting for projected future "learning" effects) of included technologies; inputs controlling the maximum pace the simulation is to "phase in" each technology; and inputs further defining the availability of each technology to specific technology classes.

Two of these inputs—the "phase-in cap" and the "phase-in start year"—apply to the manufacturer's entire estimated production and, for each technology, define a share of production in each model year that, once exceeded, will stop the model from further applying that technology to that manufacturer's fleet in that model year. The influence of these inputs varies with regulatory stringency and other model inputs. For example, setting the inputs to allow immediate 100 percent penetration of a technology will not guarantee any application of the technology if stringency increases are low and the technology is not at all cost effective. Also, even if these are set to allow only very slow adoption of a technology, other model aspects and inputs may nevertheless force more rapid application than these inputs, alone, would suggest (e.g., because an engine technology propagates quickly due to sharing across multiple vehicles, or because BEV application must increase quickly in response to ZEV requirements). For today's analysis, nearly all of these inputs are set at levels that do not limit the simulation at all.

As discussed below in Chapter 3.1, for the most advanced engines (ADEAC, variable compression ratio, variable turbocharger geometry, and turbocharging with cylinder deactivation), DOT has specified phase-in caps and phase-in start years that limit the pace at which the analysis shows the technology being adopted in the rulemaking timeframe. For example, today's analysis applies a 34 percent phase-in cap and MY 2019 phase-in start year for ADEAC, meaning that in MY 2021 (using a MY 2020 fleet, the analysis begins simulating further technology application in MY 2021), the model will stop adding ADEAC to a manufacturer's MY 2021 fleet once ADEAC reaches more than 68 percent penetration, because 34% x (2021 – 2019) = 34% x 2 = 68%.

As discussed in Chapter 3.3, today's analysis also applies phase-in caps and corresponding start years to prevent the simulation from showing unlikely rates of applying battery-electric vehicles (BEVs), such as showing that a manufacturer producing very few BEVs in MY 2020 could plausibly replace every product with a 300- or 400-mile BEV by MY 2025.. Also, as discussed in Chapter 3.4, today's analysis applies phase-in caps and corresponding start years intended to ensure that the simulation's plausible application of the highest included levels of mass reduction (20 and 28.2 percent reductions of vehicle "glider" weight) do not, for example, outpace plausible supply of raw materials and development of entirely new manufacturing facilities.

These model logical structures and inputs act together to produce estimates of ways each manufacturer could potentially shift to new fuel-saving technologies over time, reflecting some measure of protection against rates of change not reflected in, for example, technology cost inputs. This does not mean that every modeled solution would necessarily be economically practicable. Using technology adoption features like phase-in caps and phase-in start years is one mechanism that can be used so that the analysis better represents the potential costs and benefits of technology application in the rulemaking timeframe.

2.6 Technology Costs

We estimate present and future costs for fuel-saving technologies taking into consideration the type of vehicle, or type of engine if technology costs vary by application. These cost estimates are based on three main inputs. First, direct manufacturing costs (DMCs), or the component and labor costs of producing and assembling the physical parts and systems, are estimated assuming high volume production. DMCs generally do not include the indirect costs of tools, capital equipment, financing costs, engineering, sales, administrative support or return on investment. We account for these indirect costs via a scalar markup of direct manufacturing costs (the retail price equivalent, or RPE). Finally, costs for technologies may change over time as industry streamlines design and manufacturing processes. To reflect this, we estimate potential cost improvements with learning effects (LE). The retail cost of equipment in any future year is estimated to be equal to the product of the DMC, RPE, and LE. Considering the retail cost of equipment, instead of merely direct manufacturing costs, is important to account for the real-world price effects of a technology, as well as market realities.

2.6.1 Direct Manufacturing Costs

Direct manufacturing costs (DMCs) are the component and assembly costs of the physical parts and systems that make up a complete vehicle. The analysis uses agency-sponsored tear-down studies of vehicles and parts to estimate the DMCs of individual technologies, in addition to independent tear-down studies, other publications, and confidential business information. In the simplest cases, the agency-sponsored studies produced results that confirmed third-party industry estimates and aligned with confidential information provided by manufacturers and suppliers. In cases with a large difference between the tear-down study results and credible independent sources, we scrutinized the study assumptions, and sometimes revised or updated the analysis accordingly.

Due to the variety of technologies and their applications, and the cost and time required to conduct detailed tear-down analyses, the agency did not sponsor teardown studies for every technology. In addition, the analysis includes some fuel-saving technologies that are pre-production or sold in very small pilot volumes. For those technologies, we could not conduct a tear-down study to assess costs because the product is not yet in the marketplace for evaluation. In these cases, we rely upon third-party estimates and confidential information from suppliers and manufacturers; however, there are some common pitfalls with relying on confidential business information to estimate costs. The agency and the source may have had incongruent or incompatible definitions of "baseline." The source may have provided DMCs at a date many years in the future, and assumed very high production volumes, important caveats to consider for agency analysis. In addition, a source may provide incomplete and/or misleading information. In other cases, intellectual property considerations and strategic business partnerships may have contributed to a manufacturer's cost information and could be difficult to account for in the CAFE Model as not all manufacturers may have access to proprietary technologies at stated costs. We carefully evaluate new information in light of these common pitfalls, especially regarding emerging technologies.

While costs for fuel-saving technologies reflect the best estimates available today, technology cost estimates will likely change in the future as technologies are deployed and as production is expanded. For emerging technologies, we use the best information available at the time of the analysis and will continue to update cost assumptions for any future analysis. Chapter 3 discusses each category of technologies (e.g., engines, transmissions, electrification) and the cost estimates we use for this analysis.

2.6.2 Indirect Costs (Retail Price Equivalent)

As discussed above, direct costs represent the cost associated with acquiring raw materials, fabricating parts, and assembling vehicles with the various technologies manufacturers are expected to use to meet future CAFE standards. They include materials, labor, and variable energy costs required to produce and assemble the vehicle. However, they do not include overhead costs required to develop and produce the vehicle, costs incurred by manufacturers or dealers to sell vehicles, or the profit manufacturers and dealers make from their investments. All of these items contribute to the price consumers ultimately pay for the vehicle. These components of retail prices are illustrated in Table 2-21.

Table 2-21 – Retail Price Components

Direct Costs	
Manufacturing Cost	Cost of materials, labor, and variable energy needed for production
Indirect Costs	
Production Overhead	
Warranty	Cost of providing product warranty
Research and Development	Cost of developing and engineering the product
Depreciation and amortization	Depreciation and amortization of manufacturing facilities and equipment
Maintenance, repair, operations	Cost of maintaining and operating manufacturing facilities and equipment
Corporate Overhead	

General and Administrative	Salaries of nonmanufacturing labor, operations of corporate offices, etc.
Retirement	Cost of pensions for nonmanufacturing labor
Health Care	Cost of health care for nonmanufacturing labor
Selling Costs	
Transportation	Cost of transporting manufactured goods
Marketing	Manufacturer costs of advertising manufactured goods
Dealer Costs	
Dealer selling expense	Dealer selling and advertising expense
Dealer profit	Net Income to dealers from sales of new vehicles
Net income	Net income to manufacturers from production and sales of new vehicles

To estimate the impact of higher vehicle prices on consumers, we must consider both direct and indirect costs. To estimate total consumer costs, we multiply direct manufacturing costs by an indirect cost factor to represent the average price for fuel-saving technologies at retail.

Historically, the method most commonly used to estimate indirect costs of producing a motor vehicle has been the RPE. The RPE markup factor is based on an examination of historical financial data contained in 10-K reports filed by manufacturers with the Securities and Exchange Commission. It represents the ratio between the retail price of motor vehicles and the direct costs of all activities that manufacturers engage in.

Figure 2-6 indicates that for more than three decades, the retail price of motor vehicles has been, on average, roughly 50 percent above the direct cost expenditures of manufacturers. This ratio has been remarkably consistent, averaging roughly 1.5 with minor variations from year to year over this period. At no point has the RPE markup exceeded 1.6 or fallen below 1.4.[143] During this time frame, the average annual increase in real direct costs was 2.5 percent, and the average annual increase in real indirect costs was also 2.5 percent. Figure 2-6 illustrates the historical relationship between retail prices and direct manufacturing costs.[144]

An RPE of 1.5 does not imply that manufacturers automatically mark up each vehicle by exactly 50 percent. Rather, it means that, over time, the competitive marketplace has resulted in pricing structures that average out to this relationship across the entire industry. Prices for any individual model may be marked up at a higher or lower rate depending on market demand. The consumer who buys a popular vehicle may, in effect, subsidize the installation of a new technology in a less marketable vehicle. But, on average, over time and across the vehicle fleet,

[143] Based on data from 1972-1997 and 2007. Data were not available for intervening years, but results for 2007 seem to indicate no significant change in the historical trend.
[144] Rogozhin, A., Gallaher, M., & McManus, W., 2009, Automobile Industry Retail Price Equivalent and Indirect Cost Multipliers. Report by RTI International to Office of Transportation Air Quality. U.S. Environmental Protection Agency, RTI Project Number 0211577.002.004, February, Research Triangle Park, N.C.
Spinney, B.C., Faigin, B., Bowie, N., & St. Kratzke, 1999, Advanced Air Bag Systems Cost, Weight, and Lead Time analysis Summary Report, Contract NO. DTNH22-96-0-12003, Task Orders – 001, 003, and 005. Washington, D.C., U.S. Department of Transportation.

the retail price paid by consumers has risen by about $1.50 for each dollar of direct costs incurred by manufacturers.

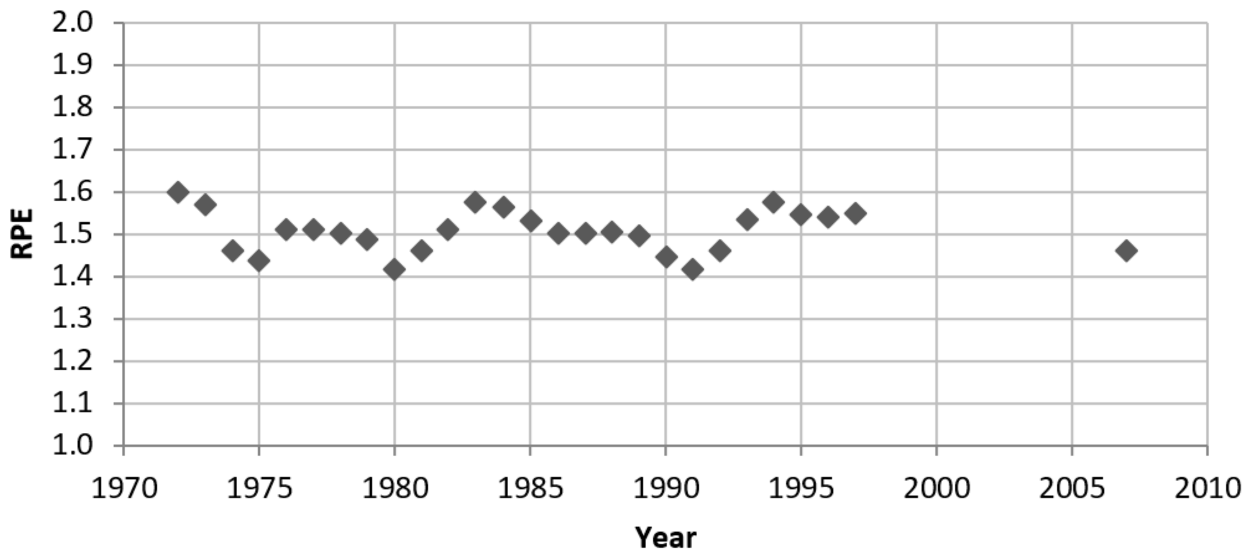

Figure 2-6 – Historical Data for Retail Price Equivalent (RPE), 1972-1997 and 2007

It is also important to note that direct costs associated with any specific technology will change over time as some combination of learning and resource price changes occurs. Resource costs, such as the price of steel, can fluctuate over time and can experience real long-term trends in either direction, depending on supply and demand. However, the normal learning process generally reduces direct production costs as manufacturers refine production techniques and seek out less costly parts and materials for increasing production volumes. By contrast, this learning process does not generally influence indirect costs. The implied RPE for any given technology would thus be expected to grow over time as direct costs decline relative to indirect costs. The RPE for any given year is based on direct costs of technologies at different stages in their learning cycles, and that may have different implied RPEs than they did in previous years. The RPE averages 1.5 across the lifetime of technologies of all ages, with a lower average in earlier years of a technology's life, and, because of learning effects on direct costs, a higher average in later years.

NHTSA has used RPE in all of the safety and most previous CAFE rulemakings to estimate costs. In 2011 the National Academy of Sciences recommended RPEs of 1.5 for suppliers and 2.0 for in-house production be used to estimate total costs.[145] The former Alliance of Automobile Manufacturers also advocated these values as appropriate markup factors for estimating costs of technology changes.[146] In their 2015 report, the National Academy of

[145] Effectiveness and Impact of Corporate Average Fuel Economy Standards, Washington, D.C. - The National Academies Press; NRC, 2011.

[146] Communication from Chris Nevers (Alliance) to Christopher Lieske (EPA) and James Tamm (NHTSA) VIA Regulations.gov http://www.regulations.gov Docket ID Nos. NHTSA-2018-0067; EPA-HQ-OAR-2018-0283, p. 143.

Sciences recommend 1.5 as an overall RPE markup.[147] An RPE of 2.0 has also been adopted by a coalition of environmental and research groups (Northeast States Center for a Clean Air Future [NESCCAF], ICCT, Southwest Research Institute, and TIAX-LLC) in a report on reducing heavy truck emissions, and 2.0 is recommended by the U.S. Department of Energy for estimating the cost of hybrid-electric and automotive fuel cell costs (see Vyas et al. (2000) in Table 2-22 below). Table 2-22 below also lists other estimates of the RPE. Note that all RPE estimates vary between 1.4 and 2.0, with most in the 1.4 to 1.7 range.

Table 2-22 – Alternate Estimates of the RPE[148]

Author and Year	Value, Comments
Jack Faucett Associates for EPA, 1985	1.26 initial value, later corrected to 1.7+ by Sierra research
Vyas et al., 2000	1.5 for outsourced, 2.0 for OEM, electric, and hybrid vehicles
NRC, 2002	1.4 (corrected to > by Duleep)
McKinsey and Company, 2003	1.7 based on European study
CARB, 2004	1.4 (derived using the Jack Faucett Associates initial 1.26 value, not the corrected 1.7+ value)
Sierra Research for American Automobile Association (AAA), 2007	2.0 or >, based on Chrysler data
Duleep, 2008	1.4, 1.56, 1.7 based on integration complexity
NRC, NAS 2011	1.5 for Tier 1 supplier, 2.0 for OEM
NRC, NAS 2015	1.5 for OEM

The RPE has thus enjoyed widespread use and acceptance by a variety of governmental, academic, and industry organizations.

As in previous CAFE and safety rulemaking analyses, we relied on the RPE to account for indirect manufacturing costs. The RPE accounts for indirect costs like engineering, sales, and

[147] Assessment of Fuel Economy Technologies for Light Duty Vehicles. Washington, D.C. - The National Academies Press; Cost, Effectiveness, and Deployment of Fuel Economy Technologies in Light Duty Vehicles. Washington, D.C. – The National Academies Press, 2015.

[148] Duleep, K.G. "*2008 Analysis of Technology Cost and Retail Price*." Presentation to Committee on Assessment of Technologies for Improving Light Duty Vehicle Fuel Economy, January 25, Detroit, MI.; Jack Faucett Associates, September 4, 1985. Update of EPA's Motor Vehicle Emission Control Equipment Retail Price Equivalent (RPE) Calculation Formula. Chevy Chase, MD - Jack Faucett Associates; McKinsey & Company, October 2003. Preface to the Auto Sector Cases. *New Horizons - Multinational Company Investment in Developing Economies*, San Francisco, CA.; NRC (National Research Council), 2002. Effectiveness and Impact of Corporate Average Fuel Economy Standards, Washington, D.C. - The National Academies Press; NRC, 2011. Assessment of Fuel Economy Technologies for Light Duty Vehicles. Washington, D.C. - The National Academies Press; Cost, Effectiveness, and Deployment of Fuel Economy Technologies in Light Duty Vehicles. Washington, D.C. – The National Academies Press, 2015; Sierra Research, Inc., November 21, 2007, Study of Industry-Average Mark-Up Factors used to Estimate Changes in Retail Price Equivalent (RPE) for Automotive Fuel Economy and Emissions Control Systems, Sacramento, CA - Sierra Research, Inc.; Vyas, A. Santini, D., & Cuenca, R. 2000. Comparison of Indirect Cost Multipliers for Vehicle Manufacturing. Center for Transportation Research, Argonne National Laboratory, April. Argonne, Ill.

administrative support, as well as other overhead costs, business expenses, warranty costs, and return on capital considerations.

In past rulemakings a second type of indirect cost multiplier has also been examined. Known as the "Indirect Cost Multiplier" (ICM) approach. ICMs were first examined alongside the RPE approach in the 2010 rulemaking regarding standards for MYs 2012-2016. Both methods have been examined in subsequent rulemakings.

Consistent with the 2020 final rule, we continue to employ the RPE approach as a cost multiplier for this analysis. A detailed discussion of indirect cost methods and the basis for our use of the RPE to reflect these costs is available in the FRIA for the 2020 SAFE rule.[149]

2.6.3 Stranded Capital Costs

The idea behind stranded capital is that manufacturers amortize research, development, and tooling expenses over many years, especially for engines and transmissions. The traditional production life-cycles for transmissions and engines have been a decade or longer. If a manufacturer launches or updates a product with fuel-saving technology, and then later replaces that technology with an unrelated or different fuel-saving technology before the equipment and research and development investments have been fully paid off, there will be unrecouped, or stranded, capital costs. Quantifying stranded capital costs accounts for such lost investments.

As we observed previously, manufacturers may be shifting their investment strategies in ways that may alter how stranded capital could be considered. For example, some suppliers sell similar transmissions to multiple manufacturers. Such arrangements allow manufacturers to share in capital expenditures or amortize expenses more quickly. Manufacturers share parts on vehicles around the globe, achieving greater scale and greatly affecting tooling strategies and costs.

As a proxy for stranded capital in recent CAFE analyses, the CAFE Model has accounted for platform and engine sharing and includes redesign and refresh cycles for significant and less significant vehicle updates. This analysis continues to rely on the CAFE Model's explicit year-by-year accounting for estimated refresh and redesign cycles, and shared vehicle platforms and engines, to moderate the cadence of technology adoption and thereby limit the implied occurrence of stranded capital and the need to account for it explicitly. In addition, confining some manufacturers to specific advanced technology pathways through technology adoption features acts as a proxy to indirectly account for stranded capital. Adoption features specific to each technology, if applied on a manufacturer-by-manufacturer basis, are discussed in each technology section. We will monitor these trends to assess the role of stranded capital moving forward.

2.6.4 Cost Learning

Manufacturers make improvements to production processes over time, which often result in lower costs. "Cost learning" reflects the effect of experience and volume on the cost of

[149] Final Regulatory Impact Analysis, The Safer Affordable Fuel-Efficient (SAFE) Vehicles Rule for Model Year 2021-2026 Passenger Cars and Light Trucks, USDOT, EPA, March, 2020, pp. 354-76.

production, which generally results in better utilization of resources, leading to higher and more efficient production. As manufacturers gain experience through production, they refine production techniques, raw material and component sources, and assembly methods to maximize efficiency and reduce production costs. Typically, a representation of this cost learning, or learning curves, reflects initial learning rates that are relatively high, followed by slower learning as additional improvements are made and production efficiency peaks. This eventually produces an asymptotic shape to the learning curve, as small percent decreases are applied to gradually declining cost levels. These learning curve estimates are applied to various technologies that are used to meet CAFE standards.

We estimate cost learning by considering methods established by T.P. Wright and later expanded upon by J.R. Crawford.[150,151] Wright, examining aircraft production, found that every doubling of cumulative production of airplanes resulted in decreasing labor hours at a fixed percentage. This fixed percentage is commonly referred to as the progress rate or progress ratio, where a lower rate implies faster learning as cumulative production increases. J.R. Crawford expanded upon Wright's learning curve theory to develop a single unit cost model, which estimates the cost of the n^{th} unit produced given the following information is known: (1) cost to produce the first unit; (2) cumulative production of n units; and (3) the progress ratio.

As pictured in Figure 2-7, Wright's learning curve shows the first unit is produced at a cost of $1,000. Initially cost per unit falls rapidly for each successive unit produced. However, as production continues, cost falls more gradually at a decreasing rate. For each doubling of cumulative production at any level, cost per unit declines 20 percent, so that 80 percent of cost is retained. The CAFE Model uses the basic approach by Wright, where cost reduction is estimated by applying a fixed percentage to the projected cumulative production of a given fuel economy technology.

[150] Wright, T. P., Factors Affecting the Cost of Airplanes. *Journal of Aeronautical Sciences*, Vol. 3 (1936), pp.124-25. Available at http://www.uvm.edu/pdodds/research/papers/others/1936/wright1936a.pdf. (Accessed: February 15, 2022).
[151] Crawford, J.R., *Learning Curve, Ship Curve, Ratios, Related Data*, Burbank, California-Lockheed Aircraft Corporation (1944).

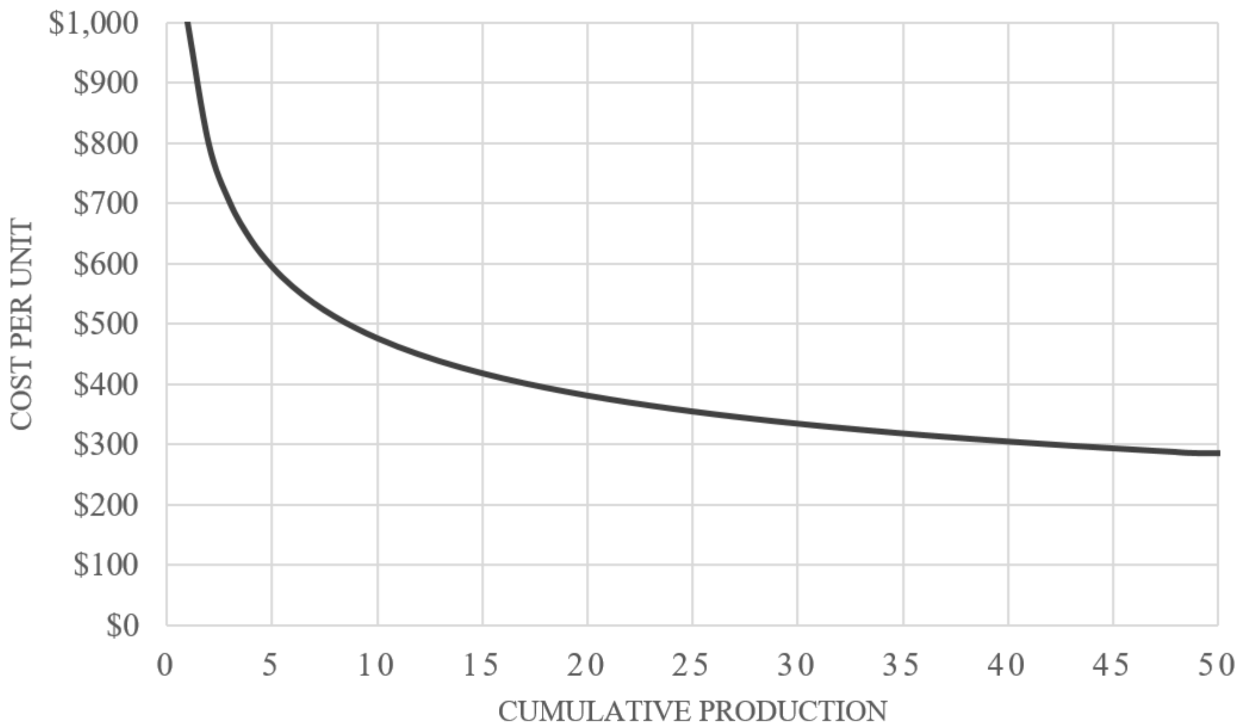

Figure 2-7 – Wright's Learning Curve (Progress Ratio = 0.8)

The analysis accounts for learning effects with model year-based cost learning forecasts for each technology that reduces direct manufacturing costs over time. We evaluate the historical use of technologies and review industry forecasts to estimate future volumes to develop the model year-based technology cost learning curves.

The following section discusses the development of model year-based cost learning forecasts, including how the approach has evolved from the 2012 rulemaking for MY 2017-2025 vehicles, and how we developed the progress ratios for different technologies considered in the analysis. Finally, we discuss how these learning effects are applied in the CAFE Model.

2.6.4.1 Time versus Volume-Based Learning

For the 2012 joint CAFE and GHG rulemaking, we developed learning curves as a function of vehicle model year.[152] Although the concept of this methodology is derived from Wright's cumulative production volume-based learning curve, its application for CAFE technologies was more of a function of time. More than a dozen learning curve schedules were developed, varying between fast and slow learning, and assigned to each technology corresponding to its level of complexity and maturity. The schedules were applied to the base year of direct manufacturing cost and incorporate a percentage of cost reduction by model year, declining at a decreasing rate through the technology's production life. Some newer technologies experience 20 percent cost reductions for introductory model years, while mature or less complex technologies experience 0-3 percent cost reductions over a few years.

[152] CAFE 2012 Final Rule, NHTSA DOT, 77 Fed. Reg. 62624 (Oct. 15, 2012).

In their 2015 report to Congress, the National Academy of Sciences (NAS) recommended NHTSA "continue to conduct and review empirical evidence for the cost reductions that occur in the automobile industry with volume, especially for large-volume technologies that will be relied on to meet the CAFE/GHG standards."[153]

In response, we incorporated statically projected cumulative volume production data of fuel economy improving technologies, representing an improvement over the previously used time-based method. Dynamic projections of cumulative production are not feasible with current CAFE Model capabilities, so we developed one set of projected cumulative production data for most vehicle technologies for the purpose of determining cost impact. We obtained historical cumulative production data for many technologies produced and/or sold in the United States to establish a starting point for learning schedules. Groups of similar technologies or technologies of similar complexity may share identical learning schedules.

The slope of the learning curve, which determines the rate at which cost reductions occur, has been estimated using research from an extensive literature review and automotive cost tear-down reports (see below). The slope of the learning curve is derived from the progress ratio of manufacturing automotive and other mobile source technologies.

2.6.4.2 Deriving the Progress Ratio Used in this Analysis

Learning curves vary among different types of manufactured products. Progress ratios can range from 70 to 100 percent, where 100 percent indicates no learning can be achieved.[154] Learning effects tend to be greatest in operations where workers often touch the product, while effects are less substantial in operations consisting of more automated processes. As automotive manufacturing plant processes become increasingly automated, a progress ratio towards the higher end would seem more suitable. We incorporated findings from automotive cost-teardown studies with EPA's 2015 literature review of learning-related studies to estimate a progress ratio used to determine learning schedules of fuel economy improving technologies.

EPA's literature review examined and summarized 20 studies related to learning in manufacturing industries and mobile source manufacturing.[155] The studies focused on many industries, including motor vehicles, ships, aviation, semiconductors, and environmental energy. Based on several criteria, EPA selected five studies providing quantitative analysis from the mobile source sector (progress ratio estimates from each study are summarized in Table 2-23, below). Further, those studies expand on Wright's learning curve function by using cumulative output as a predictor variable, and unit cost as the response variable. As a result, EPA determined a best estimate of 84 percent as the progress ratio in mobile source industries. However, of those five studies, EPA at the time placed less weight on the *Epple et al. (1991)*

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[153] *Cost, Effectiveness, and Deployment of Fuel Economy Technologies for Light-Duty Vehicles,* National Research Council of the National Academies (2015), available at https://www.nap.edu/resource/21744/deps_166210.pdf. (Accessed: February 15, 2022).

[154] Martin, J., "What is a Learning Curve?" Management and Accounting Web, University of South Florida, available at: https://www.maaw.info/LearningCurveSummary.htm. (Accessed: February 15, 2022).

[155] *Cost Reduction through Learning in Manufacturing Industries and in the Manufacture of Mobile Sources*, U.S. Environmental Protection Agency (2015). Prepared by ICF International and available at https://19january2017snapshot.epa.gov/sites/production/files/2016-11/documents/420r16018.pdf. (Accessed: February 15, 2022).

study, because of a disruption in learning due to incomplete knowledge transfer from the first shift to introduction of a second shift at a North American truck plant. While learning may have decelerated immediately after adding a second shift, we note that unit costs continued to fall as the organization gained experience operating with both shifts. We recognize that disruptions are an essential part of the learning process and should not, in and of themselves, be discredited. For this reason, the analysis uses a re-estimated average progress ratio of 85 percent from those five studies (equally-weighted).

Table 2-23 – Progress Ratios from EPA's Literature Review

Author (Publication Date)	Industry	Progress Ratio (Cumulative Output Approach)
Argote et al. (1997)[156]	Trucks	85%
Benkard (2000)[157]	Aircraft (commercial)	82%
Epple et al. (1991)[158]	Trucks	90%
Epple et al. (1996)[159]	Trucks	85%
Levitt et al. (2013)[160]	Automobiles	82%

In addition to EPA's literature review, this progress ratio estimate was informed based on NHTSA's findings from automotive cost-teardown studies. We routinely evaluate costs of previously issued Federal Motor Vehicle Safety Standards (FMVSS) for new motor vehicles and equipment. We also engage contractors to perform detailed engineering "tear-down" analyses for representative samples of vehicles, to estimate how much specific FMVSS add to the weight and retail price of a vehicle. As part of the effort, the agency examines cost and production volume for automotive safety technologies. In particular, we estimated costs from multiple cost tear-down studies for technologies with actual production data from the *Cost and weight added by the Federal Motor Vehicle Safety Standards for MY 1968-2012 passenger cars and LTVs* (2017).[161]

We chose five vehicle safety technologies with sufficient data to estimate progress ratios of each, because these technologies are large-volume technologies and are used by almost all vehicle

[156] Argote, L., Epple, D., Rao, R. D., & Murphy, K., *The acquisition and depreciation of knowledge in a manufacturing organization - Turnover and plant productivity*, Working paper, Graduate School of Industrial Administration, Carnegie Mellon University (1997).

[157] Benkard, C. L., *Learning and Forgetting - The Dynamics of Aircraft Production*, The American Economic Review, Vol. 90(4), pp. 1034–54 (2000).

[158] Epple, D., Argote, L., & Devadas, R., Organizational Learning Curves - A Method for Investigating Intra-Plant Transfer of Knowledge Acquired through Learning by Doing, Organization Science, Vol. 2(1), pp. 58–70 (1991).

[159]Epple, D., Argote, L., & Murphy, K., An Empirical Investigation of the Microstructure of Knowledge Acquisition and Transfer through Learning by Doing, Operations Research, Vol. 44(1), pp. 77–86 (1996).

[160] Levitt, S. D., List, J. A., & Syverson, C., *Toward an Understanding of Learning by Doing - Evidence from an Automobile Assembly Plant*, Journal of Political Economy, Vol. 121 (4), pp. 643-81 (2013).

[161] Simons, J. F., *Cost and weight added by the Federal Motor Vehicle Safety Standards for MY 1968-2012 Passenger Cars and LTVs* (Report No. DOT HS 812 354). Washington, D.C. - National Highway Traffic Safety Administration (November 2017), at pp. 30-33.

manufacturers. Table 2-24 includes these five technologies and yields an average progress rate of 92 percent.

Table 2-24 – Progress Ratios Researched by NHTSA

Technology	Progress Ratio
Anti-lock Brake Systems	87%
Driver Airbags	93%
Manual 3-pt lap shoulder safety belts	96%
Adjustable Head Restraints	91%
Dual Master Cylinder	95%

For the final progress ratio used in the CAFE Model, we averaged the five progress rates from EPA's literature review and five progress rates from NHTSA's evaluation of automotive safety technologies results. This resulted in an average progress rate of approximately 89 percent. The agency placed equal weight on progress ratios from all 10 sources. More specifically, we placed equal weight on the *Epple et al. (1991)* study, because disruptions have more recently been recognized as an essential part in the learning process, especially in an effort to increase the rate of output.

2.6.4.3 Obtaining Appropriate Baseline Years for Direct Manufacturing Costs to Create Learning Curves

We obtained direct manufacturing costs for each fuel economy improving technology from various sources, as discussed above. To establish a consistent basis for direct manufacturing costs in the rulemaking analysis, we adjusted each technology cost to MY 2018 dollars. For each technology, the DMC is associated with a specific model year, and sometimes a specific production volume, or cumulative production volume. The base model year is established as the MY in which direct manufacturing costs are assessed (with learning factor of 1.00). With the aforementioned data on cumulative production volume for each technology and the assumption of a 0.89 progress ratio for all automotive technologies, we can solve for an implied cost for the first unit produced. For some technologies, we used modestly different progress ratios to match detailed cost projections if available from another source (for instance, batteries for plug-in hybrids and battery electric vehicles).

This approach produces reasonable estimates for technologies already in production, and some additional steps are required to set appropriate learning rates for technologies not yet in production. Specifically, for technologies not yet in production in MY 2017, the cumulative production volume in MY 2017 is zero, because manufacturers have not yet produced the technologies. For pre-production cost estimates in previous CAFE rulemakings, we often relied on confidential business information sources to predict future costs. Many sources for pre-production cost estimates include significant learning effects, often providing cost estimates assuming high volume production, and often for a timeframe late in the first production generation or early in the second generation of the technology. Rapid doubling and re-doubling of a low cumulative volume base with Wright's learning curves can provide unrealistic cost estimates. In addition, direct manufacturing cost projections can vary depending on the initial production volume assumed. Accordingly, we carefully examined direct costs with learning, and made adjustments to the starting point for those technologies on the learning curve to better align with the assumptions used for the initial direct cost estimate.

2.6.4.4 Cost Learning as Applied in the CAFE Model

For this analysis, we apply learning effects to the incremental cost over the null technology state on the applicable technology tree. After this step, we calculate year-by-year incremental costs over preceding technologies on the tech tree to create the CAFE Model inputs.[162] The shift from incremental cost accounting to absolute cost accounting in recent CAFE analyses made cost inputs more transparently relatable to detailed model output, and relevant to this discussion, made it easier to apply learning curves in the course of developing inputs to the CAFE Model.

We group certain technologies, such as advanced engines, advanced transmissions, and non-battery electric components and assigned them to the same learning schedule. While these grouped technologies differ in operating characteristics and design, we chose to group them based on their complexity, technology integration, and economies of scale across manufacturers. The low volume of certain advanced technologies, such as hybrid and electric technologies, poses a significant issue for suppliers and prevents them from producing components needed for advanced transmissions and other technologies at more efficient high scale production. The technology groupings consider market availability, complexity of technology integration, and production volume of the technologies that can be implemented by manufacturers and suppliers.

In addition, we expanded model inputs to extend the explicit simulation of technology application through MY 2050. Accordingly, we updated the learning curves for each technology group to cover MYs through 2050. For MYs 2017-2032, we expect incremental improvements in all technologies, particularly in electrification technologies because of increased production volumes, labor efficiency, improved manufacturing methods, specialization, network building, and other factors. While these and other factors contribute to continual cost learning, we believe that many fuel economy improving technologies considered in this rule will approach a flat learning level by the early 2030s. Specifically, older and less complex internal combustion engine technologies and transmissions will reach a flat learning curve sooner when compared to electrification technologies, which have more opportunity for improvement. For batteries and non-battery electrification components, we estimate a steeper learning curve that will gradually flatten after MY 2040. For a more detailed discussion of the electrification learning curves, see Chapter 3.3. The following Table 2-25 and Table 2-26 show the learning curve schedules for CAFE Model technologies for MYs 2017-2033 and MYs 2034-2050.

[162] The Technologies file contains these CAFE Model inputs.

Table 2-25 – Learning Curve Schedule for CAFE Model Technologies, MYs 2017-2033

Technology	Model Year																
	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033
MR0	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
ROLL0	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
AERO0	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
ADSL, DSLI	0.91	0.89	0.88	0.87	0.85	0.84	0.83	0.82	0.82	0.82	0.82	0.82	0.82	0.82	0.82	0.82	0.82
VVT, VVL, SGDI, DEAC	0.96	0.95	0.94	0.94	0.93	0.93	0.92	0.91	0.91	0.90	0.90	0.89	0.89	0.89	0.88	0.88	0.88
HCR0, HCR1, HCR1D	0.80	0.78	0.77	0.75	0.74	0.73	0.73	0.73	0.73	0.73	0.72	0.72	0.72	0.72	0.72	0.72	0.72
HCR2	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04
EFR	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.96	0.94	0.92	0.90	0.89	0.87	0.85	0.83	0.83
TURBO1	0.85	0.83	0.82	0.80	0.79	0.78	0.78	0.77	0.76	0.76	0.75	0.75	0.75	0.74	0.74	0.74	0.74
TURBO2, CEGR1, VTG, VTGE, DSLIAD	1.01	1.00	0.99	0.97	0.96	0.94	0.92	0.90	0.88	0.86	0.85	0.84	0.83	0.81	0.81	0.80	0.80
CNG	0.97	0.97	0.96	0.96	0.95	0.95	0.94	0.94	0.93	0.93	0.92	0.92	0.92	0.91	0.91	0.91	0.91
ADEAC, VCR	1.04	1.00	0.97	0.95	0.92	0.90	0.88	0.87	0.86	0.84	0.83	0.82	0.82	0.81	0.80	0.80	0.80
MT5	0.98	0.97	0.97	0.96	0.96	0.96	0.96	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95
MT6	0.94	0.93	0.92	0.91	0.90	0.90	0.89	0.89	0.88	0.88	0.87	0.87	0.87	0.86	0.86	0.86	0.86
MT7	1.06	1.00	0.96	0.89	0.84	0.78	0.75	0.72	0.70	0.68	0.65	0.63	0.62	0.61	0.59	0.58	0.58
AT5, AT6, AT8, DCT6, DCT8	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.98	0.98	0.98	0.98	0.98	0.98	0.98
AT6L2, AT7, AT8L2, AT8L3, AT9, AT10, AT10L2	1.00	1.00	0.89	0.84	0.80	0.78	0.76	0.74	0.73	0.72	0.71	0.70	0.70	0.69	0.69	0.68	0.68

Technology	Model Year																
	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033
CVT, CVTL2A, CVTL2B	0.91	0.90	0.89	0.87	0.87	0.86	0.85	0.84	0.84	0.83	0.82	0.82	0.81	0.81	0.80	0.80	0.80
EPS	0.93	0.91	0.89	0.88	0.86	0.85	0.84	0.82	0.81	0.80	0.79	0.78	0.77	0.77	0.76	0.75	0.75
IACC	0.93	0.88	0.83	0.79	0.76	0.73	0.71	0.69	0.67	0.66	0.64	0.63	0.62	0.61	0.60	0.60	0.60
SS12V	1.68	1.61	1.55	1.50	1.45	1.41	1.37	1.33	1.30	1.27	1.25	1.23	1.21	1.19	1.18	1.18	1.15
BEV	1.00	0.93	0.87	0.83	0.77	0.72	0.69	0.64	0.61	0.59	0.56	0.55	0.53	0.52	0.52	0.51	0.49
BISG	1.00	0.94	0.87	0.78	0.73	0.69	0.66	0.63	0.61	0.59	0.58	0.56	0.55	0.54	0.54	0.53	0.53
SHEVPS	1.00	0.96	0.92	0.89	0.87	0.84	0.82	0.78	0.76	0.74	0.73	0.72	0.71	0.70	0.69	0.69	0.68
SHEVP2	1.00	0.96	0.93	0.90	0.87	0.85	0.82	0.79	0.76	0.75	0.74	0.73	0.71	0.70	0.69	0.69	0.69
PHEV20	1.00	0.96	0.92	0.88	0.85	0.81	0.78	0.76	0.73	0.70	0.69	0.67	0.66	0.66	0.65	0.64	0.60
PHEV50	1.00	0.96	0.92	0.88	0.84	0.81	0.78	0.74	0.71	0.69	0.68	0.66	0.64	0.63	0.63	0.62	0.59
FCV	1.71	1.64	1.57	1.50	1.43	1.37	1.31	1.25	1.19	1.14	1.09	1.04	0.99	0.95	0.90	0.86	0.83
MR1	0.77	0.74	0.71	0.68	0.66	0.65	0.63	0.62	0.61	0.60	0.59	0.58	0.57	0.56	0.56	0.55	0.55
MR2	0.69	0.67	0.64	0.63	0.61	0.59	0.58	0.57	0.56	0.55	0.54	0.53	0.53	0.52	0.51	0.51	0.51
MR3	0.73	0.70	0.68	0.67	0.65	0.64	0.63	0.61	0.60	0.59	0.58	0.57	0.56	0.56	0.55	0.55	0.55
MR4	0.87	0.82	0.79	0.75	0.70	0.67	0.64	0.63	0.61	0.59	0.57	0.56	0.55	0.54	0.53	0.53	0.53
MR5, MR6	1.00	1.00	0.93	0.88	0.84	0.80	0.78	0.76	0.73	0.71	0.69	0.67	0.66	0.65	0.64	0.63	0.63
ROLL10	0.88	0.85	0.82	0.80	0.78	0.76	0.74	0.73	0.72	0.71	0.70	0.69	0.68	0.68	0.67	0.66	0.66
ROLL20	0.85	0.77	0.72	0.68	0.65	0.62	0.60	0.58	0.57	0.56	0.55	0.54	0.53	0.52	0.52	0.51	0.51
LDB	0.93	0.91	0.89	0.87	0.85	0.84	0.82	0.80	0.79	0.77	0.76	0.75	0.74	0.73	0.72	0.72	0.72
SAX	0.73	0.70	0.67	0.65	0.64	0.62	0.61	0.60	0.59	0.58	0.57	0.56	0.55	0.54	0.54	0.53	0.53
AERO5, AERO10, AERO15, AERO20	0.87	0.84	0.81	0.79	0.77	0.75	0.73	0.72	0.70	0.69	0.68	0.67	0.66	0.66	0.65	0.64	0.64
Batteries	1.14	1.09	1.05	1.00	0.96	0.91	0.87	0.83	0.79	0.76	0.72	0.69	0.66	0.63	0.60	0.58	0.57

Table 2-26 – Learning Curve Schedules for CAFE Model Technologies, MYs 2034-2050

Technology	Model Year																
	2034	2035	2036	2037	2038	2039	2040	2041	2042	2043	2044	2045	2046	2047	2048	2049	2050
MR0	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
ROLL0	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
AERO0	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
ADSL, DSLI	0.82	0.82	0.82	0.82	0.82	0.82	0.82	0.82	0.82	0.82	0.82	0.82	0.82	0.82	0.82	0.82	0.82
VVT, VVL, SGDI, DEAC	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
HCR0, HCR1, HCR1D	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72
HCR2	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04
EFR	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83
TURBO1	0.74	0.74	0.74	0.74	0.74	0.74	0.74	0.74	0.74	0.74	0.74	0.74	0.74	0.74	0.74	0.74	0.74
TURBO2, CEGR1, VTG, VTGE, DSLIAD	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80
CNG	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91
ADEAC, VCR	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80
MT5	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95
MT6	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86
MT7	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58
AT5, AT6, AT8, DCT6, DCT8	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98
AT6L2, AT7, AT8L2, AT8L3, AT9, AT10, AT10L2	0.68	0.68	0.68	0.68	0.68	0.68	0.68	0.68	0.68	0.68	0.68	0.68	0.68	0.68	0.68	0.68	0.68

Technology	Model Year																
	2034	2035	2036	2037	2038	2039	2040	2041	2042	2043	2044	2045	2046	2047	2048	2049	2050
CVT, CVTL2A, CVTL2B	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80
EPS	0.75	0.74	0.74	0.74	0.74	0.74	0.74	0.73	0.73	0.73	0.73	0.73	0.72	0.72	0.72	0.72	0.72
IACC	0.60	0.60	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.57
SS12V	1.12	1.09	1.07	1.04	1.01	0.99	0.96	0.94	0.92	0.89	0.87	0.85	0.83	0.81	0.79	0.77	0.75
BEV	0.48	0.47	0.46	0.46	0.45	0.45	0.44	0.44	0.44	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43
BISG	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.51	0.51	0.51	0.51	0.51	0.51	0.51	0.50	0.50
SHEVPS	0.68	0.68	0.67	0.67	0.67	0.66	0.66	0.66	0.65	0.65	0.65	0.64	0.64	0.64	0.63	0.63	0.63
SHEVP2	0.68	0.67	0.67	0.66	0.66	0.65	0.65	0.64	0.64	0.63	0.63	0.62	0.62	0.61	0.60	0.60	0.59
PHEV20	0.57	0.54	0.53	0.51	0.50	0.48	0.47	0.47	0.46	0.45	0.45	0.45	0.45	0.44	0.44	0.44	0.43
PHEV50	0.57	0.54	0.53	0.51	0.50	0.49	0.48	0.47	0.47	0.46	0.46	0.46	0.46	0.45	0.45	0.45	0.45
FCV	0.80	0.76	0.75	0.73	0.72	0.70	0.69	0.68	0.67	0.66	0.65	0.65	0.65	0.65	0.65	0.65	0.64
MR1	0.55	0.55	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.53	0.53	0.53	0.53	0.53	0.53	0.53
MR2	0.51	0.51	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.49	0.49	0.49	0.49	0.49	0.49	0.49
MR3	0.55	0.55	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.53	0.53	0.53	0.53	0.53	0.53	0.53
MR4	0.53	0.53	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.51	0.51	0.51	0.51	0.51	0.51	0.51
MR5, MR6	0.63	0.63	0.62	0.62	0.62	0.62	0.62	0.62	0.61	0.61	0.61	0.61	0.61	0.61	0.61	0.60	0.60
ROLL10	0.66	0.66	0.65	0.65	0.65	0.65	0.65	0.65	0.64	0.64	0.64	0.64	0.64	0.64	0.63	0.63	0.63
ROLL20	0.51	0.51	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.49	0.49	0.49	0.49	0.49	0.49	0.49
LDB	0.72	0.71	0.71	0.71	0.71	0.71	0.71	0.70	0.70	0.70	0.70	0.70	0.70	0.69	0.69	0.69	0.69
SAX	0.53	0.53	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.51	0.51	0.51	0.51	0.51	0.51	0.51
AERO5, AERO10, AERO15, AERO20	0.64	0.64	0.63	0.63	0.63	0.63	0.63	0.63	0.62	0.62	0.62	0.62	0.62	0.62	0.61	0.61	0.61
Batteries	0.56	0.55	0.53	0.52	0.51	0.50	0.49	0.48	0.47	0.46	0.46	0.45	0.44	0.43	0.42	0.41	0.40

Each technology in the CAFE Model is assigned a learning schedule developed from the methodology explained previously. For example, the following chart shows learning rates for several technologies applicable to midsize sedans, demonstrating that while we estimate that such learning effects have already been almost entirely realized for engine turbocharging (a technology that has been in production for many years), we estimate that significant opportunities to reduce the cost of the greatest levels of mass reduction (e.g., MR5) remain, and even greater opportunities remain to reduce the cost of batteries for HEVs, PHEVs, BEVs. In fact, for certain advanced technologies, we determined that the results predicted by the standard learning curves progress ratio was not realistic, based on unusual market price and production relationships. For these technologies, we developed specific learning estimates that may diverge from the 0.89 progress rate. As shown in Figure 2-8, these technologies include: turbocharging and downsizing level 1 (TURBO1), variable turbo geometry electric (VTGE), aerodynamic drag reduction by 15 percent (AERO15), mass reduction level 5 (MR5), 20 percent improvement in low-rolling resistance tire technology (ROLL20) over the baseline, and belt integrated starter/generator (BISG).

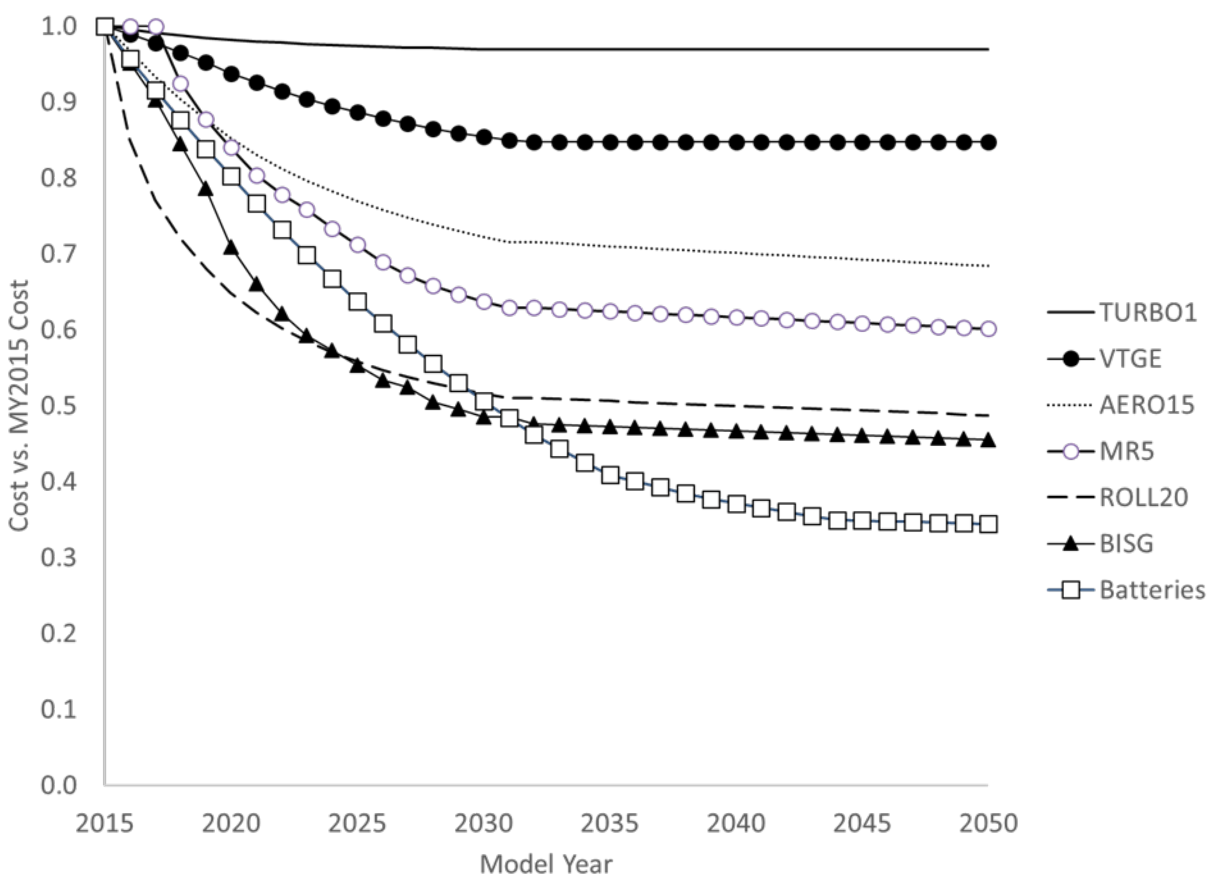

Figure 2-8 – Examples of Year-by-Year Cost Learning Effects (Midsize Sedan)

2.6.5 Cost Accounting

To facilitate specification of detailed model inputs and review of detailed model outputs, the CAFE Model continues to use absolute cost inputs relative to a known base component cost, such that the estimated cost of each technology is specified relative to a common reference point for the relevant technology pathway. For example, the cost of a 7-speed transmission is specified relative to a 5-speed transmission, as is the cost of every other transmission technology. Conversely, in some earlier versions of the CAFE Model, *incremental cost* inputs were estimated relative to the technology immediately preceding on the relevant technology pathway. For our 7-speed transmission example, the incremental cost would be relative to a 6-speed transmission. This change in the structure of cost inputs does not, by itself, change model results, but it does make the connection between these inputs and corresponding outputs more transparent. The CAFE Model Documentation accompanying our analysis presents details of the structure for model cost inputs.[163] The individual technologies sections in Chapter 3 provide a detailed discussion of cost accounting for each technology.

3 Technology Pathways, Effectiveness, and Cost

Vehicle manufacturers meet increasingly stringent fuel economy standards by applying additional fuel-economy-improving technologies to their vehicles. For us to assess what increases in fuel economy standards could be achievable and at what cost, we first need accurate characterizations of fuel-economy-improving technologies. We collected data on over 50 fuel-economy-improving technologies that manufacturers could apply to their vehicles to meet future stringency levels. This includes determining technology effectiveness values, technology costs, and how we realistically expect manufacturers could apply the technologies in the rulemaking timeframe. The characterization of these technologies, the technology effectiveness values, and technology cost assumptions build on work from DOT, EPA, the National Academy of Sciences, and other federal and state government agencies including the Department of Energy's Argonne National Laboratory and the California Air Resources Board.

After spending approximately a decade refining the technology pathways, effectiveness, and cost assumptions used in successive CAFE Model analyses, we have developed guiding principles to ensure that the CAFE Model's simulation of manufacturer compliance pathways results in impacts that we would reasonably expect to see in the real world. These guiding principles are as follows:

The fuel economy improvement from any individual technology must be considered in conjunction with the other fuel-economy-improving technologies applied to the vehicle. Certain technologies will have complimentary or non-complimentary interactions with the full vehicle technology system. For example, there is an obvious fuel economy benefit that results from converting a vehicle with a traditional internal combustion engine to a battery electric vehicle; however, the benefit of the electrification technology depends on the other road load reducing technologies (i.e., mass reduction, aerodynamic, and rolling resistance) on the vehicle.

Technologies added in combination to a vehicle will not result in a simply additive fuel economy improvement from each individual technology. As discussed above, full vehicle modeling and simulation provides the required degree of accuracy to project how different technologies will interact in the vehicle system. For example, as discussed further below, a parallel hybrid architecture powertrain improves fuel economy, in part, by allowing the internal

[163] *See* CAFE Model Documentation S4.7 Technology Cost Tables.

combustion engine to spend more time operating at efficient engine speed and load conditions. This reduces the advantage of adding advanced internal combustion engine technologies, which also improve fuel economy, by broadening the range of speed and load conditions for the engine to operate at high efficiency. This redundancy in fuel savings mechanism results in a reduced effectiveness improvement when the technologies are added to each other.

The effectiveness of a technology depends on the type of vehicle the technology is being applied to. For example, applying mass reduction technology results in varying effectiveness as the absolute mass reduced is a function of the starting vehicle mass, which varies across technology classes.

The cost and effectiveness values for each technology should be reasonably representative of what can be achieved across the entire industry. Each technology model employed in the analysis is designed to be representative of a wide range of specific technology applications used in industry. Some vehicle manufacturer's systems may perform better and cost less than our modeled systems and some may perform worse and cost more. However, employing this approach will ensure that, on balance, the analysis captures a reasonable level of costs and benefits that would result from any manufacturer applying the technology.

The baseline for cost and effectiveness values must be identified before assuming that a cost or effectiveness value could be employed for any individual technology. For example, as discussed below, this analysis uses a set of engine map models that were developed by starting with a small number of baseline engine configurations, and then, in a very systematic and controlled process, adding specific well-defined technologies to create a new map for each unique technology combination.

The following sections discuss the engine, transmission, electrification, mass reduction, aerodynamic, tire rolling resistance, and other vehicle technologies considered in this analysis. Each section discusses:

- *how we define the technology in the CAFE Model,*[164]
- *how we assigned the technology to vehicles in the analysis fleet used as a starting point for this analysis,*
- *any adoption features applied to the technology, so the analysis better represents manufacturers' real-world decisions,*
- *the technology effectiveness values, and*
- *technology cost.*

Please note that the following technology effectiveness sections provide *examples* of the *range* of effectiveness values that a technology could achieve when applied to the entire vehicle system, in conjunction with the other fuel-economy-improving technologies already in use on the vehicle. To see the incremental effectiveness values for any particular vehicle moving from one

[164] Note, due to the diversity of definitions industry sometimes employs for technology terms, or in describing the specific application of technology, the terms defined here may differ from how the technology is defined in the industry.

technology key to a more advanced technology key, see the FE_1 and FE_2 Adjustments files that are installed as part of the CAFE Model executable file, and not in the input/output folders. Similarly, the technology costs provided in each section are *examples* of absolute costs seen in specific model years, for specific vehicle classes. Please refer to the Technologies file to see all absolute technology costs used in the analysis across all model years.

3.1 Engine Paths

Internal combustion engines convert chemical energy in fuel to useful mechanical power. The chemical energy is converted to mechanical power by being burned or oxidized inside the engine. The air/fuel mixture entering the engine and burned fuel/exhaust by-products leaving the engine are the working fluids in the engine. The engine power output is a direct result of the work interaction between these fluids and the mechanical components of the engine.[165] The generated mechanical power is used to perform useful work, such as vehicle propulsion.

For this analysis, the extensive variety of light duty vehicle internal combustion (IC) engine technologies are classified into discrete engine technology paths. These paths are used to model the most representative characteristics, costs, and performance of the fuel-economy improving technologies most likely available during the rulemaking time frame. The technology paths are intended to be representative of the range of potential performance levels for each of the technologies. We did not include technologies unlikely to be feasible in the rulemaking timeframe, technologies unlikely to be compatible with U.S. fuels, or technologies for which there was not appropriate data available to allow the simulation of effectiveness across all vehicle technology classes in this analysis.

The following section discusses how IC engine technologies considered in this analysis are defined. We describe the CAFE Model's general engine technology categories and discuss the engine technologies' relative effectiveness. We also review how the categories are assigned to the baseline fleet as well as the engine paths adoptions features. Finally, we provide the modeled cost for engine technology application to vehicles.

3.1.1 Engine Modeling in the CAFE Model

This analysis models IC engine technologies manufacturers can use to improve fuel economy. Some engine technologies can be incorporated into existing engines with minor or moderate changes to the engines, but many engine technologies require an entirely new engine architecture.

For the CAFE analysis, we divide engine technologies into two categories, "basic engine technologies" and "advanced engine technologies." "Basic engine technologies" refer to technologies adaptable to an existing engine with minor or moderate changes to the engine. "Advanced engine technologies" refer to technologies that generally require significant changes or an entirely new engine architecture. The words "basic" and "advanced" are not meant to confer any information about the level of sophistication of the technology. Many advanced

[165] Heywood, John B. Internal Combustion Engine Fundamentals. McGraw-Hill Education, 2018. Chapter 1.

engine technology definitions also include some basic engine technologies, and these basic technologies are accounted for in the advanced engine's costs and effectiveness values.

3.1.2 Basic Engines

In the CAFE Model, basic engine technologies may be applied individually or in combination with other basic engine technologies. The basic engine technologies include VVT, variable valve lift (VVL), SGDI, and cylinder deactivation. Cylinder deactivation includes a basic level (DEAC) and an advanced level (ADEAC).

The model applies the basic engine technologies across two engine architectures: dual over-head camshaft (DOHC) engine architecture and single over-head camshaft (SOHC) engine architecture. A third architecture exists, over-head valves (OHV), where the camshaft is not mounted overhead. We mapped engines with this architecture to SOHC engines. Figure 3-1 shows the basic engine technologies.

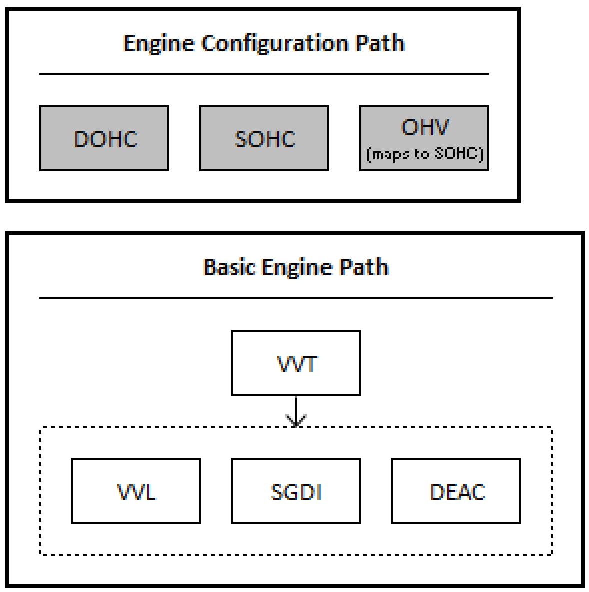

Figure 3-1 – Basic Engine Technologies Path

3.1.2.1 Variable Valve Timing

VVT is a family of valve-train designs that dynamically adjusts the timing of the intake valves, exhaust valves, or both, in relation to piston position. VVT can reduce pumping losses, provide increased engine torque and horsepower over a broad engine operating range, and allow unique operating modes, such as Atkinson cycle operation, to further enhance efficiency.[166] As discussed below, VVT is nearly universally used in the MY 2020 fleet. VVT enables more control of in-cylinder air flow for exhaust scavenging and combustion relative to fixed valve timing engines. Engine parameters such as volumetric efficiency, effective compression ratio,

[166] National Research Council 2015. Cost, Effectiveness, and Deployment of Fuel Economy Technologies for Light-Duty Vehicles. Washington, DC: The National Academies Press. https://doi.org/10.17226/21744, at p. 31 [hereinafter 2015 NAS report]. (Accessed: February 15, 2022).

and internal exhaust gas recirculation (iEGR) can all be enabled and accurately controlled by a VVT system.

3.1.2.2 Variable Valve Lift

VVL dynamically adjusts the distance a valve travels from the valve seat. The dynamic adjustment can optimize airflow over a broad range of engine operating conditions. The technology can increase effectiveness by reducing pumping losses and by affecting the fuel and air mixture motion and combustion in-cylinder.[167] VVL is less common in the MY 2020 fleet than VVT, but still prevalent. Some manufacturers have implemented a limited, discrete approach to VVL. The discrete approach allows only limited (*e.g.*, two) valve lift profiles versus allowing a continuous range of lift profiles.

3.1.2.3 Stoichiometric Gasoline Direct Injection

SGDI sprays fuel at high pressure directly into the combustion chamber, which provides cooling of the in-cylinder charge via in-cylinder fuel vaporization to improve spark knock tolerance and enable an increase in compression ratio and/or more optimal spark timing for improved efficiency.[168] SGDI is common in the MY 2020 fleet, and many advanced engines also use the technology.

3.1.2.4 Cylinder Deactivation

Basic cylinder deactivation (DEAC) disables intake and exhaust valves and turns off fuel injection for the deactivated cylinders during light load operation. DEAC is characterized by a small number of discrete operating configurations.[169] The engine runs temporarily as though it were a smaller engine, reducing pumping losses and improving efficiency. DEAC is present in the MY 2020 baseline fleet.

ADEAC systems, also known as rolling or dynamic cylinder deactivation systems, allow a further degree of cylinder deactivation than the base DEAC. ADEAC allows the engine to vary the percentage of cylinders deactivated and the sequence in which cylinders are deactivated, essentially providing “displacement on demand” for low load operations. A small number of vehicles have ADEAC in the MY 2020 baseline fleet.

3.1.2.5 Camshafts Configuration

For this analysis DOHC engine configurations have two camshafts per cylinder head, one operating the intake valves and one operating the exhaust valves.[170] The basic engine technologies that can be applied to DOHC engines include VVT, VVL, SGDI and DEAC. To represent the possible configurations of basic engine technologies in the analysis, we developed engine fuel map models for each of the technology combinations, as seen in Table 3-1. Each of these engines incrementally add technology to Eng01, a basic VVT engine with port fuel

[167] 2015 NAS report, at p. 32.
[168] 2015 NAS report, at p. 34.
[169] 2015 NAS report, at p. 33.
[170] 2015 NAS report, at p. 31.

injection (PFI), while holding all other assumptions constant, such as ambient temperature, ambient pressure, base engine geometry, and fuel type. The approach to creating the engine map models is discussed in more detail in Chapter 3.1.3. DOHC engines are the most common camshaft configuration of the baseline engine technologies in the MY 2020 baseline fleet.

We did not create specific engine map models for the application of the ADEAC technology. To simulate the application of ADEAC, a net effectiveness improvement was applied to an existing engine technology configuration. We developed the net effectiveness from performance reported in the literature,[171,172,173] and confidential business information (CBI) provided from industry. The final effectiveness values are a function of engine cylinder count and are discussed in more detail in Chapter 3.1.7.

Table 3-1 – DOHC Engine Map Models

Engines	Technologies	Notes
Eng01	DOHC VVT	Parent NA engine, Gasoline, 2.0L, 4 cyl, NA, PFI, DOHC, dual cam VVT, CR10.2
Eng02	DOHC VVT+VVL	VVL added to Eng01
Eng03	DOHC VVT+VVL+SGDI	SGDI added to Eng02, CR11
Eng04	DOHC VVT+VVL+SGDI+DEAC	Cylinder deactivation added to Eng03
Eng18	DOHC VVT + SGDI	Gasoline, 2.0L, 4 cyl, NA, SGDI, DOHC, dual cam VVT
Eng19	DOHC VVT + DEAC	Cylinder deactivation added to Eng01
Eng20	DOHC VVT + VVL + DEAC	Cylinder deactivation added to Eng02
Eng21	DOHC VVT + SGDI + DEAC	Cylinder deactivation added to Eng18

SOHC engines are characterized by having a single camshaft in the cylinder head operating both the intake and exhaust valves.[174] The model considers four basic engine technologies, VVT, VVL, SGDI, and DEAC for SOHC engines. Like DOHC engines, engine map models for SOHC engines use an incremental improvement approach. The SOHC engine maps models are based on Eng01, with the removal of one camshaft. We included SOHC VVT Eng5a in previous

[171] Wilcutts, M., Switkes, J., Shost, M., and Tripathi, A., "Design and Benefits of Dynamic Skip Fire Strategies for Cylinder Deactivated Engines," SAE Int. J. Engines 6(1):278-288, 2013, available at https://doi.org/10.4271/2013-01-0359. (Accessed: February 15, 2022).
[172] Eisazadeh-Far, K. and Younkins, M., "Fuel Economy Gains through Dynamic-Skip-Fire in Spark Ignition Engines," SAE Technical Paper 2016-01-0672, 2016, available at https://doi.org/10.4271/2016-01-0672. (Accessed: February 15, 2022).
[173] EPA, 2018. "Benchmarking and Characterization of a Full Continuous Cylinder Deactivation System." Presented at the SAE World Congress, April 10-12, 2018. Available at https://www.regulations.gov/document/EPA-HQ-OAR-2018-0283-0029. (Accessed: February 15, 2022).
[174] 2015 NAS report, at p. 31.

analyses but did not include it for this analysis. We found that the Eng5a map model's internal friction, inherited from the DOHC engine it was based on, was too high and artificially increased BSFC. As a result of the issue identified with Eng5a, the model applies friction reduction of 0.1 bar over the entire operating range for engine maps 5b, 6a, 7a, and 8a to bring performance of the engines in line with existing data (see Chapter 3.1.7 for discussion of engine map validation).[175] SOHC engines are not common in the MY 2020 baseline fleet.

Table 3-2 shows the SOHC engine map models, and Chapter 3.1.7 discusses how we modeled the configurations. To represent the effectiveness of several other SOHC engine technology combinations, the CAFE Model uses adjustments created from existing related engine map models. Table 3-3 shows the additional SOHC technology combinations with performance values drawn from alternative engine map models.

Table 3-2– SOHC Engine Map Models

Engine	Technologies	Notes
Eng5a	SOHC VVT	Eng01 converted to SOHC Reference Only
Eng5b	SOHC VVT (level 1 Engine Friction Reduction)	Eng5a 2.0L, 4cyl, NA, PFI, single cam VVT with valvetrain friction reduction
Eng6a	SOHC VVT+VVL (level 1 Engine Friction Reduction)	Eng02 converted to SOHC with valvetrain friction reduction
Eng7a	SOHC VVT+VVL+SGDI (level 1 Engine Friction Reduction)	Eng03 converted to SOHC with valvetrain friction reduction, addition of VVL and SGDI
Eng8a	SOHC VVT+VVL+SGDI+DEAC (level 1 Engine Friction Reduction)	Eng04 converted to SOHC with valvetrain friction reduction, addition of DEAC

Table 3-3 – SOHC Emulated Engines from Analogous Models

Engine Performance is Based on	Technologies	Notes
Eng18	SOHC+VVT+SGDI	See Chapter 3.1.7 for effectiveness discussion
Eng19	SOHC VVT+DEAC	See Chapter 3.1.7 for effectiveness discussion
Eng20	SOHC VVT+VVL+DEAC	See Chapter 3.1.7 for effectiveness discussion
Eng21	SOHC VVT+SGDI+DEAC	See Chapter 3.1.7 for effectiveness discussion

3.1.3 Advanced Engines

In the CAFE Model, advanced engine technologies generally refer to families of engine technology that require significant changes in engine structure, or an entirely new engine architecture. The advanced engine technologies represent the application of alternate combustion cycles or changes in the application of forced induction to the engine.

[175] Note, the engine friction reduction applied to these engines is not the engine friction reduction technology discussed later in this chapter.

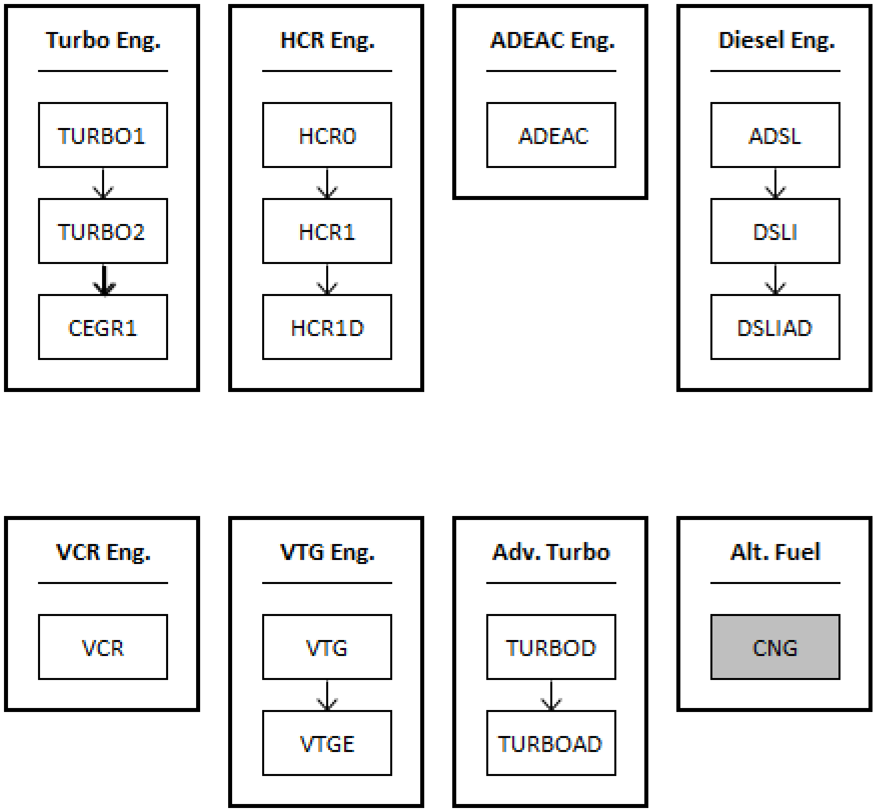

Figure 3-2 – The Advanced Engine Technology Paths

3.1.3.1 Forced Induction Engines

Forced induction engines, or turbocharged downsized engines, are characterized by technology that can create greater-than-atmospheric pressure in the engine intake manifold when higher output is needed. The raised pressure results in an increased amount of airflow into the cylinder supporting combustion, increasing the specific power of the engine. Increased specific power means the engine can generate more power per unit of cylinder volume. The higher power per cylinder volume allows the overall engine volume to be reduced, while maintaining performance. The overall engine volume decrease results in an increase in fuel efficiency by reducing parasitic loads associated with larger engine volumes.[176]

Cooled exhaust gas recirculation is also part of the advanced forced induction technology path. The basic recycling of exhaust gases using VVT is called internal EGR (iEGR) and is included as part of the performance improvements provided by the VVT basic engine technology. Cooled EGR (cEGR) is a second method for diluting the incoming air that takes exhaust gases, passes them through a heat exchanger to reduce their temperature, and then mixes them with incoming air in the intake manifold.[177] Diluting the incoming air with inert exhaust gas reduces pumping losses, improving BSFC. The dilution also reduces combustion rates, temperatures, and

[176] 2015 NAS report, at p. 34.
[177] 2015 NAS report, at p. 35.

pressures, mitigating knock and reducing the need for fuel enrichment. The exhaust gas displaces some incoming air, and heats the incoming air, lowering the air's density.

Five levels of turbocharged engine downsizing technologies are considered in this analysis: a 'basic' level of turbocharged downsized technology (TURBO1), an advanced turbocharged downsized technology (TURBO2), an advanced turbocharged downsized technology with cooled exhaust gas recirculation applied (cEGR), a turbocharged downsized tL2echnology with basic cylinder deactivation applied (TURBOD), and a turbocharged downsized technology with advanced cylinder deactivation applied (TURBOAD). See Table 3-4 for a list of the specific engine map models used to represent the technology levels.

The baseline turbocharged downsized technology (TURBO1) engine represents a basic level of forced air induction technology being applied to a DOHC-based engine. The TURBO1 engine category assumes application of SGDI, VVT and VVL to the engine. The engine map model developed to represent the baseline turbocharged downsized engine operates with enough boost pressure to achieve a brake mean effective pressure (BMEP) of 18bar.

The turbocharged engine with cylinder deactivation (TURBOD) is defined by the application of basic cylinder deactivation to the TURBO1 engine. The turbocharged downsized with advanced cylinder deactivation (TURBOAD) engine is defined by the application of an advanced cylinder deactivation technology to the TURBOD engine.

The advanced turbocharged downsized technology (TURBO2) engine category represents an advanced application of forced air induction. The engine map model assumes a DOHC-based engine and application of SGDI, VVT and VVL. The engine map model represents performance of an engine boosted to achieve a BMEP of 24bar.

The advanced turbocharged downsized technology with exhaust gas recirculation (CEGR1) represents an advanced application of forced air induction coupled with cooled exhaust gas recirculation (cEGR). The modeled engine map is based on the TURBO2 map with the cEGR technology applied.

Table 3-4 – Turbocharged Engine Downsizing Technology Engine Map Models

Engine	Technology	Notes
Eng12	TURBO1	Parent Turbocharged Engine, Gasoline, 1.6L, 4 cyl, turbocharged, SGDI, DOHC, VVT, VVL, engine BMEP 18 bar
Eng12DEAC	TURBOD	Eng12 with DEAC applied, engine BMEP 18bar
	TURBOAD	Eng12DEAC with ADEAC, see Chapter 3.1.7 for effectiveness discussion
Eng13	TURBO2	Eng12 downsized to 1.2L, Engine BMEP increased to 24 bar

Eng14	CEGR1	Cooled external EGR added to Eng13, engine BMEP 24 bar

3.1.3.2 Atkinson Engines

Atkinson engines, or high compression ratio (HCR) engines, represent a class of engines that achieve a higher level of fuel efficiency by implementing an alternate combustion cycle.[178] Historically, the Otto combustion cycle has been used by most gasoline-based spark ignition engines. Increased research into improving fuel economy has resulted in the development of alternate combustion cycles that allow for greater levels of thermal efficiency. One such alternative combustion cycle is the Atkinson cycle. Atkinson cycle operation is achieved by allowing the expansion stroke of the engine to overextend allowing the combustion products to achieve the lowest possible pressure before the exhaust stroke.[179,180,181] Currently, there are two common approaches to achieving Atkinson Cycle operation: either the exhaust valve timing is modified or the intake valve timing is modified. If the exhaust valve timing is modified, the exhaust valve will not open until enough expansion has occurred for the cylinder pressure to be as close to atmospheric pressure as the cylinder geometry allows. If the intake valve timing is modified, the intake valve will stay open during some portion of compression stroke. When the intake valve stays open, some of the fresh charge is driven back into the intake manifold by the rising piston, so the cylinder is never filled completely with fresh air, effectively creating a longer expansion stroke than compression stroke.[182] It is important to note that in both cases, the geometric compression ratio of the engine will be different (higher) than the actual, or effective, compression ratio of the engine.[183,184]

One major disadvantage of the Atkinson cycle is a significant reduction in power density.[185,186] The reduction in power density of the engine is a result of the decreased amount of air drawn into the cylinder compared to the total volume of the cylinder. The trade-off in power density for thermal efficiency generally relegates these engines to lower power applications, such as in parallel with an electric powertrain, like in the Toyota Prius, or in conjunction with road load

[178] *See* the 2015 NAS report, Appendix D, for a short discussion on thermodynamic engine cycles.
[179] Otto cycle is a four-stroke cycle that has four piston movements over two engine revolutions for each cycle. First stroke: intake or induction; seconds stroke: compression; third stroke: expansion or power stroke; and finally, fourth stroke: exhaust.
[180] Compression ratio is the ratio of the maximum to minimum volume in the cylinder of an internal combustion engine.
[181] Expansion ratio is the ratio of maximum to minimum volume in the cylinder of an IC engine when the valves are closed (*i.e.*, the piston is traveling from top to bottom to produce work).
[182] Heywood, John B. *Internal Combustion Engine Fundamentals.* McGraw-Hill Education, 2018. Chapter 5.
[183] Geometric compression ratio is the ratio of the maximum volume when a cylinder is at full expansion versus the minimum volume in a cylinder at full compression.
[184] Effective compression ratio is the difference in volume in a cylinder when the volume of gas is held constant to the volume in a cylinder at full compression.
[185] Power density is the engine power per unit of displacement (= [Engine Power]/[Engine Displacement]).
[186] Heywood, John B. Internal Combustion Engine Fundamentals. McGraw-Hill Education, 2018. Chapter 5.

reducing technologies that reduce the need for engine power to maintain vehicle performance.[187,188]

Descriptions of Atkinson cycle engines and Atkinson mode engine technologies have been used interchangeably in association with HCR engines for rulemaking analyses. Both technologies achieve a higher thermal efficiency than traditional Otto cycle-only engines, however, the two engine types operate differently. For purposes of this analysis, Atkinson technologies can be categorized into two groups: (1) Atkinson-enabled engines and (2) Atkinson engines.

3.1.3.2.1 Atkinson Enabled Engines - Non-Hybrid Electric Vehicle Engines

Atkinson-enabled engines, or high compression ratio (HCR) engines, dynamically swing between an Otto cycle like behavior (very little expansion over-stroke) to a more Atkinson cycle intensive behavior (large expansion over-stroke) based on engine demand. During high loads the engine will reduce the Atkinson level behavior by increasing the dynamic compression ratio, reducing over-stroke, sacrificing efficiency for increased power density. While at low loads the engine will increase the Atkinson level behavior by reducing the dynamic compression ratio, increasing the over-stroke, improve efficiency but reduce power density. The hybrid combustion cycle can be used to address, but not eliminate, the low power density issues that can constrain the application of an Atkinson-only engine and allow for a wider application of the technology.

The level of efficiency improvement experienced by a vehicle employing an Atkinson-enabled engine is directly related to how much of the engine's operation time is spent at high Atkinson levels. Vehicles that must maintain a high level of torque reserve, that experience operation at a high load for long portions of their operating cycle, or that have high base road loads, will see little to no benefit from this technology, over other advanced engine technologies. This power density constraint results in manufacturers typically limiting the application of this technology to vehicles with a lower road load, and lower relative need for torque reserves.

Three HCR engines are available in the analysis: (1) the baseline Atkinson-enabled engine (HCR0) with VVT and PFI, (2) the enhanced Atkinson enabled engine (HCR1) with VVT and SGDI, and finally, (3) the enhanced Atkinson enabled engine with DEAC (HCR1D). A summary of each of the engine technologies is shown in Table 3-5.

For this analysis, the effectiveness of HCR1D is represented by applying an offset to the HCR1 engine. The offset applied is the same effectiveness difference between TURBO1 technology and the TURBOD technology. The details on how this is performed are discussed in Chapter 3.1.7.

Table 3-5 – Atkinson Enabled Engine Map Models

Engine	Technology	Notes

[187] Toyota. "Under the Hood of the All-new Toyota Prius." Oct. 13, 2015. Available at https://global.toyota/en/detail/9827044. (Accessed: February 15, 2022).

[188] Road load reducing technologies include rolling resistance reduction technologies, vehicle mass reduction and aerodynamic drag reduction.

Eng22b	HCR0	Atkinson-enabled 2.5L DOHC, VVT, PFI, CR14
Eng24	HCR1	Non-HEV Atkinson mode, Gasoline, 2.0L, 4 cyl, DOHC, NA, SGDI, VVT, CR 13.1, 93 AKI
	HCR1D	Eng24 with DEAC, see Chapter 3.1.7 for effectiveness discussion.

3.1.3.2.2 Atkinson Engines - Hybrid Electric Vehicle Engines

Atkinson engines are engines that operate full-time in the Atkinson cycle. The most common method of achieving Atkinson operation is the use of late intake valve closing. This method allows backflow from the combustion chamber into the intake manifold, reducing the dynamic compression ratio, and providing a higher expansion ratio. The higher expansion ratio improves thermal efficiency but reduces power density. The low power density generally relegates these engines to hybrid vehicle applications only. Coupling the engines to electric motors and significantly reducing road loads can compensate for the lower power density and maintain desired performance levels for the vehicle.[189] The Toyota Prius is an example of a vehicle that uses an Atkinson engine. The 2017 Toyota Prius achieved a peak thermal efficiency of 40 percent.[190]

Table 3-6 shows the Atkinson engine map model used in this analysis. The engine is only used in HEV powertrains.

Table 3-6 – Atkinson Engine Map Model

Engine	Technology	Notes
Eng26	SHEVPS PHEV20 PHEV50 PHEV20H PHEV50H	1.8L Atkinson engine

3.1.3.3 Miller Cycle Engines

The Miller cycle is another type of overexpansion combustion cycle, similar to the Atkinson cycle. The Miller cycle, however, operates in combination with a forced induction system that helps address the impacts of reduced power density during high load operating conditions.

[189] Toyota. "Under the Hood of the All-new Toyota Prius." Oct. 13, 2015. Available at https://global.toyota/en/detail/9827044. (Accessed: February 15, 2022).
[190] Matsuo, S., Ikeda, E., Ito, Y., and Nishiura, H., "The New Toyota Inline 4 Cylinder 1.8L ESTEC 2ZR-FXE Gasoline Engine for Hybrid Car," SAE Technical Paper 2016-01-0684, 2016, https://doi.org/10.4271/2016-01-0684. (Accessed: February 15, 2022).

Miller cycle-enabled engines use a similar technology approach as seen in Atkinson-enabled engines to effectively create an expanded expansion stroke of the combustion cycle.

Miller cycle enabled engines have a similar trade-off in power density as Atkinson engines; the lower power density requires a larger volume engine in comparison to an Otto cycle-based turbocharged system, for similar applications.[191] However, the forced air induction does mitigate power density issues, and allows for a wider application of the engine technology. Miller cycle enabled engines may use a variable geometry turbocharger to increase engine power density over a broader range of operating conditions and increase the amount of Miller cycle operation. The application of an electronic assist or electronic boost system may further mitigate the power density reduction, particularly at low-speed operating conditions.

In the analysis, we use two engine map models to represent Miller cycle enabled engines, see Table 3-7. The baseline Miller cycle-enabled engine includes the application of a variable turbo geometry technology (VTG). The advanced Miller cycle enabled system includes the application of a 48V-based electronic boost system (VTGE). VTG technology allows the system to vary boost level based on engine operational needs. The use of a variable geometry turbocharger also supports the use of cooled exhaust gas recirculation.[192]

An electronic boost system has an electric motor added to assist a turbocharger at low engine speeds. The motor assist mitigates turbocharger lag and low boost pressure at low engine speeds. The electronic assist system can provide extra boost needed to overcome the torque deficits at low engine speeds.[193]

Table 3-7 – Miller Cycle Engine Map Models

Engine	Technology	Notes
Eng23b	VTG	Miller Cycle, 2.0L DOHC, VTG, SGDI, cEGR, VVT, VVL, CR12
Eng23c	VTGE	Eng23b with a 48V electronic supercharger and battery pack

3.1.3.4 Variable Compression Ratio Engines

Variable compression ratio (VCR) engines work by changing the length of the piston stroke of the engine to optimize the compression ratio and improve thermal efficiency over the full range of engine operating conditions. Engines that use VCR technology are currently in production, but appear to be targeted primarily towards limited production, high performance, and very high

[191] National Academies of Sciences, Engineering, and Medicine 2021. Assessment of Technologies for Improving Light-Duty Vehicle Fuel Economy 2025-2035. Washington, DC: The National Academies Press. https://doi.org/10.17226/26092, Section 4 [hereinafter 2021 NAS report]. (Accessed: February 15, 2022).
[192] 2015 NAS report, at p. 116.
[193] 2015 NAS report, at p. 62.

BMEP (27-30 bar) applications. Nissan is the only manufacturer to use this technology in the MY 2020 baseline fleet.

One engine map model represents a VCR system. See Table 3-8 for more information on the VCR technology.

Table 3-8 – Variable Compression Ratio Engine Map Model

Engine	Technology	Notes
Eng26a	VCR	VVT, SGDI, Turbo, cEGR, VCR CR 9-12

3.1.3.5 Diesel Engines

Diesel engines have several characteristics that result in superior fuel efficiency over traditional gasoline engines, including reduced pumping losses due to lack of (or greatly reduced) throttling, high pressure direct injection of fuel, a combustion cycle that operates at a higher compression ratio,[194] and a very lean air/fuel mixture relative to an equivalent-performance gasoline engine.[195] However, diesel technologies require additional enablers, such as a NO_X adsorption catalyst system or a urea/ammonia selective catalytic reduction system, for control of NO_X emissions.

For the analysis, we considered three levels of diesel engine technology (see Table 3-9). The baseline diesel engine technology (ADSL) is based on a standard 2.2L turbocharged diesel engine. We developed a more advanced diesel engine (DSLI) by starting with the ADSL system and incorporating a combination of low pressure and high pressure EGR, reduced parasitic loss, friction reduction, incorporating a highly-integrated exhaust catalyst with low temp light off temperatures, and closed loop combustion control. We developed the most advanced diesel system (DSLIAD) by adding advanced cylinder deactivation technology to the DSLI system.

Table 3-9 – Diesel Engine Map Models

Engine	Technology	Notes
Eng17	ADSL	2.2L turbocharged diesel engine,
Eng17	DSLI	Eng17 with cEGR, friction reduction, reduced parasitic loss, low temp catalyst, combustion control
Eng17	DSLIAD	Eng17 with DSLI modifications, advanced cylinder deactivation

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[194] Diesel cycle is also a four-stroke cycle like the Otto Cycle, except in the intake stroke no fuel is injected and fuel is injected late in the compression stroke at higher pressure and temperature.
[195] *See* the 2015 NAS report, Appendix D, for a short discussion on thermodynamic engine cycles.

3.1.3.6 Alternative Fuel Engines

Compressed natural gas (CNG) systems are internal combustion engines that run on natural gas as a fuel source. The fuel storage and supply systems for these engines differ tremendously from gasoline, diesel, and flex fuel vehicles.[196] CNG engines are a baseline-only technology and are not applied to any vehicle that did not already include a CNG engine. The MY 2020 baseline fleet does not include any dedicated CNG vehicles.

3.1.4 Engine Friction Reduction Technologies

The engine friction reduction (EFR) technology is a general engine improvement that represents future technologies that reduce the internal friction of an engine. EFR technology is not available for application until MY 2023. The future technologies do not significantly change the function or operation of the engine but reduce the energy loss due to the rotational or rubbing friction experienced in the bearings or cylinder during normal operation. These technologies can include improved surface coatings, lower-tension piston rings, roller cam followers, optimal thermal management and piston surface treatments, improved bearing design, reduced inertial loads, improved materials, or improved geometry.

3.1.5 Baseline Engine Assignments

Manufacturers have steadily improved the fuel economy of their vehicles through implementation of greater levels of fuel economy improving technology in their fleets.[197] We built a 2020 analysis fleet to best capture the current level of these advances and update the market data inputs for the CAFE Model. We built the fleet using mid-model year 2020 CAFE compliance data, press releases, vehicle benchmarking studies, technical publications, and CBI. We use these sources to ensure the fleet is represented as accurately as possible.

We use data for each manufacturer to determine which platforms share engines. Within each manufacturer's fleet, we assign unique identification designations (engine codes) based on configuration, technologies applied, displacement, compression ratio, and power output. We use power output to distinguish between engines that might have the same displacement and configuration but significantly different horsepower ratings.

The CAFE Model identifies leaders and followers for a manufacturer's vehicles that use the same engine, indicated by sharing the same engine code. The model automatically determines which engines are leaders by using the highest sales volume row of the highest sales volume nameplate that is assigned an engine code. This leader-follower relationship allows the CAFE Model simulation to maintain engine sharing as more technology is applied to engines.

As an example, the 2020 Chevrolet Silverado has five different engine displacements available. The engines include a 2.7L turbocharged I4, a 4.3L naturally aspirated V6, a 5.3L naturally

[196] Flexible fuel vehicles (FLEX) are designed to run on gasoline or gasoline-ethanol blends of up to 85 percent ethanol.

[197] "The 2021 EPA Automotive Trends Report, Greenhouse Gas Emissions, Fuel Economy, and Technology since 1975," EPA-420-R-21-023, November 20211975," EPA-420-R-21-003, January 2021 [hereinafter 2020 EPA Automotive Trends Report].

aspirated V8, a 6.2L naturally aspirated V8, and a 3.0L turbo diesel I6. As discussed above, we assign each engine one unique engine code or assign one engine multiple codes if there are variants that use different technologies. For example, we assign the 2020 Chevrolet Silverado naturally-aspirated 5.3L V8 engine one of three engine codes: 115301 (gasoline only with cylinder deactivation), 115302 (gasoline only with skip fire), and 115303 (flex fuel vehicle with cylinder deactivation).[198] All Silverados that use one of these engines will reference the same engine code. We then assign the appropriate corresponding technology to each engine code, and the model can accurately account for further engine improvements at each vehicle redesign and propagate them to each vehicle model that uses the engine code.

We accurately represent each engine using engine technologies and engine technology classes. We assign each engine code technology that most closely corresponds to an engine map, as discussed in Chapter 3.1.6. We use a single engine map model to represent each engine technology. We assign each individual vehicle's initial fuel economy value based on CAFE compliance data for that vehicle, and not based on these maps. Then, the compliance modeling uses these engine maps to determine a percent efficiency gain from the application of a new technology which would be applied to that baseline value for each individual vehicle, see Chapter 3.1.7.

The engine technology classes are a second identifier used in the analysis to accurately account for engine costs. The engine technology class is formatted as number of cylinders followed by the letter C, number of banks followed by the letter B, and an engine head configuration designator, which is _SOHC for single overhead cam, _ohv for overhead valve, or blank for dual overhead cam. Table 3-10 shows examples of observed engines with their corresponding assigned engine technologies as well as engine technology classes.

Table 3-10 – Examples of Observed Engines and Their Corresponding Engine Technology Class and Technology Assignments

VEHICLE	ENGINE OBSERVED	ENGINE TECHNOLOGY CLASS ASSIGNED	ENGINE TECHNOLOGY ASSIGNED
GMC Acadia	Naturally Aspirated DOHC Inline 4 cylinder	4C1B	VVT, SGDI
VW Arteon	Turbocharged DOHC Inline 4 cylinder	6C2B	TURBO1
Bentley Bentayga	Turbocharged DOHC W12 w/ cylinder deactivation	16C4B	TURBOD
Honda Passport	Naturally Aspirated SOHC V6	6C2B_SOHC	VVT, VVL, SGDI, DEAC
Honda Civic	Turbocharged DOHC Inline 4 cylinder	4C1B	TURBO1

198 Market Data file, 'Vehicles' Tab, Line 482, 484, 497, Column H.

VEHICLE	ENGINE OBSERVED	ENGINE TECHNOLOGY CLASS ASSIGNED	ENGINE TECHNOLOGY ASSIGNED
Cadillac CT5	Turbocharged DOHC V6 w/ cylinder deactivation	8C2B	TURBOD
Ford Escape	Turbocharged DOHC Inline 3 cylinder	4C1B_L	TURBO1
Chevrolet Silverado	Naturally Aspirated OHV V8 w/ skip fire	8C2B_ohv	ADEAC

As discussed in the engine cost section (see Chapter 3.1.8) the cost tables for a given engine class include downsizing (to an engine architecture with fewer cylinders) when turbocharging technology is applied; therefore, the turbocharged engines observed in the baseline fleet (that have already been downsized) often map to an engine class with more cylinders. For instance, an observed TURBO1 V6 engine would map to an 8C2B (V8) engine class, because the turbo costs on the 8C2B engine class tab assume a V6 (6C2B) engine architecture. Similarly, as indicated above, the TURBO1 I3 in the Ford Escape maps to the 4C1B_L (I4) engine class, because the turbo costs on the 4C1B_L engine class tab assume a I3 (3C1B) engine architecture. Some instances can be more complex, including low horsepower variants for 4 cylinder engines, and are shown in Table 3-11. Diesel engines map to engine technology classes that match the observed cylinder count since naturally aspirated diesel engines are not found in new light duty vehicles in the U.S. market. Table 3-12 includes the full list of engine classes included in the CAFE Model analysis and the corresponding cylinder count that would be observed on engines included in that class.

Table 3-11 – Engine Technology Class Assignment Logic

OBSERVED GASOLINE ENGINE ARCHITECTURE	OBSERVED NUMBER OF CYLINDERS	HORSEPOWER	NATURALLY ASPIRATED OR TURBO	ENGINE TECHNOLOGY CLASS ASSIGNED
Inline	3	Any	NA	3C1B
Inline	3	Any	Turbo	4C1B_L
Inline	4	<=180	NA	4C1B_L
Inline	4	<=180	Turbo	4C1B
Boxer	4	<=180	NA	4C2B_L
Boxer	4	<=180	Turbo	4C2B
Inline	4	>180	NA	4C1B
Inline	4	>180	Turbo	6C2B
Boxer	4	>180	Turbo	6C2B
Inline	5	Any	Turbo	6C2B
W	16	Any	Turbo	16C4B

Table 3-12 – Observed Cylinder Count by Engine Technology Class and Engine Technology

BROAD ENGINE TECHNOLOGY CATEGORY	BASIC ENGINE	TURBOCHARGED	ADVANCED NATURALLY ASPIRATED	DIESEL
Included Technologies	VVT, VVL, SGDI, DEAC	TURBO1, TURBO2, TURBOD, TURBOAD, CEGR1, VCR, VTG, VTGE	ADEAC, HCR0, HCR1, HCR1D, HCR2	ADSL, DSLI, DSLIAD
2C1B_SOHC	2	2	2	2
2C1B	2	-	2	2
3C1B_SOHC	3	-	3	3
3C1B	3	-	3	3
4C1B_L_SOHC	4	3	4	4
4C1B_SOHC	4	4	4	4
4C1B_L	4	3	4	4
4C1B	4	4	4	4
4C2B_SOHC	4	4	4	4
4C2B_L	4	3	4	4
4C2B	4	4	4	4
5C1B_SOHC	5	-	5	5
5C1B	5	-	5	5
6C1B_SOHC	6	-	6	6
6C1B	6	-	6	6
6C1B_ohv	6	-	6	6
6C2B_SOHC	6	-	6	6
6C2B	6	4 or 5	6	6
6C2B_ohv	6	-	6	6
8C2B_SOHC	8	-	8	8
8C2B	8	6	8	8
8C2B_ohv	8	-	8	8
10C2B_SOHC	10	-	10	10
10C2B	10	8	10	10
10C2B_ohv	10	-	10	10
12C2B_SOHC	12	-	12	12
12C2B	12	10	12	12
12C4B_SOHC	12	-	12	12
12C4B	12	10	12	12
16C4B_SOHC	16	-	16	16
16C4B	16	12 or 16	16	16

We added one new engine technology, HCR1D, to the available engine technologies in the analysis from the 2020 final rule. Having a large number of technologies modeled allows us to accurately characterize technologies present on engines in the analysis fleet. This collection of technologies represents the best available information we have, at the time of this action, regarding both currently available engine technologies and engine technologies that could be feasible for application to the U.S. fleet during the rulemaking timeframe. We believe this effort has yielded the most technology-rich and accurate analysis fleet utilized in the CAFE Model to date.

A full look at the engine technology penetration by engine technology class is detailed in Table 3-13. It is important to note that advanced engine technologies can include some of the basic engine technologies. For example, VVT is found in virtually all engines on the market and is assigned to all basic engines, all advanced engines, and all strong hybrids in the CAFE Model; only BEVs do not have VVT since they do not have engine valves. Further details on which technologies are included for each advanced engine can be found in Chapter 3.1.3. As can be seen in Table 3-13, there are many engine technology classes that are not observed in the analysis fleet but are maintained to ensure that we can accurately classify all technologies in the fleet.

Table 3-13 – Observed Engine Technologies by Engine Technology Class in Analysis Fleet

	BASIC TECHNOLOGIES				ADVANCED ENGINE TECHNOLOGIES[199]													DIESEL TECHNOLOGIES			STRONG ELECTRIFICATION										
	VVT	VVL	SGDI	DEAC	TURBO1	TURBO2	TURBOD	TURBOAD	CEGR1	VCR	VTG	VTGE	ADEAC	HCR0	HCR1	HCR1D	HCR2	ADSL	DSLI	DSLIAD	SHEVP2	SHEVPS	PHEV20	PHEV50	PHEV20T	PHEV50T	BEV200	BEV300	BEV400	BEV500	% OF FLEET[200]
2C1B_SOHC	-[201]	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
2C1B	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
3C1B_SOHC	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
3C1B	0.13%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.07%	-	-	-	0.19%
4C1B_L_SOHC	2.29%	2.29%	0.46%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	2.29%
4C1B_SOHC	-	-	-	-	0.09%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.09%
4C1B_L	9.65%	1.61%	4.76%	-	0.60%	-	1.14%	-	-	-	-	-	-	3.04%	0.84%	-	-	-	-	-	0.03%	2.49%	0.27%	0.02%	0.00%	-	-	-	-	-	18.05%

[199] Note that advanced engines often include basic engine technologies as well. Further discussion on this is found throughout Chapter 3.1.
[200] All basic engines include VVT so it is used as a proxy for all basic engine technologies. This sum excludes VVL, SGDI, DEAC, and SHEVP2 since including them would only serve to double count vehicles because there are no vehicles that exclusively have these technologies.
[201] Dashes indicate no vehicles with this combination were observed while any numbers, including 0.00 percent, indicate that the combination was observed.

	BASIC TECHNOLOGIES				ADVANCED ENGINE TECHNOLOGIES													DIESEL TECHNOLOGIES			STRONG ELECTRIFICATION										
	VVT	VVL	SGDI	DEAC	TURBO1	TURBO2	TURBOD	TURBOAD	CEGR1	VCR	VTG	VTGE	ADEAC	HCR0	HCR1	HCR1D	HCR2	ADSL	DSLI	DSLIAD	SHEVP2	SHEVPS	PHEV20	PHEV50	PHEV20T	PHEV50T	BEV200	BEV300	BEV400	BEV500	% OF FLEET
4C1B	4.93%	0.23%	4.13%	-	4.42%	-	-	-	-	-	0.17%	-	-	-	3.82%	0.94%	-	0.02%	-	-	-	0.19%	-	-	-	-	0.05%	0.23%	-	-	14.79%
4C2B_SOHC	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
4C2B_L	1.47%	-	1.47%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.03%	-	-	-	-	-	-	-	1.50%
4C2B	2.76%	-	2.76%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.01%	-	-	-	2.76%
5C1B_SOHC	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
5C1B	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
6C1B_SOHC	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
6C1B	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.31%	-	-	-	-	-	-	-	0.35%	-	-	-	0.66%
6C1B_ohv	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
6C2B_SOHC	2.26%	2.26%	2.23%	2.25%	0.11%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.02%	-	-	-	-	-	-	-	-	-	2.37%

	BASIC TECHNOLOGIES				ADVANCED ENGINE TECHNOLOGIES													DIESEL TECHNOLOGIES			STRONG ELECTRIFICATION										
	VVT	VVL	SGDI	DEAC	TURBO1	TURBO2	TURBOD	TURBOAD	CEGR1	VCR	VTG	VTGE	ADEAC	HCR0	HCR1	HCR1D	HCR2	ADSL	DSLI	DSLIAD	SHEVP2	SHEVPS	PHEV20	PHEV50	PHEV20T	PHEV50T	BEV200	BEV300	BEV400	BEV500	% OF FLEET
6C2B	15.42%	2.44%	8.59%	0.94%	17.13%	0.00%	0.68%	-	-	0.17%	1.54%	-	-	0.00%	1.22%	-	-	0.01%	0.14%	-	0.00%	0.10%	0.05%	-	0.11%	0.00%	-	-	-	-	36.58%
6C2B_OHV	0.35%	-	0.35%	0.35%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.35%
8C2B_SOHC	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.01%	-	-	-	0.01%
8C2B	2.32%	0.36%	1.45%	-	5.66%	0.36%	0.05%	-	-	-	-	-	-	-	-	-	-	-	-	-	0.00%	-	-	-	0.03%	-	0.01%	-	-	-	8.44%
8C2B_ohv	4.49%	-	1.91%	4.41%	-	-	-	-	-	-	-	-	2.72%	-	-	-	-	-	-	-	-	-	-	-	-	-	0.00%	0.78%	-	-	7.99%
10C2B_SOHC	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
10C2B	0.14%	-	0.14%	0.01%	3.25%	0.00%	0.12%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.00%	-	0.01%	0.06%	0.23%	-	3.82%
10C2B_ohv	-	-	-	-	0.04%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.02%	-	0.02%	-	0.08%
12C2B_SOHC	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

	BASIC TECHNOLOGIES				ADVANCED ENGINE TECHNOLOGIES													DIESEL TECHNOLOGIES			STRONG ELECTRIFICATION										% OF FLEET
	VVT	VVL	SGDI	DEAC	TURBO1	TURBO2	TURBOD	TURBOAD	CEGR1	VCR	VTG	VTGE	ADEAC	HCR0	HCR1	HCR1D	HCR2	ADSL	DSLI	DSLIAD	SHEVP2	SHEVPS	PHEV20	PHEV50	PHEV20T	PHEV50T	BEV200	BEV300	BEV400	BEV500	
12C2B	0.00%	-	-	0.00%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.00%
12C4B_SOHC	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
12C4B	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
16C4B_SOHC	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
16C4B	-	-	-	-	0.01%	0.00%	0.01%	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.02%
All Tech Classes	46.21%	9.19%	28.25%	7.95%	31.33%	0.37%	2.00%	-	-	0.17%	1.70%	-	2.72%	3.04%	5.88%	0.94%	-	0.03%	0.45%	-	0.05%	2.78%	0.34%	0.02%	0.14%	0.00%	0.53%	1.07%	0.25%	-	

3.1.6 Engine Adoption Features

Engine adoption features are defined through a combination of technology path logic, refresh and redesign cycles, and phase-in capacity limits. Figure 3-3 shows the technology paths available for engines in the CAFE Model. Engine technology development and application typically results in an engine design moving from the basic engine tree to one of the advanced engine trees. Once an engine design moves to the advanced engine tree it is not allowed to move to alternate advanced engine trees. Table 3-14 provides a brief description of each technology and details when a technology can be applied for the first time or indicates if a technology can only be assigned as a baseline technology. Technologies applicable only during a platform redesign can be applied during a platform refresh, if another vehicle platform that shares engine codes (i.e., uses the same engine) has already applied the technology during a redesign, first. For example, models of the GMC Acadia and the Cadillac XT4 use the same engine (represented by engine code 112011 in the Market Data file); if the XT4 adds a new engine technology during a redesign, then the Acadia may also add the same engine technology during the next refresh or redesign. This allows the model to maintain engine sharing relationships while also maintaining refresh and redesign schedules. See Chapter 2.2.1.7 for more discussion on platform refresh and redesign cycles.

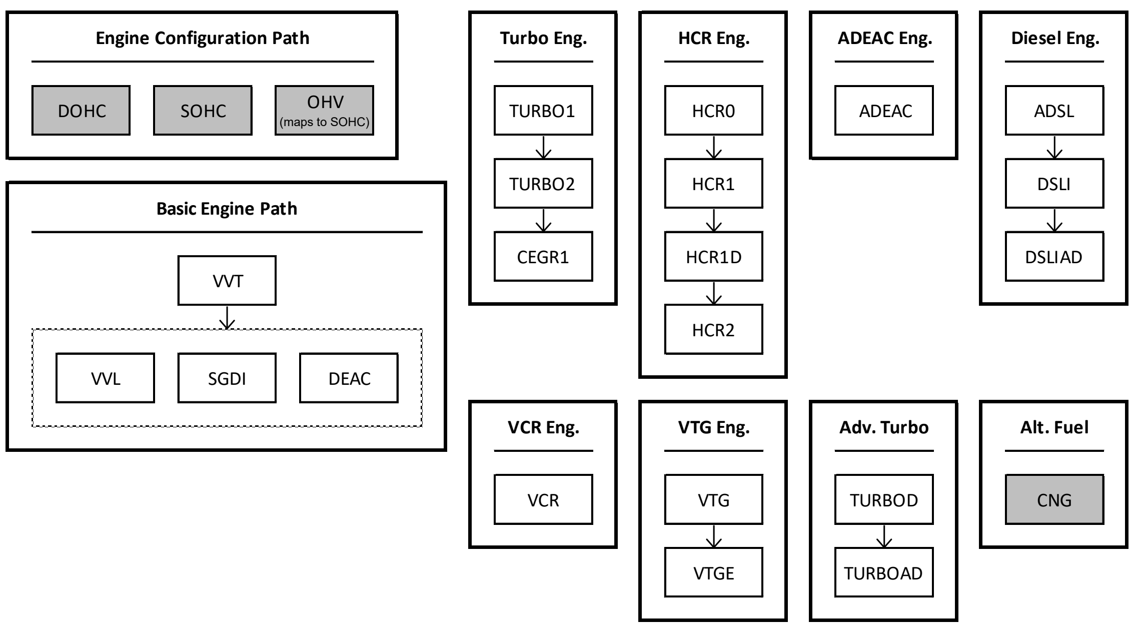

Figure 3-3 – Engine Technology Paths Available

Table 3-14 – Technology Application Schedule

Technology	Application Level	Application Schedule	Description
SOHC	Engine	Baseline Only	Single Overhead Camshaft Engine
DOHC	Engine	Baseline Only	Double Overhead Camshaft Engine

Technology	Application Level	Application Schedule	Description
OHV	Engine	Baseline Only	Overhead Valve Engine (maps to SOHC)
EFR	Engine	Redesign Only	Improved Engine Friction Reduction
VVT	Engine	Baseline Only	Variable Valve Timing
VVL	Engine	Redesign Only	Variable Valve Lift
SGDI	Engine	Redesign Only	Stoichiometric Gasoline Direct Injection
DEAC	Engine	Redesign Only	Cylinder Deactivation
TURBO1	Engine	Redesign Only	Turbocharging and Downsizing, Level 1
TURBO2	Engine	Redesign Only	Turbocharging and Downsizing, Level 2
CEGR1	Engine	Redesign Only	Cooled Exhaust Gas Recirculation, Level 1
HCR0	Engine	Redesign Only	High Compression Ratio Engine, Level 0
HCR1	Engine	Redesign Only	High Compression Ratio Engine, Level 1
HCR1D	Engine	Redesign Only	High Compression Ratio Engine, Level 1 with Cylinder Deactivation
HCR2	Engine	Redesign Only	High Compression Ratio Engine, Level 2
ADEAC	Engine	Redesign Only	Advanced Cylinder Deactivation
ADSL	Engine	Redesign Only	Advanced Diesel
DSLI	Engine	Redesign Only	Diesel Engine Improvements
DSLIAD	Engine	Redesign Only	Diesel Engine Improvements with ADEAC
VCR	Engine	Redesign Only	Variable Compression Ratio Engine
VTG	Engine	Redesign Only	Variable Turbo Geometry
VTGE	Engine	Redesign Only	Variable Turbo Geometry (Electric)
TURBOD	Engine	Redesign Only	Turbocharging and Downsizing with DEAC
TURBOAD	Engine	Redesign Only	Turbocharging and Downsizing with ADEAC
CNG	Engine	Baseline Only	Compressed Natural Gas Engine

Engine technology adoption depends on technology path and phase-in caps. Figure 3-4 shows a flowchart of how engines can progress from one engine path to another. These paths are primarily tied to ease of implementation of additional technology and how closely related the technologies are. Table 3-15 details the phase-in caps that apply to engine technology. Few of the caps in the model would restrict implementation of engine technology during the rulemaking timeframe. In reality, the phase-in caps are not binding because the model has several other less advanced technologies available to apply first at a lower cost, as well as the redesign schedules. As discussed earlier in Chapter 2.2, 100 percent of the analysis fleet will not redesign by 2025, which is the last year that phase-in caps could apply to the engine technologies discussed in this section.

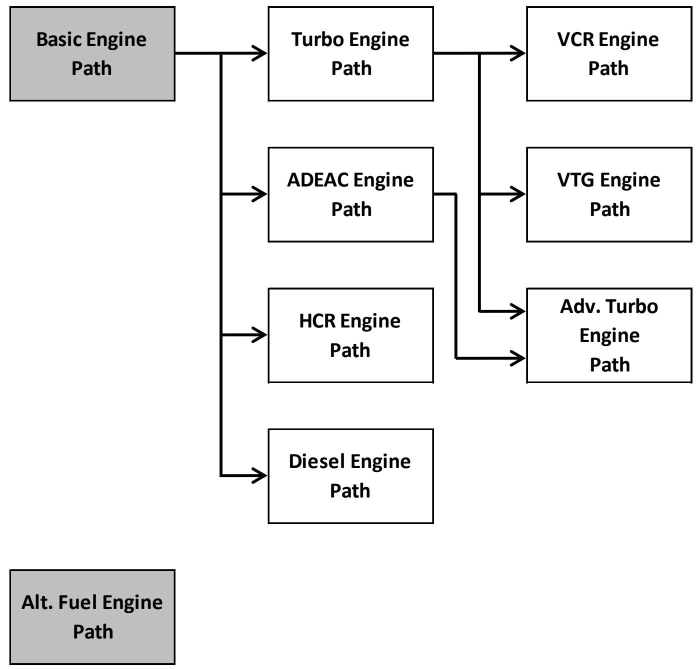

Figure 3-4 – Engine Path Flowchart

Table 3-15 – Engine Technology Phase-In Caps

Technology	Technology Pathway	Phase-In Cap	Phase-In Start Year	First Year 100% Phase-In Allowed
EFR	Engine Improvements	20%	2017	2021
VVL	Basic Engine	100%	2000	2000
SGDI	Basic Engine	100%	2000	2000
DEAC	Basic Engine	100%	2004	2004
TURBO1	Turbo Engine	100%	2004	2004
TURBO2	Turbo Engine	100%	2010	2010
CEGR1	Turbo Engine	100%	2010	2010
HCR0	HCR Engine	100%	2010	2010
HCR1	HCR Engine	100%	2017	2017
HCR1D	HCR Engine	100%	2017	2017
HCR2	HCR Engine	100%	2017	2017
ADEAC	ADEAC Engine	34%	2019	2021
ADSL	Diesel Engine	100%	2010	2010
DSLI	Diesel Engine	100%	2010	2010
DSLIAD	Diesel Engine	34%	2023	2025
VCR	VCR Engine	20%	2019	2023
VTG	VTG Engine	34%	2016	2018
VTGE	VTG Engine	20%	2016	2020
TURBOD	Advanced Turbo Engine	20%	2016	2020
TURBOAD	Advanced Turbo Engine	34%	2020	2022

3.1.6.1 Basic Engines

Basic engine technologies in the CAFE Model are represented by four technologies: VVT, VVL, SGDI, and DEAC. We assume that 100 percent of basic engine platforms use VVT as a baseline, based on wide proliferation of the technology in the U.S. fleet. The remaining three technologies, VVL, SGDI, and DEAC, can all be applied individually or in any combination of the three. An engine can jump from the basic engines path to any other engine path except the Alternative Fuel Engine Path.

3.1.6.2 Turbocharged Downsized Engines

Turbo downsizing allows manufacturers to maintain vehicle performance characteristics while reducing engine displacement and cylinder count. Any basic engine can adopt one of the turbo engine technologies (TURBO1, TURBO2 and CEGR1). Vehicles that have turbocharged engines in the baseline fleet will stay on the turbo engine path to prevent unrealistic engine technology change in the short timeframe considered in the rulemaking analysis. Turbo technology is a mutually exclusive technology in that it cannot be adopted for HCR, diesel, ADEAC, or CNG engines.

3.1.6.3 Non-HEV Atkinson Mode Engines

Non-HEV Atkinson mode engines are a collection of engines in the HCR engine pathway (HCR0, HCR1, HCR1D and HCR2). Atkinson engines excel in lower power applications for lower load conditions, such as driving around a city or steady state highway driving without large payloads, thus their adoption is more limited than some other technologies. We expanded the availability of HCR technology compared to the 2020 final rule because of new observed applications in the market.[202] However, currently there are three categories of adoption features specific to the HCR engine pathway:[203] currently, we do not allow vehicles with 405 or more horsepower to adopt HCR engines due to their prescribed duty cycle being more demanding and likely not supported by the lower power density found in HCR-based engines.[204] Currently, we also exclude pickup trucks and vehicles that share engines with pickup trucks from receiving HCR engines; the duty cycle for these heavy vehicles, particularly when hauling cargo or towing, are required to have significant torque reserves. Maintenance of a significant torque reserve requires a calibration of an HCR based engine that minimizes the advantages.[205] Finally, we currently restrict HCR engine application for some manufacturers that are heavily performance-

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[202] For example, the Hyundai Palisade and Kia Telluride have a 291 hp V6 HCR1 engine. The specification sheets for these vehicles are located in the docket for this action.

[203] *See* Chapter 3.1.4 for a discussion of why HCR2 and P2HCR2 were not used in the central analysis. "SKIP" logic was used to remove this engine technology from application, however as discussed below, we maintain HCR2 and P2HCR2 in the model architecture for sensitivity analysis and for future engine map model updates.

[204] Heywood, John B. Internal Combustion Engine Fundamentals. McGraw-Hill Education, 2018. Chapter 5.

[205] This is based on CBI conversation with manufacturers that currently employ HCR-based technology but saw no benefit when the technology was applied to truck platforms in their fleet.

focused, and have demonstrated a significant commitment to power dense technologies such as turbocharged downsizing.[206]

3.1.6.4 Advanced Cylinder Deactivation Technology

ADEAC technology, or dynamic cylinder deactivation (*e.g.*, Dynamic Skip Fire), can be applied to any engine with basic technology. This technology represents a naturally aspirated engine with ADEAC. Additional technology can be applied to these engines by moving to the Advanced Turbo Engine Path.

3.1.6.5 Miller Cycle Engines

Miller cycle (VTG and VTGE) engines can be applied to any basic and turbocharged engine. VTGE technology is enabled using a 48V system that presents an improvement from traditional turbocharged engines, and accordingly VTGE includes the application of a mild hybrid (BISG) system.

3.1.6.6 Variable Compression Ratio Engines

VCR engines can be applied to basic and turbocharged engines, but the technology is limited to OEMs and partnered OEMs that have already implemented the technology.[207] VCR technology requires a complete redesign of the engine, and in the analysis fleet, only two of Nissan's models had incorporated this technology.

Few manufacturers and suppliers provided information about VCR technologies, and we reviewed several design concepts that could achieve a similar functional outcome. In addition to design concept differences, intellectual property ownership complicates the ability to define a VCR hardware system that could be widely adopted across the industry. VCR engines are complex, costly by design, and address many of the same efficiency losses as mainstream technologies like downsize turbocharging, making it unlikely that a manufacturer that has already started down an incongruent technology path would adopt VCR technology. Because of these issues, we limited adoption of the VCR engine technology to OEMs that have already employed the technology and their partners. We do not believe any other manufacturers will invest to develop and market this technology in their fleet in the rulemaking time frame.

3.1.6.7 Advanced Turbocharged Downsized Engines

Advanced turbo engines are becoming more prevalent as the technologies mature. TURBOD combines TURBO1 and DEAC technologies and represents the first advanced turbo. TURBOAD combines TURBO1 and ADEAC technologies and is the second and last level of advanced turbos. Engines from either the Turbo Engine Path or the ADEAC Engine Path can adopt these technologies.

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[206] There are three manufactures that met the criteria (near 100 percent turbo downsized fleet, and future hybrid systems are based on turbo-downsized engines) described and were excluded: BMW, Daimler, and Jaguar Land Rover.

[207] Nissan and Mitsubishi are strategic partners and members of the Renault-Nissan-Mitsubishi Alliance.

3.1.6.8 Diesel Engines

Any basic engine technologies (VVT, VVL, SGDI, and DEAC) can adopt ADSL and DSLI engine technologies. Any basic engine and diesel engine can adopt DSLIAD technology in this analysis; however, we applied a phase-in cap and year for this technology at 34 percent and MY 2023, respectively. In our engineering judgement, this is a rather complex and costly technology to adopt and it would take significant investment for a manufacturer to develop. For more than a decade, diesel engine technologies have been used in less than one percent of the total light-duty fleet production and have been found mostly on medium and heavy-duty vehicles.

3.1.6.9 Alternative Fuel Engines

Adoption features for alternative fueled compressed natural gas (CNG) engines have been carried over from the 2020 final rule. Because CNG is considered an alternative fuel under EPCA/EISA, it cannot be adopted during the rulemaking timeframe for NHTSA's standard setting analysis.

3.1.6.10 Engine Lubrication and Friction Reduction

We allow the CAFE Model to apply EFR to any engine technology except for DSLI and DSLIAD. DSLI and DSLIAD inherently have incorporated engine friction technologies from ADSL. In addition, friction reduction technologies that apply to gasoline engines cannot necessarily be applied to diesel engines due to the higher temperature and pressure operation in diesel engines.

3.1.7 Engine Effectiveness

The CAFE Model considers both effectiveness and cost in selecting any technology changes. Technology effectiveness is the fuel consumption reduction achieved by changing a vehicle from one combination of technologies to another combination of technologies, see Chapter 2.4.

We simulate effectiveness values for engine technologies in two ways. We either calculate the value based on the difference in full vehicle simulation results created using the Autonomie modeling tool, or we determine the effectiveness values using an alternate calculation method, including analogous improvement or fuel economy improvement factors.

The effectiveness values for the engine technologies, for all ten vehicle technology classes, are shown in Figure 3-5. Each of the effectiveness values shown is representative of the improvements seen for upgrading only the listed engine technology for a given combination of other technologies. In other words, the range of effectiveness values seen for each specific technology (*e.g.*, TURBO1) represents the addition of the TURBO1 technology to every technology combination that could select the addition of TURBO1. See Table 3-16 for several specific examples. We show the change in fuel consumption values between entire technology keys,[208] and not the individual technology effectiveness values. Using the change between

[208] Technology key is the unique collection of technologies that constitutes a specific vehicle, see Chapter 2.4.7.

whole technology keys captures the complementary or non-complementary interactions among technologies.

Table 3-16 – Example of Effectiveness Calculations Shown in Figure 3 5*

Tech	Vehicle Tech Class	Initial Technology Key	Fuel Consumption Initial (gal/mile)	Fuel Consumption New (gal/mile)	Effectiveness (%)
TURBO1	Medium Car	DOHC;VVT;;;;;AT8L2;SS12V; ROLL10;AERO5;MR2	0.0282	0.0248	12.15
TURBO1	Medium Car	DOHC;VVT;;;;;AT8L2;CONV; ROLL10;AERO5;MR2	0.0292	0.0254	13.13
TURBO1	Medium Car	DOHC;VVT;;;;;AT8L2;BISG; ROLL10;AERO5;MR2	0.0275	0.0237	13.80
TURBO1	Medium Car	DOHC;VVT;;;;;AT6;SS12V; ROLL10;AERO5;MR2	0.0312	0.0269	13.80

*The 'Tech' is added to the 'Initial Technology Key' replacing the existing engine technology, resulting in the new fuel consumption value. The percent effectiveness is found by determining the percent improved fuel consumption of the new value versus the initial value.[209]

Some advanced engine technologies have values that indicate low effectiveness. We determined the low effectiveness resulted from the application of advanced engines to existing SHEVP2 architectures. This effect is expected and illustrates the importance of using the full vehicle modeling to capture interactions between technologies, and capture instances of both complimentary technologies and non-complimentary technologies. In this instance, the SHEVP2 powertrain improves fuel economy, in part, by allowing the engine to spend more time operating at efficient engine speed and load conditions. This reduces the advantage of adding advanced engine technologies, which also improve fuel economy, by broadening the range of speed and load conditions for the engine to operate at high efficiency. This redundancy in fuel savings mechanism results in a lower effectiveness when the technologies are added to each other.

[209] The full data set we used to generate this example can be found in the FE_1 Improvements file.

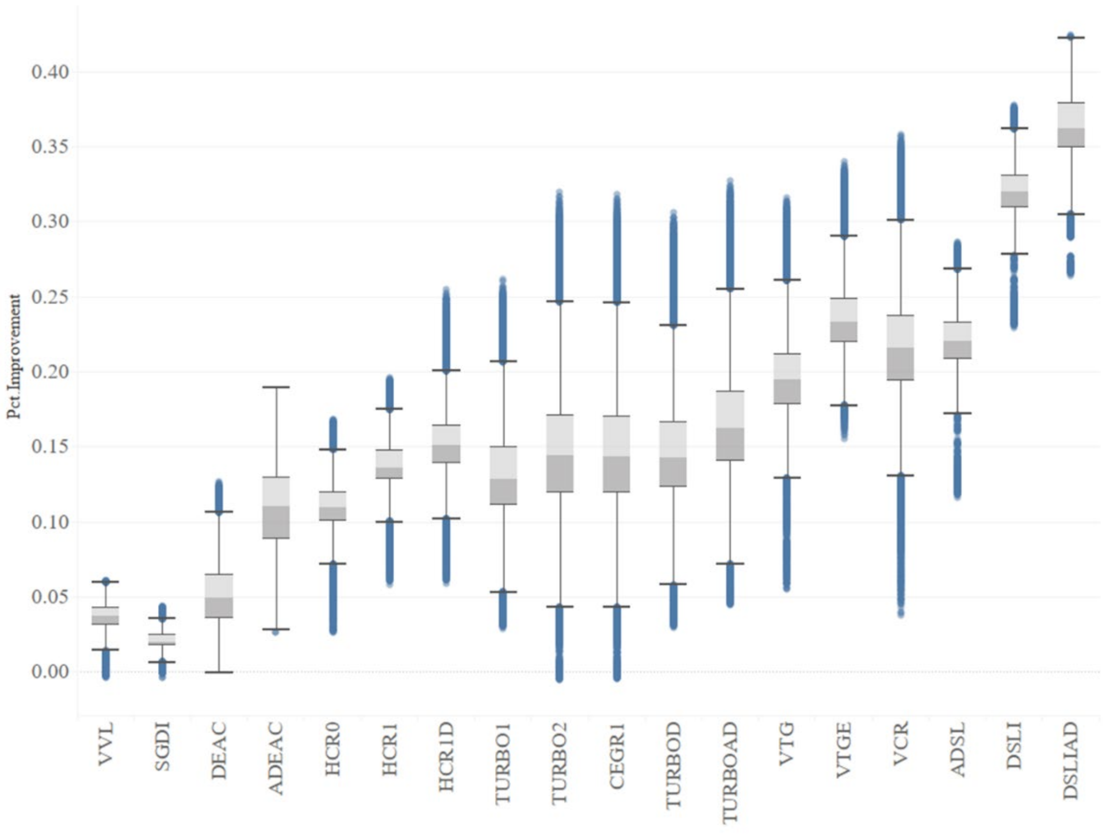

Figure 3-5 – Engine Technologies Effectiveness Values for all Vehicle Technology Classes[210]

The following sections discuss how we determined the effectiveness of the engine technologies on the simulated vehicle system's performance in the rulemaking analysis. We first discuss the values determined directly from the Autonomie simulations, followed by the values that are determined using alternative modeled approaches.

3.1.7.1 Autonomie Modeled Values

The Autonomie model's full vehicle simulation results provide most of the effectiveness values that we use as inputs to the CAFE Model. For a full discussion of the Autonomie modeling see Chapter 2.4.1. The Autonomie modeling uses engine map models as the primary inputs for simulating the effects of different engine technologies.

Engine maps provide a three-dimensional representation of engine performance characteristics at each engine speed and load point across the operating range of the engine. Engine maps have the appearance of topographical maps, typically with engine speed on the horizontal axis and engine torque, power, or brake mean effective pressure (BMEP)[211] on the vertical axis. A third engine

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[210] The box shows the inner quartile range (IQR) of the effectiveness values and whiskers extend out 1.5 x IQR. The blue dots show effectiveness values outside those thresholds. The full data set we used to generate this example can be found in the FE_1 Improvements file.

[211] Brake mean effective pressure is an engineering measure, independent of engine displacement, that indicates the actual work an engine performs.

characteristic, such as brake-specific fuel consumption (BSFC),[212] is displayed using contours overlaid across the speed and load map. The contours provide the values for the third characteristic in the regions of operation covered on the map. Other characteristics typically overlaid on an engine map include engine emissions, engine efficiency, and engine power. We refer to the engine maps developed to model the behavior of the engines in this analysis as engine map models.

The engine map models we use in this analysis are representative of technologies that are currently in production or are expected to be available in the rulemaking timeframe. We develop the engine map models to be representative of the performance achievable across industry for a given technology, and they are not intended to represent the performance of a single manufacturer's specific engine. We target a broadly representative performance level because the same combination of technologies produced by different manufacturers will have differences in performance, due to manufacturer-specific designs for engine hardware, control software, and emissions calibration.

Accordingly, we expect that the engine maps developed for this analysis will differ from engine maps for manufacturers' specific engines. However, we intend and expect that the incremental changes in performance modeled for this analysis, due to changes in technologies or technology combinations, will be similar to the incremental changes in performance observed in manufacturers' engines for the same changes in technologies or technology combinations.

Note that we never apply absolute BSFC levels from the engine maps to any vehicle model or configuration for the rulemaking analysis. We only use the absolute fuel economy values from the full vehicle Autonomie simulations to determine incremental effectiveness for switching from one technology to another technology. The incremental effectiveness is applied to the absolute fuel economy of vehicles in the analysis fleet, which are based on CAFE compliance data. For subsequent technology changes, we apply incremental effectiveness changes to the absolute fuel economy level of the previous technology configuration. Therefore, for a technically sound analysis, it is most important that the differences in BSFC among the engine maps be accurate, and not the absolute values of the individual engine maps. However, achieving this can be challenging.

For this analysis, we use a small number of baseline engine configurations with well-defined BSFC maps, and then, in a very systematic and controlled process, add specific well-defined technologies to create a BSFC map for each unique technology combination. This could theoretically be done through engine or vehicle testing, but we would need to conduct tests on a single engine, and each configuration would require physical parts and associated engine calibrations to assess the impact of each technology configuration, which is impractical for the rulemaking analysis because of the extensive design, prototype part fabrication, development, and laboratory resources that are required to evaluate each unique configuration. We and the automotive industry use modeling as an approach to assess an array of technologies with more limited testing. Modeling offers the opportunity to isolate the effects of individual technologies by using a single or small number of baseline engine configurations and incrementally adding technologies to those baseline configurations. This provides a consistent reference point for the

[212] Brake-specific fuel consumption is the rate of fuel consumption divided by the power being produced.

BSFC maps for each technology and for combinations of technologies that enables us to carefully identify and quantify the differences in effectiveness among technologies.

The Autonomie model documentation provides a detailed discussion on how the Autonomie model uses engine map models as inputs to the full vehicle simulations. Additionally, the Autonomie model documentation contains the engine map model topographic figures, and additional engine map model data can be found in the Autonomie input files.[213]

3.1.7.1.1 IAV Engine Map Models

IAV GmbH (IAV) Engineering developed most of the engine map models we use in this analysis. IAV is one of the world's leading automotive industry engineering service partners with an over 35-year history of performing research and development for powertrain components, electronics, and vehicle design.[214] The primary outputs of IAV's work for this analysis are engine maps that model the operating characteristics of engines equipped with specific technologies.

IAV developed the engine map models using the GT-POWER© Modeling tool (GT-POWER). GT-POWER is a commercially available, industry standard, engine performance simulation tool. GT-POWER can be used to predict detailed engine performance characteristics such as power, torque, airflow, volumetric efficiency, fuel consumption, turbocharger performance and matching, and pumping losses.[215] IAV developed the engine maps using software within the GT-Suite developed by Gamma Technologies. IAV's GT-POWER engine modeling includes sub-models to enforce operating constraints for the engine. The sub-models interface with base GT-POWER model as shown in Figure 3-6, and are listed below.

- Heat release through a predictive combustion model
- Knock characteristic through a kinetic fit knock model
- Physics-based heat flow model
- Physics based friction model
- IAV's proprietary Optimization Toolbox[216]

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[213] ANL - All Assumptions_Summary_NPRM_022021.xlsx, ANL - Data Dictionary_January 2021.xlsx, ANL - Summary of Main Component Performance, Assumptions_NPRM_022021.xlsx, ANL_BatPac_Lookup_tables_Feb2021v2.xlsx.

[214] IAV Automotive Engineering, https://www.iav.com/en. (Accessed: February 15, 2022).

[215] For additional information on the GT-POWER tool please see: https://www.gtisoft.com/gt-suite-applications/propulsion-systems/gt-power-engine-simulation-software. (Accessed: February 15, 2022).

[216] IAV's Optimization Toolbox is a module of IAV Engine. IAV Engine is the basic platform for designing engine mechanics and provides many tools that have proven their worth across the globe in several decades of automotive development work at IAV. The modules help designers, computation engineers and simulation specialists in designing mechanical engine components—for example, in laying out valvetrains and timing gears as well as crankshafts.

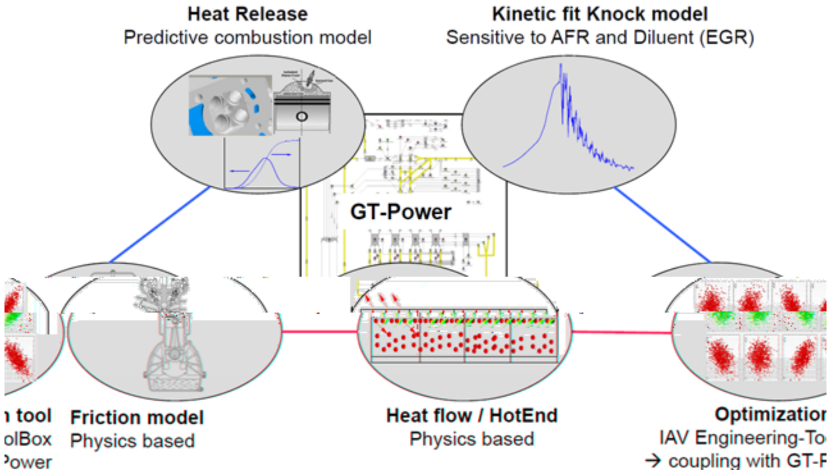

Figure 3-6 – Overview of the Engine Model and Sub-Models Used to Develop Engine Maps

IAV uses benchmark production engine test data, component test data, and manufacturers' and suppliers' technical publications to develop a one-dimensional GT-POWER engine model that serves as the baseline, or root, engine technology configuration (Eng01) for the maps in this analysis. IAV then incrementally adds technologies to the root model to create the families of engine map models. IAV develops each new engine model using a similar overall method. IAV defines the characteristics of the root engine, Eng01 in the case of basic DOHC engines, and optimizes the root engine's combustion parameters while minimizing fuel consumption and maintaining performance. IAV then uses the optimized engine model to simulate operation and develop a BMEP/BSFC-based engine map for the modeled engine.

IAV then starts with the root engine model (Eng01, DOHC+VVT only) and integrates a new technology, such as SGDI. IAV re-optimizes the new engine (Eng18, DOHC+VVT+SGDI) for all combustion parameters while minimizing fuel consumption and maintaining performance. IAV then again uses the resultant new engine model to simulate operation and develop a new BMEP/BSFC based engine map, in this case Eng18. The new engine map (Eng18) can then be directly compared to the root engine map (Eng01) and the differences in those engine maps specifically shows the impact of adding the SGDI technology. IAV repeats this process starting from each of the root engine maps to create the engine technology groups discussed in Chapters3.1.2 and 3.1.3, see Table 3-17 for information about all engine maps.

IAV uses the following baseline engine modeling assumptions and techniques across the sub-models to isolate the effect of adding technologies to an engine.

- All gasoline engine optimization assumes the use of Tier 3 (E10 87 Anti-Knock Index (AKI))[217] fuel to ensure the engines are capable of operating on regular gasoline (87 pump octane = (R+M)/2).[218,219]

- Ambient conditions are fixed at 25 degrees C and 990 mbar barometric pressure.

- Relevant engine geometries/parameters are measured and modeled with friction/flow losses, heat transfer, etc. and calibrated to match measurements.

- Displacement normalized mechanical friction is modeled as a function of engine speed and specific load.

- A combustion model is trained and used to predict fuel heat release rate in response to physical effects such as cylinder geometry, pressure, temperature, turbulence, residual gas concentration, etc.

- The combustion stability model is trained using Coefficient of Variation (COV) of Indicated Mean Effective Pressure (IMEP)[220,221] data to estimate EGR tolerance and to identify the maximum amount of EGR that may be used without adversely impacting vehicle driveability, especially at low loads.

    - The knock[222] correlation model based on in-cylinder conditions and fuel octane rating is trained and used to predict if knock occurs (and at what intensity). Furthermore, a COV of IMEP threshold of 3 percent or less is applied.[223]

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[217] Currently, throughout the United States, pump fuel is a blend of 90 percent gasoline and 10 percent ethanol.
[218] Octane rating or the Anti-Knock Index (AKI) rating of the fuel is expressed as the average of Research Octane + Motor Octane (R+M/2). In the United States, typically there are three distinct grades of fuel available, each provides a different octane rating. In most regions of the United States, the lowest octane fuel is 87 AKI, midgrade typically 89-90 AKI, and premium 91-94 AKI. In higher altitude regions, the lowest octane fuel is typically 85 AKI.
[219] "Octane in depth" U.S. Energy Information Administration: https://www.eia.gov/energyexplained/gasoline/octane-in-depth.php. (Accessed: February 15, 2022).
[220] Indicated Mean Effective Pressure (IMEP) is the mean effective pressure calculated with indicated (theoretical) power of the engine.
[221] Industry and researchers use a measurement known as coefficient of variation of indicated mean effective pressure (COV of IMEP) to evaluate combustion stability.
[222] Engine knock in spark ignition engines occurs when combustion of some of the air/fuel mixture in the cylinder does not result from propagation of the flame front ignited by the spark plug, but one or more pockets of air/fuel mixture explodes outside of the envelope of the normal combustion front. Engine knock can result in unsteady operation and damage to the engine.
[223] Industry commonly recognizes values of COV of IMEP greater than 3.0 percent as unacceptable because above those levels the combustion instability creates a noticeable and objectionable drivability problem for vehicle occupants, referred to as "surge." Surge is perceived as the vehicle accelerating and decelerating erratically, instead of running smoothly.

- In high load and speed engine operational regions, fuel enrichment is used to mitigate knock per best industry practice. Fuel enrichment was tuned in parallel with cEGR addition, when cEGR was integrated on an engine.[224]

- The behavior of engine air intake and exhaust systems and fuel injection systems is simulated by developing load controllers for fuel/air path actuators. Engine combustion control, through use of onboard sensors, is simulated by developing targeting controllers to drive optimal combustion phasing, constrained by knock, just as in a physical engine.

- Careful modeling practice is used to provide confidence that calibrations will scale and predict reasonable and reliable values as parameters are changed across the various engine technology combinations.

Before use in the Autonomie analysis, IAV validates the generated engine maps against IAV's global database of benchmarked data, engine test data, single cylinder test data, prior modeling studies, technical studies, and information presented at conferences.[225] IAV also validates the effectiveness values from the simulation results against detailed engine maps produced from the Argonne engine benchmarking programs, as well as published information from industry and academia, which ensures reasonable representation of simulated engine technologies.[226]

IAV provides the families of engine BMEP/BSFC maps to Argonne as an input for the full vehicle modeling and simulation. For a full discussion on how Argonne integrates the engine map models into the Autonomie simulations, refer to the Autonomie model documentation.[227] The engine map models that we use in this analysis and their specifications are shown in Table 3-17.

[224] Fuel enrichment is extra fuel is injected at the intake manifold port or directly into the cylinder. Fuel vaporization and the fuel's thermal mass reduces combustion and exhaust temperatures. Changes to the air/fuel ratio also impact combustion speed which impacts the knock limit.

[225] Friedrich, I., Pucher, H., and Offer, T., "Automatic Model Calibration for Engine-Process Simulation with Heat-Release Prediction," SAE Technical Paper 2006-01-0655, 2006, https://doi.org/10.4271/2006-01-0655. (Accessed: February 15, 2022).
Rezaei, R., Eckert, P., Seebode, J., and Behnk, K., "Zero-Dimensional Modeling of Combustion and Heat Release Rate in DI Diesel Engines," SAE Int. J. Engines 5(3):874-885, 2012, https://doi.org/10.4271/2012-01-1065. (Accessed: February 15, 2022).
Multistage Supercharging for Downsizing with Reduced Compression Ratio (2015). MTZ Rene Berndt, Rene Pohlke, Christopher Severin, and Matthias Diezemann IAV GmbH. Symbiosis of Energy Recovery and Downsizing (2014). September 2014 MTZ Publication Heiko Neukirchner, Torsten Semper, Daniel Luederitz and Oliver Dingel IAV GmbH.

[226] Bottcher, L., Grigoriadis, P. "ANL – BSFC map prediction Engines 22-26." IAV (April 30, 2019). IAV_20190430_ANL_Eng 22-26 Updated_Docket.pdf.

[227] Islam, E. S., A. Moawad, N. Kim, R. Vijayagopal, and A. Rousseau. A Detailed Vehicle Simulation Process to Support CAFE Standards for the MY 2024-2026 Analysis. ANL/ESD-21/9.

Table 3-17 – Engine Map Models Used in This Analysis

Engines	Technologies	Notes
Eng01	DOHC+VVT	Parent NA engine, Gasoline, 2.0L, 4 cyl, NA, PFI, DOHC, dual cam VVT, CR10.2
Eng02	DOHC+VVT+VVL	VVL added to Eng01
Eng03	DOHC+VVT+VVL+SGDI	SGDI added to Eng02, CR11
Eng04	DOHC+VVT+VVL+SGDI +DEAC	Cylinder deactivation added to Eng03
Eng5a	SOHC+VVT+PFI	Eng01 converted to SOHC (gasoline, 2.0L, 4cyl, NA, PFI, single cam VVT) For Reference Only
Eng5b	SOHC+VVT (level 1 Red. Friction)	Eng5a with valvetrain friction reduction (small friction reduction)
Eng6a	SOHC+VVT+VVL (level 1 Red. Friction)	Eng02 with valvetrain friction reduction (small friction reduction)
Eng7a	SOHC+VVT+VVL+SGDI (level 1 Red. Friction)	Eng03 with valvetrain friction reduction (small friction reduction), addition of VVL and SGDI
Eng8a	SOHC+VVT+VVL+SGDI +DEAC (level 1 Red. Friction)	Eng04 with valvetrain friction reduction (small friction reduction), addition of DEAC
Eng12	DOHC Turbo 1.6l 18bar	Parent Turbocharged Engine, Gasoline, 1.6L, 4 cyl, turbocharged, SGDI, DOHC, dual cam VVT, VVL Engine BMEP: 18 bar
Eng12 DEAC	DOHC Turbo 1.6l 18bar	Eng12 with DEAC applied, Engine BMEP 18bar
Eng13	DOHC Turbo 1.2l 24bar	Eng12 downsized to 1.2L, Engine BMEP 24 bar
Eng14	DOHC Turbo 1.2l 24bar + Cooled EGR	Cooled external EGR added to Eng13 Engine BMEP 24 bar
Eng17	Diesel	Diesel, 2.2L (measured on test bed)
Eng18	DOHC+VVT+SGDI	Gasoline, 2.0L, 4 cyl, NA, SGDI, DOHC, VVT
Eng19	DOHC+VVT+DEAC	Cylinder deactivation added to Eng01
Eng20	DOHC+VVT+VVL+DEAC	Cylinder deactivation added to Eng02
Eng21	DOHC+VVT+SGDI+DEAC	Cylinder deactivation added to Eng18
Eng22b	DOHC+VVT	Atkinson-enabled 2.5L DOHC, VVT, PFI, CR14
Eng24	Current SkyActiv 2.0l 93AKI	Non-HEV Atkinson mode, Gasoline, 2.0L, 4 cyl, DOHC, NA, SGDI, VVT, CR 13.1, 93 AKI
Eng25	Future SkyActiv 2.0l CEGR 93AKI+DEAC	Non-HEV Atkinson mode, Gasoline, 2.0L, 4 cyl, DOHC, NA, SGDI, VVT, cEGR, DEAC CR 14.1, 93 AKI For Reference Only
Eng26	Atkinson Cycle Engine	HEV and PHEV Atkinson Cycle Engine 1.8L
Eng23b	DOHC+VTG+VVT+VVL+SGDI +cEGR	Miller Cycle, 2.0L DOHC, VTG, SGDI, cEGR, VVT, VVL, CR12
Eng23c	DOHC+VTG+VVT+SGDI +cEGR+Eboost	Eng23b with an 48V Electronic supercharger and battery pack
Eng26a	DOHC+VCR+VVT+SGDI +Turbo+cEGR	VVT, SGDI, Turbo, cEGR, VCR CR 9-12

3.1.7.1.2 Non-IAV Engine Map Models

Two engine map models shown in Table 3-17, Eng24 and Eng25, were not developed as part of the IAV modeling effort, and only Eng24 is used in this analysis.

The Eng24 and Eng25 engine maps are equivalent to the ATK and ATK2 models developed for the 2016 Draft TAR, EPA Proposed Determination, and Final Determination.[228] The ATK1 engine model is based directly on the 2.0L 2014 Mazda SkyActiv-G (ATK) engine. The ATK2 represents an Atkinson engine concept based on the Mazda engine, adding cEGR, cylinder deactivation, and an increased compression ratio (14:1). In this analysis, Eng24 and Eng25 correspond to the HCR1 and HCR2 technologies.

The following sections discuss the approach for inclusion of the existing HCR1 engine map, additional engine maps, and research underway to develop an updated family of HCR engine map models.

3.1.7.1.2.1 High Compression Ratio 1 (HCR1)

We use the HCR1 engine map model despite using high octane fuel in model development because the performance of an existing engine (Mazda SkyActiv) on low octane fuel can be observed.[229] We are careful to maintain vehicle performance and utility attributes when considering the application of Atkinson-type technologies for manufacturers that indicated interest in pursuing that technology pathway. Current Atkinson-capable engines have incorporated other technologies to reduce load to maximize time in Atkinson operation and to offset the decrease in power density. This includes improved accessories, addition of friction reduction technologies, and other technologies that reduce engine load. Although modern improvements to engines have allowed Atkinson operation to occur more often (because of lower engine loads) for passenger cars, larger vehicles capable of carrying more cargo and occupants, and towing larger and heavier trailers, have more limited potential Atkinson operation. Adoption features considered for HCR engines are discussed further in Chapter 3.1.6.

We believe the HCR1 engine map does reflect improvements that are representative of the technology in the rulemaking timeframe, and the simulated effectiveness of the engine map model is incremental to other Atkinson-based engine technologies modeled for this analysis, see Figure 3-5. We use the engine map models for HCR0 and HCR1D in conjunction with the HCR1 map model to reflect the incremental effectiveness path for applying HCR technology, see Chapter 3.1.3.

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228 Ellies, B., Schenk, C., and Dekraker, P., "Benchmarking and Hardware-in-the-Loop Operation of a 2014 MAZDA SkyActiv 2.0L 13:1 Compression Ratio Engine," SAE Technical Paper 2016-01-1007, 2016, doi:10.4271/2016-01-1007; Schenk, C. and Dekraker, P., "Potential Fuel Economy Improvements from the Implementation of cEGR and CDA on an Atkinson Cycle Engine," SAE Technical Paper 2017-01-1016, 2017, doi:10.4271/2017-01-1016.

229 Ellies, B., Schenk, C., and Dekraker, P., "Benchmarking and Hardware-in-the-Loop Operation of a 2014 MAZDA SkyActiv 2.0L 13:1 Compression Ratio Engine," SAE Technical Paper 2016-01-1007, 2016, doi:10.4271/2016-01-1007.

3.1.7.1.2.2 High Compression Ratio 2 (HCR2)

We do not allow application of the HCR2 engine in this analysis for all vehicles in the baseline fleet.[230] We believe the use of HCR0, HCR1, and the new addition of HCR1D reasonably represent the application of Atkinson Cycle engine technologies within the current light-duty fleet and the anticipated applications of Atkinson Cycle technology in the MY 2024-2026 timeframe.

We are currently working with IAV and Argonne to develop an updated family of HCR engine map models that will include cEGR, cylinder deactivation and a combination thereof. The new engine map models will closely align with the baseline assumptions used in the other IAV-based HCR engine map models used for our analysis. These engine map models will be available for future actions after model testing and validation is complete. We believe the timing for including the new engine map models is reasonable, because a manufacturer that could apply this technology in response to CAFE standards is likely not do so before MY 2026, as the application of this technology will require an engine redesign. We also believe this is reasonable given manufacturer's statements that there are diminishing returns to additional conventional engine technology improvements considering vehicle electrification commitments.

3.1.7.2 Alternative Modeled Values

For most engine technologies considered in the analysis, we derive the fuel economy improvements from the database of Autonomie full-vehicle simulation results. However, the analysis also incorporates a handful of engine technologies not explicitly simulated in Autonomie. The total effectiveness of these technologies either could not be captured on the 2-cycle test, or there are no robust data that could be used as an input to the full-vehicle simulation.

We use two alternate methods for modeling the effectiveness of these engine technologies. The methods include application of analogous simulation results or the application of static improvement factors.

3.1.7.2.1 Analogous Effectiveness Values

We determine analogous effectiveness values by using representative effectiveness values for a given technology when applied to a reasonably similar base engine, an example of this is the application of SGDI to the baseline SOHC engine. Currently there is no engine map model for the SOHC+VVT+SGDI engine configuration. To create the effectiveness data required as an input to the CAFE Model, first, we conduct a pairwise comparison between technology configurations that included the DOHC+VVT engine (Eng1) and the DOHC+VVT+SGDI (Eng18) engine. Then, we use the results of that comparison to generate a data set of emulated performance values for adding the SGDI technology to the SOHC+VVT engine (Eng5b) systems.

[230] See 85 FR. 24425-27 for more information (Apr. 30, 2020).

We perform the pairwise comparison by finding the difference in fuel consumption performance between every technology configuration using the analogous base technology (*e.g.*, Eng1) and every technology configuration that only changes to the analogous technology (*e.g.*, Eng18). The individual changes in performance between all the technology configurations are then added to the same technology configurations that use the new base technology (*e.g.*, Eng5b) to create a new set of performance values for the new technology (*e.g.*, SOHC+VVT+SGDI). Table 3-18 shows the engine technologies where analogous effectiveness values are used.

Table 3-18 – Engine Technology Performance Values Determined by Analogous Effectiveness Values

Analogous Baseline	Analogous Technology	New Base Technology	New Technology
Eng1 DOHC+VVT	Eng18 DOHC+VVT+SGDI	Eng5b SOHC+VVT	SOHC+VVT+SGDI
Eng1 DOHC+VVT	Eng19 SOHC+VVT+DEAC	Eng5b SOHC+VVT	SOHC+VVT+DEAC
Eng1 DOHC+VVT	Eng20 DOHC+VVT+VVL+ DEAC	Eng5b SOHC+VVT	SOHC+VVT+VVL+ DEAC
Eng1 DOHC+VVT	Eng21 DOHC+VVT+SGDI+D EAC	Eng5b SOHC+VVT	SOHC+VVT+SGDI+ DEAC
Eng12 (TURBO1)	Eng12DEAC (TURBOD)	Eng24 (HCR1)	HCR1D

3.1.7.2.2 Fuel Efficiency Improvement Factors

We apply a static fuel efficiency improvement factor for some technologies where there is either no appropriate analogous technology or where there are not sufficient data to create a full engine map model. The improvement factors are generally based on literature review or CBI provided by stakeholders. Table 3-19 provides a summary of the technology effectiveness values that we simulate using improvement factors, and the value and rules for how we apply the improvement factors. Advanced cylinder deactivation (ADEAC, TURBOAD, DSLIAD), advanced diesel engines (DSLIA), and engine friction reduction (EFR) are the three technologies that we model using improvement factors.

The application of the advanced cylinder deactivation is responsible for three of the five technologies using an improvement factor in this analysis. The initial advanced cylinder deactivation technology was based on a technical publication that used a MY 2010 SOHC VVT basic engine.[231] Additional information about the technology effectiveness came from a

[231] Wilcutts, M., Switkes, J., Shost, M., and Tripathi, A., "Design and Benefits of Dynamic Skip Fire Strategies for Cylinder Deactivated Engines," SAE Int. J. Engines 6(1):278-288, 2013, available at https://doi.org/10.4271/2013-01-0359. Eisazadeh-Far, K. and Younkins, M., "Fuel Economy Gains through Dynamic-Skip-Fire in Spark Ignition Engines," SAE Technical Paper 2016-01-0672, 2016, available at https://doi.org/10.4271/2016-01-0672. (Accessed: February 15, 2022).

benchmarking analysis of pre-production 8-cylinder OHV prototype systems.[232] However, at the time of the analysis no studies of production versions of the technology were available, and the only technology effectiveness data that could be garnered was from existing studies, not operational information. Thus, only estimates of effect could be developed and not a full model of operation. No engine map model could be developed, and no other technology pairs were analogous.

To model the effects of advanced cylinder deactivation, we use an improvement factor based on the information referenced above and apply it across the engine technologies. We predict the effectiveness values for naturally aspirated engines by using full vehicle simulations of a basic engine with DEAC, SGDI, VVL, and VVT, and adding 3 percent or 6 percent improvement based on engine cylinder count: 3 percent for engines with 4 cylinders or less and 6 percent for all other engines. We predict the effectiveness values for turbocharged engines using full vehicle simulations of the TURBOD engine and adding 1.5 percent or 3 percent improvement based on engine cylinder count: 1.5 percent for engines with 4 cylinders or less and 3 percent for all other engines. For diesel engines, we predict effectiveness values by using the DSLI effectiveness values and adding 4.5 percent or 7.5 percent improvement based on vehicle technology class: 4.5 percent improvement for small and medium non-performance cars, small performance cars, and small non-performance SUVs, and 7.5 percent improvement for all other vehicle technology classes.

We model advanced engine technology application to the baseline diesel engine by applying an improvement factor to the ADSL engine technology combinations. A 12.8 percent improvement factor is applied to the ADSL technology combinations to create the DSLI technology combinations. We base the performance improvement on the application of a combination of low pressure and high pressure EGR, reduced parasitic loss, advanced friction reduction, incorporation of highly-integrated exhaust catalyst with low-temp-light-off temperatures, and closed loop combustion control.[233,234,235,236]

As discussed in Chapter 3.1.4, the application of the EFR technology does not simulate the application of a specific technology, but the application of an array of potential improvements to an engine. All reciprocating and rotating components in the engine are potential candidates for friction reduction, and minute improvements in several components can add up to a measurable

[232] EPA, 2018. "Benchmarking and Characterization of a Full Continuous Cylinder Deactivation System." Presented at the SAE World Congress, April 10-12, 2018. Retrieved from https://www.epa.gov/sites/default/files/2019-04/documents/sae-2018-benchmarking-characterization-full-continuous-cylinder-deactivation-system.pdf. (Accessed: February 15, 2022).
[233] NAS 2015 p. 104.
[234] Hatano, J., Fukushima, H., Sasaki, Y., Nishimori, K., Tabuchi, T., Ishihara, Y. "The New 1.6L 2-Stage Turbo Diesel Engine for HONDA CR-V." 24th Aachen Colloquium - Automobile and Engine Technology 2015.
[235] Steinparzer, F., Nefischer, P., Hiemesch, D., Kaufmann, M., Steinmayr, T. "The New Six-Cylinder Diesel Engines from the BMW In-Line Engine Module." 24th Aachen Colloquium - Automobile and Engine Technology 2015.
[236] Eder, T., Weller, R., Spengel, C., Böhm, J., Herwig, H., Sass, H. Tiessen, J., Knauel, P. "Launch of the New Engine Family at Mercedes-Benz." 24th Aachen Colloquium - Automobile and Engine Technology 2015.

fuel economy improvement.[237,238,239,240] Because of the incremental nature of this analysis, a range of 1-2 percent improvement was identified initially, and narrowed further to a specific 1.39 percent improvement. The final value is likely representative of a typical value industry may be able to achieve in future years.

Table 3-19 – Engine Technologies Modeled Using Efficiency Improvement Factors

Baseline Technology	Fuel Efficiency Improvement Factor	New Technology
DEAC	3% for ≤ 4 Cylinders 6% for > 4 Cylinders	ADEAC
TURBOD	1.5% for ≤ 4 Cylinders 3% for > 4Cylinders	TURBOAD
ADSL	12.8%	DSLI
DSLI	4.5% for small and medium non-performance cars and SUVs, and small performance cars. 7.5% for all other technology classes	DSLIAD
All Engine Technologies	1.39%	EFR

3.1.8 Engine Costs

The CAFE Model considers both cost and effectiveness in selecting any technology changes. We allocate considerable resources to sponsoring research to determine direct manufacturing costs (DMCs) for fuel saving technologies.[241] We apply a learning factor and RPE to the DMC values to determine the total overall cost of the technology for a given model year. The full list of engine technology costs used in this analysis, across all model years, and in 2018 dollars, can be found in the Technologies file. We discuss the application of RPE and cost learning to the DMCs in Chapter 2.6.

We use absolute costs in this analysis instead of relative costs, which were used prior to the 2020 CAFE rulemaking. We use absolute costs to ensure the full cost of the IC engine is removed when electrification technologies are applied, specifically for the transition to BEVs. This

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237 "Polyalkylene Glycol (PAG) Based Lubricant for Light- & Medium-Duty Axles," 2017 DOE Annual Merit Review. Ford Motor Company, Gangopadhyay, A., Ved, C., Jost, N. https://energy.gov/sites/prod/files/2017/06/f34/ft023_gangopadhyay_2017_o.pdf. (Accessed: February 15, 2022).

238 "*Power-Cylinder Friction Reduction through Coatings, Surface Finish, and Design*," 2017 DOE Annual Merit Review. Ford Motor Company. Gangopadhyay, A. Erdemir, A. https://energy.gov/sites/prod/files/2017/06/f34/ft050_gangopadhyay_2017_o.pdf. (Accessed: February 15, 2022).

239 "*Nissan licenses energy-efficient engine technology to HELLER,"* https://newsroom.nissan-global.com/releases/170914-01-e?lang=en-US&rss&la=1&downloadUrl=%2Freleases%2F170914-01-e%2Fdownload. (Accessed: February 15, 2022).

240 "*Infiniti's Brilliantly Downsized V-6 Turbo Shines,"* http://wardsauto.com/engines/infiniti-s-brilliantly-downsized-v-6-turbo-shines. (Accessed: February 15, 2022).

241 FEV prepared several cost analysis studies for EPA on subjects ranging from advanced 8-speed transmissions to belt alternator starter, or start/stop systems. NHTSA contracted Electricore, EDAG, and Southwest Research for teardown studies evaluating mass reduction and transmissions. The 2015 NAS report on fuel economy technologies for light-duty vehicles also evaluated the agencies' technology costs developed based on these teardown studies.

analysis models the cost of adopting BEV technology by first removing the costs associated with IC powertrain systems, then applying the BEV system costs. Interested readers can still determine relative costs through comparison of the absolute costs for the initial technology combination and the new technology combination.

The costs that we use to model the application of engine technologies can be found across multiple tabs of the Technologies file. We determine engine costs based on engine size and configuration, instead of vehicle technology class. We designate the engine cost tabs in the Technologies file based on number of cylinders and number of cylinder banks. An example of the designations is 4C1B, which is a 4-cylinder 1 bank engine; this engine configuration is more commonly known as an I-4 engine. There are also tabs for SOHC engines, OHV engines (1 camshaft per bank) and 'L' designated engines. The 'L' designation accounts for the cost of turbo downsizing for smaller engines, which is new for this analysis.

The cost tabs use DOHC (2 camshafts per bank) architecture as the baseline, so the SOHC (1 camshaft per bank) engine and OHV (1 camshaft per bank) engine designations are for engines with a SOHC architecture or OHV architectures respectively. However, for costing purposes, we assume all engines are DOHC once advanced engine technologies are applied. We determine cylinder count, engine architecture, and configuration by assignment in the analysis fleet file, see Chapter 3.1.2. Table 3-20 gives a summary of some of the more common engine designations. For a full discussion about the Technologies file, see the CAFE Model Documentation.

Table 3-20 – Summary of Common Engine Configurations in CAFE Model Input File

Engine Costing Designation	Cylinders	Camshafts	Represented Cylinder Configurations
2C1B	2	2	2-cylinder engine
3C1B	3	2	'I' configuration engine
4C1B	4	2	'I' configuration engine
4C2B	4	4	'V' or 'H' configuration engine
5C1B	5	2	'I' configuration engine
6C1B	6	2	'I' configuration engine
6C2B	6	4	'V' or 'H' configuration engine
8C2B	8	4	'V' or 'H' configuration engine

When the model applies forced-induction technology to a naturally aspirated engine, the engine has a significant boost in power density and can be reduced in size, while maintaining similar performance.[242] The analysis models this reduction in engine size, and, thus, cost, by assuming a reduction in the total cylinder count when determining the absolute costs of the new engine in the Technologies file. For example, the cost of forced induction-based technologies (*e.g.*, TURBO1) is found in the DOHC V8 naturally aspirated tab (8C2B) of the Technologies file, however, it assumes only 6-cylinders when calculating costs. Table 3-21 provides a small example set of the costing configurations for turbo downsized technologies versus the base engine configuration costing tab.

[242] Heywood 2018, Chapter 6.2.8.

Table 3-21 – Examples of how Engine Configuration is Assumed to Change for Cost Purposes when Turbo-Downsizing Technology is Applied

NATURALLY ASPIRATED COSTING CONFIGURATIONS	TURBO DOWNSIZED COSTING CONFIGURATION
4C1B	4C1B*
6C2B	4C1B
8C2B	6C2B
10C2B	8C2B
* NOTE: For this analysis, cost for turbo downsizing a low output 4-cylinder naturally aspirated engine assumes transition to a 3-cylinder turbocharged engine.	

We allow additional downsizing beyond what has been previously modeled because manufacturers have downsized low output naturally aspirated engines to small architecture turbo engines.[243,244,245] We identify low-output naturally aspirated 4-cylinder engines in the baseline fleet that are allowed to downsize to turbocharged 3-cylinder engines, see Chapter 3.1.2. These engines use the costing tabs in the Technologies file with the 'L' designation.

Table 3-22 shows the assumed cylinder count and camshaft count used for determining technology costs for each engine architecture. The CAFE Model only uses the assumed cylinder count for determining technology cost, and initial cylinder count is based on the baseline fleet assignment, see Chapter 3.1.2. For effectiveness, Autonomie modeling uses engine displacement and power only, and does not directly use cylinder count.

[243] Richard Truett, "GM Bringing 3-Cylinder back to North America." Automotive News, December 01, 2019. https://www.autonews.com/cars-concepts/gm-bringing-3-cylinder-back-na. (Accessed: February 15, 2022).
[244] Stoklosa, Alexander, "2021 Mini Cooper Hardtop." Car and Driver, December 2, 2014. https://www.caranddriver.com/reviews/a15109143/2014-mini-cooper-hardtop-manual-test-review. (Accessed: February 15, 2022).
[245] Leanse, Alex "2020 For Escape Options: Hybrid vs. 3-Cylinder EcoBoost vs. 4-Cylinder EcoBoost." MotorTrend, Sept 24, 2019. https://www.motortrend.com/news/2020-ford-escape-engine-options-pros-and-cons-comparison. (Accessed: February 15, 2022).

Table 3-22 – Assumed Cylinder and Camshaft Count Used for Costing for each Engine Architecture for Applied Technology

Engine Architecture	Basic Engine (Cyl/Cam)	TURBO1 (Cyl/Cam)	TURBO2 (Cyl/Cam)	CEGR1 (Cyl/Cam)	ADEAC (Cyl/Cam)	HCR0 (Cyl/Cam)	HCR1 (Cyl/Cam)	HCR1D (Cyl/Cam)	VCR (Cyl/Cam)	VTG (Cyl/Cam)	TURBOD (Cyl/Cam)	TURBOAD (Cyl/Cam)
2C1B_SOHC	2/1	2/2	2/2	2/2	2/1	2/1	2/1	2/1	2/2	2/2	2/2	2/2
2C1B	2/2	2/2	2/2	2/2	2/2	2/2	2/2	2/2	2/2	2/2	2/2	2/2
3C1B_SOHC	3/1	3/2	3/2	3/2	3/1	3/1	3/1	3/1	3/2	3/2	3/2	3/2
3C1B	3/2	3/2	3/2	3/2	3/2	3/2	3/2	3/2	3/2	3/2	3/2	3/2
4C1B_L_SOHC	4/1	3/2	3/2	3/2	4/1	4/1	4/1	4/1	3/2	3/2	3/2	3/2
4C1B_SOHC	4/1	4/2	4/2	4/2	4/1	4/1	4/1	4/1	4/2	4/2	4/2	4/2
4C1B_L	4/2	3/2	3/2	3/2	4/2	4/2	4/2	4/2	3/1	3/1	3/1	3/1
4C1B	4/2	4/2	4/2	4/2	4/2	4/2	4/2	4/2	4/2	4/2	4/2	4/2
4C2B_SOHC	4/2	4/4	4/4	4/4	4/2	4/2	4/2	4/2	4/4	4/4	4/4	4/4
4C2B_L	4/4	3/2	3/2	3/2	4/4	4/4	4/4	4/4	3/2	3/2	3/2	3/2
4C2B	4/2	4/2	4/2	4/2	4/2	4/2	4/2	4/2	4/2	4/2	4/2	4/2
5C1B_SOHC	5/1	4/2	4/2	4/2	5/1	5/1	5/1	5/1	4/2	4/2	4/2	4/2
6C1B_SOHC	6/1	4/2	4/2	4/2	6/1	6/1	6/1	6/1	4/2	4/2	4/2	4/2
6C1B	6/2	4/2	4/2	4/2	6/2	6/2	6/2	6/2	4/2	4/2	4/2	4/2
6C1B_ohv	6/1	4/2	4/2	4/2	6/1	6/1	6/1	6/1	4/2	4/2	4/2	4/2
6C2B_SOHC	6/2	4/2	4/2	4/2	6/2	6/2	6/2	6/2	4/2	4/2	4/2	4/2
6C2B	6/4	4/2	4/2	4/2	6/4	6/4	6/4	6/4	4/2	4/2	4/2	4/2
6C2B_OHV	6/2	4/2	4/2	4/2	6/2	6/2	6/2	6/2	4/2	4/2	4/2	4/2
8C2B_SOHC	8/2	6/2	6/2	6/2	8/2	8/2	8/2	8/2	6/2	6/2	6/2	6/2
8C2B	8/4	6/4	6/4	6/4	8/4	8/4	8/4	8/4	6/4	6/4	6/4	6/4
8C2B_ohv	8/2	6/2	6/2	6/2	8/2	8/2	8/2	8/2	6/2	6/2	6/2	6/2
10C2B_SOHC	10/2	8/2	8/2	8/2	10/2	10/2	10/2	10/2	8/2	8/2	8/2	8/2
10C2B	10/4	8/4	8/4	8/4	10/4	10/4	10/4	10/4	8/4	8/4	8/4	8/4
10C2B_ohv	10/2	8/2	8/2	8/2	10/2	10/2	10/2	10/2	8/2	8/2	8/2	8/2
12C2B_SOHC	12/2				12/2	12/2	12/2	12/2				
12C2B	12/4				12/4	12/4	12/4	12/4				
12C4B_SOHC	12/4				12/4	12/4	12/4	12/4				
12C4B	12/8				12/8	12/8	12/8	12/8				
16C4B_SOHC	16/4				16/4	16/4	16/4	16/4				
16C4B	16/8				16/8	16/8	16/8	16/8				

3.1.8.1 Basic Engines

DMCs for basic engine technologies are based on engine cylinder and bank count and configuration. DMC examples are shown in Table 3-23. We source these costs from publications and historical cost studies,[246,247] and update them to 2018$ for the analysis. The DMC for each technology is a function of unit cost times either the number of cylinders or number of banks, based on how the technology is applied to the system.

Table 3-23 – Examples of Basic Engine Technology DMC Used for this Analysis in 2018$

Engine Technologies – Direct Manufacturer Costs (2018$) for Basic Engine Technologies								
Tech	Basis	Unit DMC	DMC for 4-Cylinder 1-Bank Engine	DMC for 4-Cylinder 2-Bank Engine	DMC for 6-Cylinder 1-Bank Engine	DMC for 6-Cylinder 2-Bank Engine	DMC for 8-Cylinder 2-Bank Engine	**Incremental To**
VVT	bank	81.72	81.72	163.44	81.72	163.44	163.44	Base Engine
VVL	cylinder	55.76	223.04	223.05	334.57	334.57	446.09	VVT
SGDI	cylinder	61.68	246.73	246.73	370.09	370.09	493.46	VVT
DEAC	cylinder	31.95	127.80	127.80	191.70	191.70	255.60	VVT
ADEAC SOHC	cylinder	45.99	183.96	183.96	275.94	275.94	367.92	VVT, SGDI, DEAC
ADEAC DOHC	cylinder	85.85	343.40	343.40	515.10	515.10	686.80	VVT, SGDI, DEAC

We apply RPE and learning to the incremental DMCs, see Chapter 2.6. To reach an absolute cost baseline, we sum the basic engine technology costs to establish an overall absolute cost for the technology combinations. For a full listing of all absolute costs see the Technologies file. For the basic engines, to calculate an absolute cost, we assign a base engine cost to the engine, examples are shown in Table 3-24, then add an incremental cost for each basic engine technology, examples are shown in Table 3-25. As an example, a 4C1B DOHC engine with VVT and VVL has an absolute cost of $5516.82 (5,090.94+114.19+311.69) in MY 2020 in 2018$.

[246] Kolwich, Greg, "Diesel Cost Analysis," FEV, Oct. 13, 2015. FEV P311732-02 at p. 259.
[247] 2015 NAS report, at p. 7.

Table 3-24 – Examples of Base Absolute Costs for MY 2020 Basic Engine Technologies in 2018 Dollars

	4C1B (2018$)	6C2B (2018$)	8C2B (2018$)
SOHC	5,013.49	5,675.87	6,306.65
DOHC	5,090.94	5,830.76	6,461.54
OHV	NA	5,490.91	6,306.65

Table 3-25 – Example Incremental Costs for Adding Basic Engine Technologies for MY 2020 in 2018$.

	4C1B (2018$)	6C2B (2018$)	8C2B (2018$)
VVT	114.19	228.39	228.39
VVL	311.69	467.53	623.37
SGDI	344.78	517.17	689.55
DEAC	177.65	209.63	236.28
ADEAC*	564.8	879.31	753.07

*NOTE: ADEAC costs appear as absolute costs in the Technologies file.

3.1.8.2 Advanced Engines

We determine the costs of the advanced engine technologies by adding the lump cost of the advanced engine technology to the basic engine technology costs, and then applying the RPE and learning factor based on the year that the technology is applied. The costs for forced induction, Atkinson engines, Miller engines, VCR engines, diesel engines, and alternative fuel engines are discussed below.

3.1.8.2.1 Forced Induction Engines

We calculate the absolute cost for TURBO1 by adding the advanced engine cost to the baseline VVT engine. We calculate the TURBO2 absolute cost by adding the incremental cost to the TURBO1 engine cost. We calculate the CEGR absolute cost by adding the incremental cost to the TURBO2 cost. The cost relationship is summarized in Table 3-26.

For TURBOD technology costs, we add the incremental cost of DEAC to the TURBO1 technology, applying the rules for cost downsizing discussed above. For TURBOAD costs, we add the incremental cost of ADEAC to the TURBOD technology cost, also applying the same rules for cost downsizing discussed above.

Table 3-26 below shows the DMCs for forced induction engines in this analysis, in 2018 dollars. Table 3-27 shows example absolute costs for the 4C1B turbo engines,[248] across multiple model years, demonstrating the application of both the RPE and learning rates. Table 3-28 shows example absolute costs for the 6C2B turbo engines, across multiple model years, with RPE and learning rates applied. These costs can be found in the Technologies file.

[248] These costs represent the cost for a 6C2B naturally aspirated engine to become a forced induction (turbo) engine, per examples discussed in .

Table 3-26 – Examples of Turbocharged Downsized Engine DMC in 2018 Dollars

Engine Technologies – Direct Manufacturer Costs (2018$) for Turbocharged Technologies								Incremental To
Tech	Basis	Unit DMC	DMC for 4-Cylinder 1-Bank Engine	DMC for 4-Cylinder 2-Bank Engine	DMC for 6-Cylinder 1-Bank Engine	DMC for 6-Cylinder 2-Bank Engine	DMC for 8-Cylinder 2-Bank Engine	
TURBO1	None	-	874.77	874.77	881.13	881.13	1443.80	VVT
TURBO2	None	-	241.14	241.14	241.14	241.14	406.48	TURBO1
CEGR1	None	-	288.83	288.83	288.83	288.83	288.83	TURBO2
TURBOD	-	-	172.33	172.33	172.33	172.33	204.17	TURBO1
TURBOAD	-	-	364.93	364.93	364.93	364.93	547.39	TURBOD

Table 3-27 – Examples Absolute Costs Used for I4 Turbocharged Engines in 2018 Dollars (costs include DMCs, RPE and learning rate factor)

	4C1B Costs (2018$)			
Technology	MY 2018	MY 2021	MY 2026	MY 2029
TURBO1	6,264.69	6,215.86	6,173.75	6,156.88
TURBOD	6,444.89	6,392.32	6,345.15	6,325.78
TURBOAD	7,042.71	6,942.03	6,847.59	6,811.54
TURBO2	6,861.47	6,772.50	6,616.76	6,554.61
CEGR1	7,288.46	7,178.04	6,984.74	6,907.60

Table 3-28 – Examples Absolute Costs used for V6 Turbocharged Engines in 2018 Dollars (costs include DMC, RPE and learning rate factor)

	6C2B Costs (2018$)			
Technology	MY 2018	MY 2021	MY 2025	MY 2029
TURBO1	7,112.60	7,059.27	7,020.02	6,994.87
TURBOD	7,292.80	7,235.74	7,192.35	7,163.77
TURBOAD	7,890.63	7,785.45	7,701.57	7,649.52
TURBO2	7,731.51	7,636.00	7,498.58	7,402.08
CEGR1	8,158.51	8,041.54	7,873.26	7,755.08

3.1.8.2.2 Atkinson Engines

We use DMCs for HCR0 and HCR1 based on the 2015 NAS analysis, but the cost accounting is aggregated differently than the 2015 NAS report. We include other types of technology present in the engines, like SGDI, and the configuration of the engine, such as SOHC versus DOHC in the cost estimates. Finally, we determine the HCR1D technology cost by adding the DEAC cost to the HCR1 engine costs. Examples of the DMC values are shown in Table 3-29.

We then apply an RPE factor and learning curve. Table 3-30 and Table 3-31 show examples of the full absolute costs used for the engine technologies. To see all costs across all model years, please see the Technologies file.

Table 3-29 – Examples of HCR Technology DMC Used for the Final Rule Analysis in 2018 Dollars

<table>
<tr><th colspan="8">Engine Technologies – Direct Manufacturer Costs (2018$) for Atkinson Enabled Technologies</th><th rowspan="4">Incremental To</th></tr>
<tr><th rowspan="3">Tech</th><th rowspan="3">Basis</th><th rowspan="3">Unit DMC</th><th>DMC for</th><th>DMC for</th><th>DMC for</th><th>DMC for</th><th>DMC for</th></tr>
<tr><th>4-Cylinder</th><th>4-Cylinder</th><th>6-Cylinder</th><th>6-Cylinder</th><th>8-Cylinder</th></tr>
<tr><th>1-Bank Engine</th><th>2-Bank Engine</th><th>1-Bank Engine</th><th>2-Bank Engine</th><th>2-Bank Engine</th></tr>
<tr><td>HCR0</td><td>none</td><td>-</td><td>573.61</td><td>573.61</td><td>846.07</td><td>846.07</td><td>1155.26</td><td>VVT</td></tr>
<tr><td>HCR1</td><td>none</td><td>-</td><td>618.89</td><td>618.89</td><td>891.35</td><td>891.35</td><td>1200.54</td><td>HCR0</td></tr>
<tr><td>HCR1D</td><td>-</td><td>-</td><td>127.80</td><td>127.80</td><td>191.70</td><td>191.70</td><td>255.60</td><td>HCR1</td></tr>
</table>

Table 3-30 – Examples of Absolute Costs for I4 HCR Engines (costs include DMC, RPE and learning rate factor) in 2018 Dollars

	4C1B Costs (2018$)			
Technology	MY 2018	MY 2021	MY 2026	MY 2029
HCR0	5,843.55	5,812.69	5,803.22	5,801.68
HCR1	5,898.80	5,851.67	5,831.19	5,826.67
HCR1D	6,079.00	6028.13	6,002.59	5,995.57

Table 3-31 – Examples of Absolute Costs for V6 HCR Engines (costs include DMC, RPE and learning rate factor) in 2018 Dollars

	6C2B Costs (2018$)			
Technology	MY 2018	MY 2021	MY 2025	MY 2029
HCR0	6,990.13	6,942.58	6,928.79	6,925.64
HCR1	7,045.38	6,981.56	6,958.18	6,950.62
HCR1D	7,258.02	7,189.79	7,161.53	7,149.92

3.1.8.2.3 Miller Cycle Engines

We use cost data from an FEV technology cost assessment, performed for ICCT, to estimate the DMC for Miller cycle engines with VTG.[249] We considered costs from the 2015 NAS study that

[249] Aaron Isenstadt and John German (ICCT); Mihai Dorobantu (Eaton); David Boggs (Ricardo); Tom Watson (JCI) "Downsized, boosted gasoline engines," ICCT. Working Paper 2016-22, 28 October 2016.

referenced a NESCCAF 2004 report,[250] but believe the reference material from the FEV report provides more updated cost estimates for the VTG technology.

Despite not using the 2015 NAS report cost data, we did use the NAS 2015 methodology for aggregating the individual component and system costs to establish a DMC for the Miller cycle engine for each engine configuration. We use a value of \$525 (2010\$) plus cost of cEGR1, minus cost of VVT, VVL, and SGDI for the VTG cost estimate. From the VTG estimate we build a cost for electrically-assisted variable supercharger VTGE (Eng23c) engines based on the 2015 NAS report that uses a cost of \$1050 (2010\$) plus the cost of the mild hybrid battery. Examples of the DMC for these technologies are shown in Table 3-32. Example costs are shown in Table 3-33 for 4C1B engines and Table 3-34 for 6C2B engines, and include application of the RPE and learning factors. Costs for all engine architectures and model years can be seen in the Technologies file.

Table 3-32 – Examples of DMC Used for Miller Cycle Engines (VTG, VTGE) in 2018 Dollars

Engine Technologies - Direct Manufacturer Costs (2018$) for Miller Technologies					Incremental To
Tech	DMC for 4-Cylinder 1-Bank Engine	DMC for 6-Cylinder 1-Bank Engine	DMC for 6-Cylinder 2-Bank Engine	DMC for 8-Cylinder 2-Bank Engine	
VTG (w/cEGR)	603.14	603.14	603.14	603.14	VVT
VTGE	1499.78	1499.78	1499.78	1499.78	VTG

Table 3-33 – Examples of Miller Cycle I4 Engines' Absolute Costs Used for VTG and VTGE Technology (costs include DMC, RPE and learning rate factor)

	4C1B Costs (2018$)			
Technology	MY 2018	MY 2021	MY 2026	MY 2029
VTG	7,663.31	7,547.20	7,343.96	7,262.86
VTGE	9,148.86	8,772.73	8,326.43	8,146.77

[250] "Reducing Greenhouse Gas Emissions from Light-Duty Motor Vehicles." NESCCAF. September 23, 2004 Report. Available at https://www.nesccaf.org/documents/rpt040923ghglightduty.pdf. (Accessed: February 15, 2022).

Table 3-34 – Examples of Miller Cycle V6 Engines' Absolute Costs Used for VTG and VTGE Technologies (costs include DMC, RPE and learning rate factor)

	6C2B Costs (2018$)			
Technology	MY 2018	MY 2021	MY 2025	MY 2029
VTG	8,532.58	8,410.25	8,234.25	8,110.65
VTGE	10,018.13	9,635.78	9,257.62	8,994.56

3.1.8.2.4 Variable Compression Ratio Engines

The base DMCs that we use for VCR engines are based on data from the 2015 NAS report.[251] The 2015 NAS cost for VCR in MY 2025 uses a naturally aspirated engine; however, for this analysis, we add the cost of cEGR. Table 3-35 shows an example estimated DMC for the VCR technology. Examples of the absolute costs for 4C1B and 6C2B engines, respectively, are in Table 3-36 and Table 3-37.

Table 3-35 – Examples of VCR DMCs in 2018$

Engine Technologies - Direct Manufacturer Costs (2018$)						Incremental To
Tech	Basis	Unit DMC	DMC for 4-Cylinder 1-Bank Engine	DMC for 6-Cylinder 2-Bank Engine	DMC for 8-Cylinder 2-Bank Engine	
VCR	cylinder	171.47	685.87	1028.80	1371.73	TURBO1

Table 3-36 – Examples of Absolute VCR Engine Costs for I4 Engine Configuration (costs include DMC, RPE and learning rate factor)

	4C1B Costs (2018$)			
Technology	MY 2018	MY 2021	MY 2026	MY 2029
VCR	7,472.47	7,326.44	7,188.83	7,138.25

Table 3-37 – Examples of Absolute VCR Engine Costs for V6 Engine Configuration (costs include DMC, RPE and learning rate factor)

	6C2B Costs (2018$)			
Technology	MY 2018	MY 2021	MY 2025	MY 2029
VCR	8,320.38	8,169.86	8,048.82	7,976.24

[251] 2015 NAS report, at p. 7.

3.1.8.2.5 Diesel Engines

Diesel engine DMCs are based on the baseline engine cost. The baseline diesel engine (ADSL) cost is based on the cost of a modern light duty diesel engine.[252] The second level of diesel technology (DSLI) includes the cost of incorporating a combination of low pressure and high pressure EGR, reduced parasitic loss, advanced friction reduction, incorporation of highly-integrated exhaust catalyst with low temperature light-off, and closed loop combustion control. In both packages, the cost includes after-treatment systems to meet the emissions standards for criteria pollutants.[253] For DSLIAD technologies, we add the incremental cost of ADEAC to DSLI.

Example costs for the diesel technologies are shown in Table 3-38 and Table 3-39. All diesel engine technology costs are shown in the Technologies file.

Table 3-38 – Examples of Absolute Diesel Engine Costs for I4 Engine Configuration (costs include DMC, RPE and learning rate factor)

	4C1B Costs (2018$)			
Technology	MY 2018	MY 2021	MY 2026	MY 2029
ADSL	9,832.87	9,619.75	9,438.06	9,373.18
DSLI	10,344.73	10,108.61	9,907.31	9,835.43
DSLIAD	10,942.56	10,658.32	10,409.75	10,321.18

Table 3-39 – Examples of Absolute Diesel Engine Costs for V6 Engine Configuration (costs include DMC, RPE and learning rate factor)

	6C2B Costs (2018$)			
Technology	MY 2018	MY 2021	MY 2025	MY 2029
ADSL	11,512.42	11,257.06	11,065.55	10,961.64
DSLI	12,179.07	11,893.75	11,679.77	11,563.66
DSLIAD	13,075.80	12,718.32	12,443.61	12,292.29

3.1.8.2.6 Alternative Fuel Engines

Examples of costs for CNG engine technologies are shown in Table 3-40 and Table 3-41.[254] CNG engine costs across all model years can be found in the Technologies file.

[252] 2015 NAS report, at pp. 104–05.
[253] 2015 NAS report, at p. 104.
[254] 2015 NAS report, at p. 61.

Table 3-40 – Examples of Absolute CNG Engine Costs for I4 Engine Configuration (costs include DMC, RPE and learning rate factor)

	4C1B Costs (2018$)			
Technologies	MY 2018	MY 2021	MY 2026	MY 2029
CNG	11,893.10	11,752.83	11,611.72	11,541.17

Table 3-41 – Examples of CNG Engine Costs for V6 Engine Configuration (costs include DMC, RPE and learning rate factor)

	6C2B Costs (2018$)			
Technologies	MY 2018	MY 2021	MY 2025	MY 2029
CNG	12,748.76	12,606.09	12,462.91	12,389.57

3.1.8.3 Engine Friction Reduction Technologies

EFR costs are based on the 2015 NAS assessment for low friction lubrication and engine friction reduction level 2 (LUB2_EFR2).[255] The 2015 NAS report provides estimates of $51 (I4 DOHC), and $72 (V6 SOHC and DOHC) for midsize cars, in 2015 dollars, relative to level 1 engine friction reduction (EFR1), which costs about $12 per cylinder. For this analysis, we estimate EFR DMCs to be $14.05 per cylinder in 2016 dollars. Table 3-42 shows the EFR DMC for the final rule analysis in 2018 dollars and MY 2017 learning rate. Examples are shown in Table 3-43 and Table 3-44.

Table 3-42 – Example of EFR DMC Used in 2018 Dollars

Engine Technologies - Direct Manufacturer Costs (2018$) for EFR								Incremental To
Tech	Basis	Unit DMC	DMC for 4-Cylinder 1-Bank Engine	DMC for 4-Cylinder 2-Bank Engine	DMC for 6-Cylinder 1-Bank Engine	DMC for 6-Cylinder 2-Bank Engine	DMC for 8-Cylinder 2-Bank Engine	
EFR	cylinder	11.10	44.40	44.40	66.61	66.61	88.81	VVT

Table 3-43 – Example of EFR Costs Used for the I4 Engine in 2018 Dollars (cost includes DMC, RPE and learning rate factor)

	Costs (2018$)			
Technology	MY 2018	MY 2021	MY 2025	MY 2029
EFR	66.61	66.61	63.97	59.01

[255] 2015 NAS report, at p. 7.

Table 3-44 – Example of EFR Costs Used for V6 in 2018 Dollars (cost includes DMC, RPE and learning rate factor)

	Costs (2018$)			
Technology	MY 2018	MY 2021	MY 2025	MY 2029
EFR	99.92	99.92	95.96	88.51

3.2 Transmission Paths

Transmissions transmit torque from the engine to the wheels. Transmissions primarily use two mechanisms to improve fuel efficiency: (1) a wider gear range, which allows the engine to operate longer at higher efficiency speed-load points; and (2) improvements in friction or shifting efficiency (*e.g.*, improved gears, bearings, seals, and other components), which reduce parasitic losses.

For this analysis, we classify all light duty vehicle transmission technologies into discrete transmission technology paths. We use the paths to model the most representative characteristics, costs, and performance of the fuel-economy improving transmissions most likely available during the rulemaking time frame.

The following sections discuss how we define the transmission technologies in this analysis, the CAFE Model's general technology categories, and the transmission technologies' relative effectiveness and costs. The following sections also provide an overview of how we assign transmission technologies to the MY 2020 fleet, as well as the transmission adoption features.

3.2.1 Transmission Modeling in the CAFE Model

We model two major categories of transmissions for this analysis: automatic and manual. Automatic transmissions are characterized by automatically selecting and shifting between transmission gears for the driver during vehicle operation. We further subdivide automatic transmissions into four subcategories: traditional automatic transmissions (AT), dual clutch transmissions (DCT), continuously variable transmissions (CVT and eCVT), and direct drive transmissions (DD). Manual transmissions (MT) require direct control by the driver to select and shift between gears during vehicle operation.

We also include the application of high efficiency gearbox (HEG) technology improvements as options to the transmission technologies. HEG improvements for transmissions represent incremental advancements in technology that improve efficiency, such as reduced friction seals, bearings and clutches, super finishing of gearbox parts, and improved lubrication. These advancements are all aimed at reducing frictional and other parasitic loads in transmissions to improve efficiency. We consider three levels of HEG improvements in this analysis based on the National Academy of Sciences (NAS) 2015 recommendations, and CBI data.[256] We apply HEG efficiency improvements to ATs and CVTs, as those transmissions inherently have higher friction and parasitic loads related to hydraulic control systems and greater component

[256] 2015 NAS Report, at p. 191.

complexity, compared to MTs and DCTs. We identify transmissions by technology type, gear count, and HEG technology level using the naming conventions shown in Table 3-45, below.

Table 3-45 – Naming Conventions used for Transmission Technology Pathways

Transmission	Name
5-speed automatic	AT5
6-speed automatic baseline	AT6
6-speed automatic level 2 HEG	AT6L2
7-speed automatic level 2 HEG	AT7L2
8-speed automatic baseline	AT8
8-speed automatic level 2 HEG	AT8L2
8-speed automatic level 3 HEG	AT8L3
9-speed automatic level 2 HEG	AT9L2
10-speed automatic level 2 HEG	AT10L2
10-speed automatic level 3 HEG	AT10L3
6-speed dual-clutch	6DCT
8-speed dual-clutch	8DCT
Continuous variable transmission	CVT
Continuous variable transmission level 2HEG	CVTL2
5-speeed manual transmission	MT5
6-speed manual transmission	MT6
7-speed manual transmission	MT7

The CAFE Model pathways for transmission technologies are shown in Figure 3-7. We assign baseline-only technologies (the greyed MT5, AT5, AT7L2, AT9L2, and CVT nodes) only as initial vehicle transmission configurations.

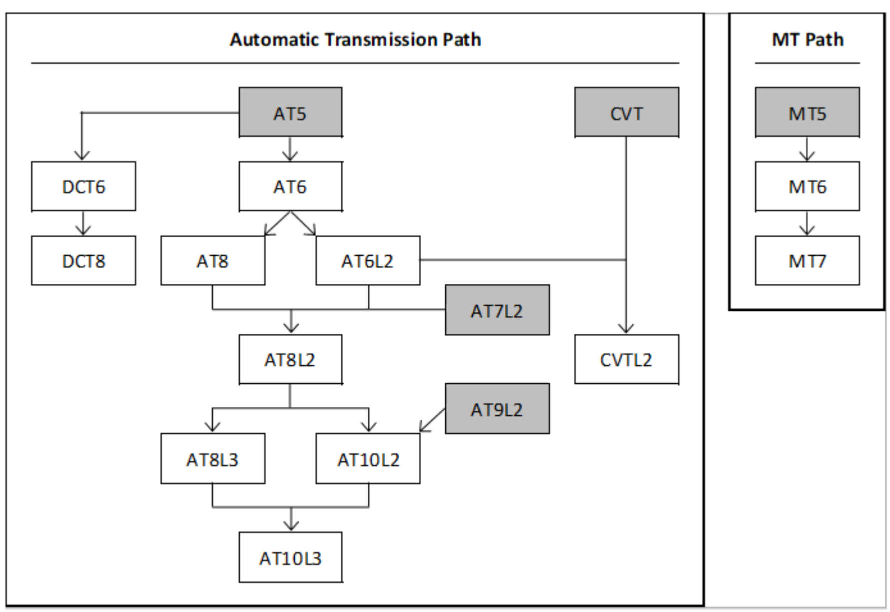

Figure 3-7 – CAFE Model Pathways for Transmission Technologies

3.2.1.1 Automatic Transmissions

We separate automatic transmissions into three major 'branches' as shown in Figure 3-7: ATs, DCTs, and CVTs.

Direct drive transmissions are not discussed in detail in this analysis and are not specifically shown in the technology pathways. DD transmissions are classified as automatic transmissions but have a direct connection between the wheels and a drive motor. In a DD transmission, the ratio between wheel speed and motor speed remains constant. DD transmissions are considered integral parts of electrified drivetrains (such as in BEVs) and are not applied as a standalone technology. See Chapter 3.2.3 for a discussion of how we assign the DD transmission in the baseline fleet.

Electronic continuously variable transmissions (eCVT) are also not discussed in detail in this analysis and are not specifically shown in the technology pathways. eCVTs are classified as CVTs, but the eCVT module contains both an electric traction motor and generator coupled to the ICE through a single planetary gear set.[257] eCVTs are considered integral parts of electrified drivetrains (such as power-split hybrids) and are not applied as a standalone technology. See Chapter 3.2.3 for a discussion of how we assign the eCVT in the baseline fleet.

3.2.1.1.1 Traditional Automatic Transmissions

Conventional planetary gear automatic transmissions (AT) are the most popular transmission.[258] ATs typically contain three or four planetary gear sets that provide the various gear ratios. Gear ratios are selected by activating solenoids that engage or release multiple clutches and brakes as needed. We include ATs with gear counts ranging from five speeds to ten speeds in this analysis, see Figure 3-7.[259]

ATs are packaged with torque converters, which provide a fluid coupling between the engine and the driveline and provide a significant increase in launch torque. When transmitting torque through this fluid coupling, energy is lost due to the churning fluid. These losses can be eliminated by engaging the torque convertor clutch to directly connect the engine and transmission ("lockup").

In general, ATs with a greater number of forward gears and with larger overall ratio spread offer more potential for fuel consumption reduction, but at the expense of higher control complexity. Transmissions with a higher number of gears typically offer a wider overall speed ratio and more opportunity to operate the engine near its most efficient point. For the Draft TAR and 2020 final rule, we and EPA surveyed automatic transmissions in the market to assess trends in gear count

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[257] Light Duty Technology Cost Analysis, Power-Split and P2 HEV Case Studies, EPA-420-R-11-015 (November 2011).

[258] 2021 EPA Automotive Trends Report.

[259] Specifically, we considered five-speed automatic transmissions (AT5), six-speed automatic transmissions (AT6), seven-speed automatic transmission (AT7), eight-speed automatic transmissions (AT8), nine-speed automatic transmissions (AT9), and ten-speed automatic transmissions (AT10).

and purported fuel economy improvements.[260] Based on that survey, and also EPA's more recent Automotive Trends Reports,[261] we model ATs with a range of 5 to 10 gears with three levels of HEG technology.

3.2.1.1.2 Continuously Variable Transmissions

Conventional continuously variable transmissions (CVT) consist of two cone-shaped pulleys, connected with a belt or chain. Moving the pulley halves allows the belt to ride inward or outward radially on each pulley, effectively changing the speed ratio between the pulleys. This ratio change is smooth and continuous, unlike the step changes of other transmission varieties.[262]

One advantage of CVTs is that they continue to transmit torque during ratio changes. In ATs and some DCTs, energy from the engine is wasted during a ratio change or shift. ATs and some DCTs have a delay during shifts caused by the torque disruption during gear changes. Another advantage of a CVT is that with its effectively "infinite" number of gear steps, within its ratio range it can maintain engine operation closer to the maximum efficiency for the required power. AT's efficiency peaks with 9 to 10 gears,[263,264] and approaches the CVT's ability to operate the engine at the most efficient operating point. While a CVT can improve fuel economy over ATs with fewer gears, it typically provides minimal improvement over 9- and 10-speed ATs.

We model two types of CVT systems in the analysis, the baseline CVT and a CVT with HEG technology applied, see Figure 3-7. As discussed above, eCVTs are not modeled as a standalone technology but are incorporated in power split hybrids (SHEVPS).

3.2.1.1.3 Dual Clutch Transmissions

Dual clutch transmissions (DCT), like automatic transmissions, automate shift and launch functions. DCTs use separate clutches for even-numbered and odd-numbered gears, allowing the next gear needed to be pre-selected, resulting in faster shifting. The use of multiple clutches in place of a torque converter results in lower parasitic losses than ATs.[265]

However, DCTs have limited penetration in the fleet.[266] DCTs have encountered issues with customer acceptance.[267] The NAS also stated in its 2021 report, "... attempts by some automakers to introduce this technology to the U.S. market were met with significant customer acceptance issues; for instance, customers accustomed to a torque convertor based automatic transmission performance seem to have concerns with a start-up clutch, mostly at lower speeds.

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[260] Draft TAR at 5-50, 5-51; Final Regulatory Impact Analysis accompanying the 2020 final rule, at p. 549.
[261] 2021 EPA Automotive Trends Report
[262] 2015 NAS report, at 171.
[263] Robinette, D. & Wehrwein, D. "Automatic Transmission Technology Selection Using Energy Analysis," presented at the CTI Symposium 9th International 2015 Automotive Transmissions, HEV and EV Drives.
[264] Greimel, H. "ZF CEO - We're not chasing 10-speeds," Automotive News, November 23, 2014, http://www.autonews.com/article/20141123/OEM10/311249990/zf-ceo:-were-not-chasing-10-speeds. (Accessed: February 15, 2022).
[265] 2015 NAS report, at p. 170.
[266] 2020 EPA Automotive Trends Report, at p. 57.
[267] See 2015 NAS report, at 170-1. For example, Honda has tried adding additional technology like torque converts to the DCT to improve consumer acceptance, with limited success.

Therefore, some automakers have since transitioned away from DCTs, and other automakers scrapped introduction plans prior to launch."[268]

Generally, DCTs are very cost-effective technologies in the simulation, but consumer acceptance issues limit their appeal in the American market. Because of the limited appeal, we constrain application of additional DCT technology to vehicles already using DCT technology, and only models two types of DCTs in the analysis, see Figure 3-7.

3.2.1.2 Manual Transmissions

Manual transmissions (MT) are transmissions that require direct control by the driver to operate the clutch and shift between gears. In a manual transmission, gear pairs along an output shaft and parallel layshaft are always engaged. The driver selects gears via a shift lever. The lever operates synchronizers, which speed match the output shaft and the selected gear before engaging the gear with the shaft. During shifting operations (and during idle), the driver disengages a clutch between the engine and transmission to decouple engine output from the transmission.

Automakers today offer a minimal selection of new vehicles with manual transmissions.[269] The NAS also recognizes in its 2021 report that "Manual transmissions have all but left the U.S. light-duty market except in sports performance categories."[270] As a result of reduced market presence, we only include three variants of manual transmissions in the analysis, see Figure 3-7.

3.2.2 Transmission Analysis Fleet Assignments

To understand manufacturers' potential pathways for compliance and the feasibility of different potential stringencies, it is important to first understand the baseline state of technology in their fleets. The analysis fleet provides a snapshot of the U.S. vehicle market for the 2020 model year. It includes transmission assignments for each vehicle and the degree of transmission sharing among those vehicles. Assignments map the transmissions modeled in Autonomie to the real-world transmissions they best represent in terms of configuration, cost, and effectiveness.

3.2.3 Transmission Characteristics Considered in Baseline Fleet Assignments

"Assignment" refers to the process of identifying which Autonomie transmission model is most like a vehicle's real-world transmission, taking into account the transmission's configuration and generic costs. Table 3-46 lists the Autonomie transmission models and their acronyms that we use in the CAFE Model input files. For convenience, we refer to these technologies by their acronyms in this section.

We classify the wide variety of transmissions on the market into discrete transmission technology paths. We use the paths to model the most representative characteristics, costs, and

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[268] National Academies of Sciences, Engineering, and Medicine 2021. Assessment of Technologies for Improving Light-Duty Vehicle Fuel Economy 2025-2035. Washington, DC: The National Academies Press. https://doi.org/10.17226/26092, at pp. 4-56 [hereinafter 2021 NAS report]. (Accessed: February 15, 2022).
[269] 2020 EPA Automotive Trends Report, at p. 61.
[270] 2021 NAS report, at pp. 4-54.

performance of the fuel economy-improving technologies most likely available during the rulemaking time frame. Due to uncertainty regarding the costs and capabilities of emerging technologies, some new and pre-production technologies are not a part of this analysis.

To assess the feasibility of different stringencies, it is important to accurately establish the baseline technology content of the fleet. Underestimating the amount of technology in the baseline would lead to overestimating the actual technology application needed for manufacturers to comply with standards and cause the analysis to incorrectly apply technologies that are already present on baseline vehicles. Conversely, overestimating the technology present in the analysis fleet would artificially (and incorrectly) limit the technologies manufacturers might apply to meet standards.

Manufacturer mid-model year CAFE compliance submissions and publicly available manufacturer specification sheets serve as the basis for baseline transmission assignments. We use these data to assign transmissions in the analysis fleet and determine which platforms share transmissions. Common transmissions and how we characterize them are discussed in Chapter 3.2.3.

Table 3-46 – Transmission Technologies

Transmission	Name
5-speed automatic	AT5
6-speed automatic baseline	AT6
6-speed automatic level 2 high-efficiency gearbox (HEG)	AT6L2
7-speed automatic level 2 HEG	AT7L2
8-speed automatic baseline	AT8
8-speed automatic level 2 HEG	AT8L2
8-speed automatic level 3 HEG	AT8L3
9-speed automatic level 2 HEG	AT9L2
10-speed automatic level 2 HEG	AT10L2
10-speed automatic level 3 HEG	AT10L3
6-speed dual-clutch	DCT6
8-speed dual-clutch	DCT8
Continuously variable transmission	CVT
Continuously variable transmission level 2 HEG	CVTL2
5-speed manual transmission	MT5
6-speed manual transmission	MT6
7-speed manual transmission	MT7
Direct drive	DD
Electronic continuously variable transmission	eCVT

We specify transmission type, number of gears, and high-efficiency gearbox (HEG) level for the baseline fleet assignment. Transmission types in the analysis include automatic, manual, dual-clutch, and continuously variable, as described in Chapter 3.2.1. HEG levels represent incremental improvements in transmission technology that improve efficiency for automatic and continuously variable transmissions. See Chapter 3.2.1 for further discussion of HEG levels.

The number of gears in the assignments for automatic and manual transmissions usually match the number of gears listed by the data sources, with some exceptions. We did not model four-speed transmissions in Autonomie due to their rarity and low likelihood of being used in the future, so we assign 2020 vehicles with an AT4 or MT4 to an AT5 or MT5 baseline, respectively. Some dual-clutch transmissions are also an exception; we assign dual-clutch transmissions with seven gears to DCT6.

For automatic and continuously variable transmissions, identifying the most appropriate transmission path model requires additional steps; this is because identifying HEG level from specification sheets alone is not always straightforward. We review age of the transmission design, relative performance versus previous designs, and technologies incorporated to assign an HEG level.

No automatic transmissions in the MY 2020 analysis fleet are at HEG Level 3. In addition, we did not assign HEG Level 2 technology to any six-speed automatic transmissions. However, we found all 7-speed, all 9-speed, all 10-speed, and some 8-speed automatic transmissions to be advanced transmissions operating at HEG Level 2 equivalence. Eight-speed automatic transmissions developed after MY 2017 are assigned HEG Level 2. All other transmissions are assigned to their respective transmission's baseline level. The baseline (HEG level 1) technologies available include AT6, AT8, and CVT.

We assign any vehicle in the analysis fleet with an electric powertrain a direct drive (DD) transmission. We assign any vehicle in the analysis fleet with a power-split hybrid (SHEVPS) powertrain an electronic continuously variable transmission (eCVT). These designations are for informational purposes only. If specified, the transmission will not be individually replaced or updated by the model, because of the integrated nature of these transmissions. For further discussion of how the model handles transmissions on electrified vehicles, see Chapter 3.2.1.

Table 3-47 shows the prevalence of each technology as assigned in the baseline fleet.

Table 3-47 – Penetration Rates of Transmission Technologies in the 2020 Baseline Fleet

Transmission Technology	Sales Volume	Penetration Rate
MT5	11,116	0.08%
MT6	141,093	1.04%
MT7	455	0.003%
AT5	137,622	1.01%
AT6	2,223,646	16.36%
AT6L2	-	0%
AT7L2	67,193	0.49%
AT8	3,253,670	23.94%
AT8L2	372,087	2.74%
AT8L3	-	0%
AT9L2	1,539,691	11.33%
AT10L2	1,407,973	10.36%
AT10L3	-	0%

DCT6	162,334	1.19%
DCT8	156,656	1.15%
CVT	1,184,424	8.71%
CVTL2	2,248,223	16.54%
DD/eCVT (Total HEV/BEV)	686,368	5.05%
Total Automatic	9,001,882	66.23%
Total Manual	152,664	1.12%
Total Dual-Clutch	318,990	2.35%
Total Continuously Variable	3,432,647	25.25%

3.2.4 Other Transmission Characteristics Recorded and Used to Identify Common Transmissions

Manufacturers often use transmissions that are the same or similar on multiple vehicles. To reflect this, we consider shared transmissions for manufacturers as appropriate. For more information, see Chapter 2.2.1.6.

In addition to technology type, gear count, and HEG level, we characterize transmissions in the analysis fleet by drive type and vehicle architecture. We consider front-, rear-, all-, and four-wheel drive in the analysis. The definition of drive types in the analysis does not always align with manufacturers' drive type designations; see the end of this subsection for further discussion. These characteristics, supplemented by information such as gear ratios and production locations, show that manufacturers use transmissions that are the same or similar on multiple vehicle models. Manufacturers have told us they do this to control component complexity and associated costs for development, manufacturing, assembly, and service. If multiple vehicle models share technology type, gear count, drive configuration, internal gear rations, and production location, the transmissions are treated as a single group for the analysis. Vehicles in the analysis fleet with the same transmission configuration adopt additional fuel-saving transmission technology together, as described in Chapter 2.2.1.6.

We designate and track common transmissions in the CAFE Model input files using transmission codes. Transmission codes are six-digit numbers that are assigned to each transmission and encode information about them. This information includes the manufacturer, drive configuration, transmission type, and number of gears. Table 3-48 lists the possible values for each digit in the transmission code and its meaning.

Table 3-48 – Transmission Codes Guide

Transmission Code Digit	Meaning	Values	Notes
First and Second	Manufacturer	11 - General Motors 12 - Fiat-Chrysler 13 - Ford 14 - Tesla 21 - Honda 22 - Nissan 23 - Toyota 24 - Mazda 25 - Mitsubishi 26 - Subaru 31 - Hyundai 32 - Kia 41 - BMW 42 - Volkswagen 43 - Daimler 44 - Jaguar-Land Rover 45 - Volvo	First digit indicates manufacturer heritage region: 1 - USA 2 - Japan 3 - South Korea 4 - Europe
Third	Drive Configuration	1 - Front-Wheel Drive 2 - All-Wheel Drive 3 - Rear-Wheel Drive 4 - Four-Wheel Drive	Drive configuration determined by vehicle architecture
Fourth	Transmission Type	1 - Manual 2 - Automatic 3 - Continuously Variable 4 - Dual-Clutch	
Fifth	Number of Gears	0 - 10-speed 1 - Continuously variable 5 - 5-speed 6 - 6-speed 7 - 7-speed 8 - 8-speed 9 - 9-speed	
Sixth	Transmission Variant	1 through 9	

An example of a transmission code is 132281, which corresponds to the Ford Escape's all-wheel drive (AWD), 8-speed automatic transmission. Transmission codes can be decoded by reading the code from left to right: "13" is the manufacturer code for Ford, "2" indicates an AWD vehicle, "2" indicates an automatic transmission, "8" indicates eight speeds, and "1" means this is the first variant of this particular transmission.

We assign different transmission codes to variants of a transmission that may appear to be similar based on the characteristics considered in the analysis but are not mechanically identical. We distinguish among transmission variants by comparing their internal gear ratios and production locations. For example, several Ford nameplates carry a rear-wheel drive, 10-speed automatic transmission (AT10). These nameplates comprise a wide variety of body styles and use cases, so the analysis assigns different transmission codes to these different nameplates. Because the nameplates have different transmission codes, they are not treated as “shared” for the purposes of analysis in the CAFE Model and can adopt transmission technologies independently.

Note that when determining the drive type of a transmission, the assignment of aAWD versus four-wheel drive is determined by vehicle architecture. This assignment does not necessarily match the drive type used by the manufacturer in specification sheets and marketing materials. Vehicles with a powertrain capable of providing power to all wheels and a transverse engine (front-wheel drive architecture) are assigned AWD. Vehicles with power to all four wheels and a longitudinal engine (rear-wheel drive architecture) are assigned four-wheel drive.

3.2.5 Transmission Adoption Features

When evaluating transmission technologies to improve fuel economy, the CAFE Model considers current transmission architecture. If a manufacturer has already committed to advanced automatic, manual, continuously variable, or dual-clutch transmissions on a vehicle, the CAFE Model will consider higher-tier fuel-saving technologies along the current path. Transmission level technology pathways are illustrated in Figure 3-8 below.[271]

Technology pathways are designed to prevent “branch hopping” – changes in transmission type that would correspond to significant changes in transmission architecture – for vehicles that are relatively advanced on a given pathway. For example, any automatic transmission with more than five gears cannot move to a dual-clutch transmission. For a more detailed discussion of path logic applied in the analysis, including technology supersession logic and technology mutual exclusivity logic, please see CAFE Model Documentation S4.5 Technology Constraints (Supersession and Mutual Exclusivity).[272] Additionally, the CAFE Model prevents “branch hopping” to prevent stranded capital associated with moving from one transmission architecture to another. Stranded capital is discussed in more detail in Chapter 2.6.3.

[271] Technologies that were not assigned in the baseline fleet include MT5, AT5, AT7L2, AT9L2, and CVT; they are indicated by the grey boxes.
[272] Available at https://www.nhtsa.gov/corporate-average-fuel-economy/compliance-and-effects-modeling-system. (Accessed: February 15, 2022).

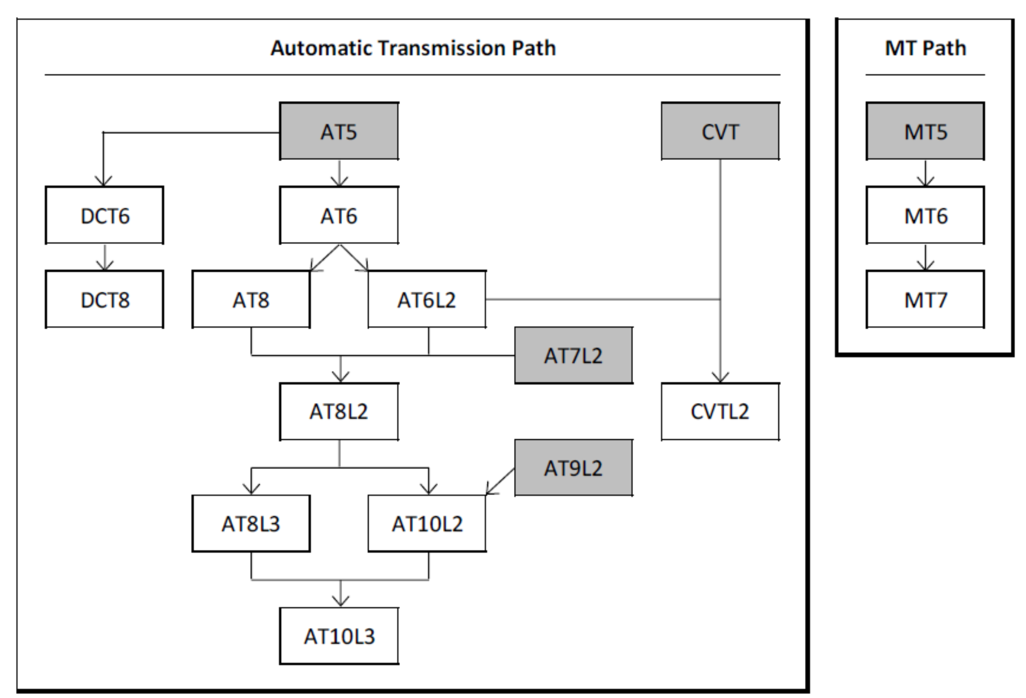

Figure 3-8 – Transmission-Level Technology Pathways

Some technologies that we model in the analysis are not yet in production, and therefore are not assigned in the baseline fleet. Nonetheless, these technologies, which we project will be available in the analysis timeframe, are available for future adoption. For instance, we do not observe any AT10L3s in the baseline fleet, but it is plausible that manufacturers that employ 10-speed automatic transmission, Level 2 (AT10L2) technology may improve the efficiency of those AT10L2s in the rulemaking timeframe.

Note that when electrification technologies are adopted, the transmissions associated with those technologies will supersede the existing transmission on a vehicle. The transmission technology is superseded if the model applies P2 hybrid, plug-in hybrid, or battery electric vehicle technologies. For more information, see Chapter 3.3.3.

The following sections discuss specific adoption features applied to each type of transmission technology.

3.2.5.1 Automatic Transmissions (AT)

The automatic transmission path precludes adoption of other transmission types once a platform progresses past an AT6. We use this restriction to avoid the significant level of stranded capital loss that could result from adopting a completely different transmission type shortly after adopting an advanced transmission, which would occur if a different transmission type were adopted after AT6 in the rulemaking timeframe.

Vehicles that did not start out with AT7L2 or AT9L2 transmissions cannot adopt those technologies in the model. Vehicles with those technologies are primarily luxury performance vehicles. It is likely that other vehicles will not adopt those technologies, as vehicles that have moved to more advanced automatic transmissions have overwhelmingly moved to 8-speed and 10-speed transmissions.[273]

3.2.5.2 Continuously Variable Transmissions (CVT)

CVT adoption is limited by technology path logic. Vehicles that do not originate with a CVT or vehicles with multispeed transmissions beyond AT6 in the baseline fleet cannot adopt CVTs. Vehicles with multispeed transmissions greater than AT6 demonstrate increased ability to operate the engine at a highly efficient speed and load. Once on the CVT path, the platform is only allowed to apply improved CVT technologies. The analysis restricts the application of CVT technology on larger vehicles because of the higher torque (load) demands of those vehicles and CVT torque limitations based on durability constraints. Additionally, this restriction is used to avoid stranded capital.

3.2.5.3 Dual-Clutch Transmissions (DCT)

The analysis allows vehicles in the baseline fleet that have DCTs to apply an improved DCT and allows vehicles with an AT5 to consider DCTs. Drivability and durability issues with some DCTs have resulted in a low relative adoption rate over the last decade. This is also broadly consistent with manufacturers' technology choices.[274]

3.2.5.4 Manual Transmissions (MT)

Manual transmissions can only move to more advanced manual transmissions because other transmission types do not provide a similar driver experience. Manual transmissions cannot adopt AT, CVT, or DCT technologies. Other transmissions cannot move to MT because manual transmissions lack automatic shifting associated with the other transmission types and in recognition of the low customer demand for manual transmissions.[275]

3.2.6 Transmission Effectiveness

We use the Autonomie full vehicle simulation tool to understand how transmissions work within the full vehicle system to improve fuel economy, and how changes to the transmission subsystem influence the performance of the full vehicle system. The full vehicle simulation approach clearly defines the contribution of individual transmission technologies and separates those contributions from other technologies in the full vehicle system. The modeling approach follows the recommendations of the National Academy of Sciences in its 2015 light duty vehicle fuel economy technology report to use full vehicle modeling supported by application of collected improvements at the sub-model level.[276]

The Autonomie tool models transmissions as a sequence of mechanical torque gains. The torque and speed are multiplied and divided, respectively, by the current ratio for the selected operating condition. Furthermore, torque losses corresponding to the torque/speed operating point are

[273] 2021 EPA Automotive Trends Report, at p. 64, figure 4.21.
[274] Ibid.
[275] Ibid.
[276] 2015 NAS report, at 292.

subtracted from the torque input. Torque losses are defined based on a three-dimensional efficiency lookup table that has the following inputs: input shaft rotational speed, input shaft torque, and operating condition. A detailed discussion of the Autonomie transmission modeling can be found in Chapters 4 and 5 of the Autonomie model documentation.

We populate transmission template models in Autonomie with characteristics data to model specific transmissions. Characteristics data are typically tabulated data for transmission gear ratios, maps for transmission efficiency, and maps for torque converter performance, as applicable. Different transmission types require different quantities of data. The characteristics data for these models come from peer-reviewed sources, transmission and vehicle testing programs, results from simulating current and future transmission configurations, and confidential data obtained from OEMs and suppliers.[277]

For example, the 10-speed automatic transmission (AT10L2) efficiency curve uses data from South-West Research Institute (SWRI) for the 2017 Ford F-150 10R80 transmission.[278,279] The 10R80 transmission is a 10-speed, rear-wheel-drive transmission that Ford is currently using in both cars and trucks, including the Ford F-150, Ford Mustang, Ford Expedition, Lincoln Navigator, and Ford Ranger.[280] Since this transmission is used in both cars and trucks, the SWRI data for this transmission are applicable to multiple vehicle classes.

We model HEG improvements by modeling improvements to the efficiency map of the transmission. As an example, the baseline AT8 model data comes from a transmission characterization study.[281] The AT8L2 has the same gear ratios as the AT8, however, we improve the gear efficiency map to represent application of the HEG level 2 technologies. The AT8L3 models the application of HEG level 3 technologies using the same principle, further improving the gear efficiency map over the AT8L2 improvements.

As discussed above, we determine effectiveness values for the transmission technologies using Autonomie modeling; however, we did not use Autonomie to calculate effectiveness values for the AT6L2. The model for this specific technology is inconsistent with the other transmission models and overpredicts effectiveness results as a result of an overestimated efficiency map. To address the issue, we use an analogous effectiveness value from the AT7L2 transmission model

[277] Downloadable Dynamometer Database.: https://www.anl.gov/energy-systems/group/downloadable-dynamometer-database (Accessed: February 15, 2022); Kim, N., Rousseau, N., Lohse-Bush, H.., "Advanced Automatic Transmission Model Validation Using Dynamometer Test Data," SAE 2014-01-1778, SAE World Congress, Detroit, April 2014; Kim, N., Lohse-Bush, H., Rousseau, A.., "Development of a model of the dual clutch transmission in Autonomie and validation with dynamometer test data," International Journal of Automotive Technologies, March 2014, Volume 15, Issue 2, pp 263–71.
[278] Autonomie model documentation, Chapter 5.3.
[279] Wileman, C. (2021, July). Light-duty vehicle transmission benchmarking, 2017 Ford F-150 with 10R80 and 2018 Honda Accord with Earth Dreams CVT (Report No. DOT HS 813 163). National Highway Traffic Safety Administration.
[280] The More You Know About The 10R80…The Better Off You Are!, Gears Magazine (September 1, 2020), https://gearsmagazine.com/magazine/the-more-you-know-about-the-10r80-the-better-off-you-are. (Accessed: February 15, 2022).
[281] Autonomie model documentation, Chapter 5.3.

in place of the effectiveness value from the AT6L2 map. For additional discussion on how we use analogous effectiveness values please see Chapter 3.2.6.

We group transmissions by technology type (AT, DCT, CVT, etc.) and gear count (5,6,7, etc.). We subdivide the transmission groups further by HEG technology level. The effectiveness values for the transmission technologies, for all ten vehicle technology classes, are shown in Figure 3-9. Each of the effectiveness values shown is representative of the improvements seen for upgrading only the listed transmission technology for a given combination of other technologies. In other words, the range of effectiveness values seen for each specific technology, *e.g.*, AT10L3, represents the addition of the AT10L3 technology to every technology combination that could add AT10L3. We emphasize that the graph shows the change in fuel consumption values between entire technology keys,[282] and not the individual technology effectiveness values. Using the change between whole technology keys captures the complementary or non-complementary interactions among technologies. In the graph, the box shows the inner quartile range (IQR) of the effectiveness values and whiskers extend out 1.5 x IQR. The blue dots show values for effectiveness that are outside these bounds.

Note that the effectiveness for the MT5, AT5, eCVT and DD technologies is not shown. The DD and eCVT transmissions do not have a standalone effectiveness because it is only implemented as part of Electrification powertrains. The MT5 and AT5 also have no effectiveness values because both technologies are baseline technologies against which all other technologies are compared.

[282] Technology key is the unique collection of technologies that constitutes a specific vehicle (see Chapter 2.4.7).

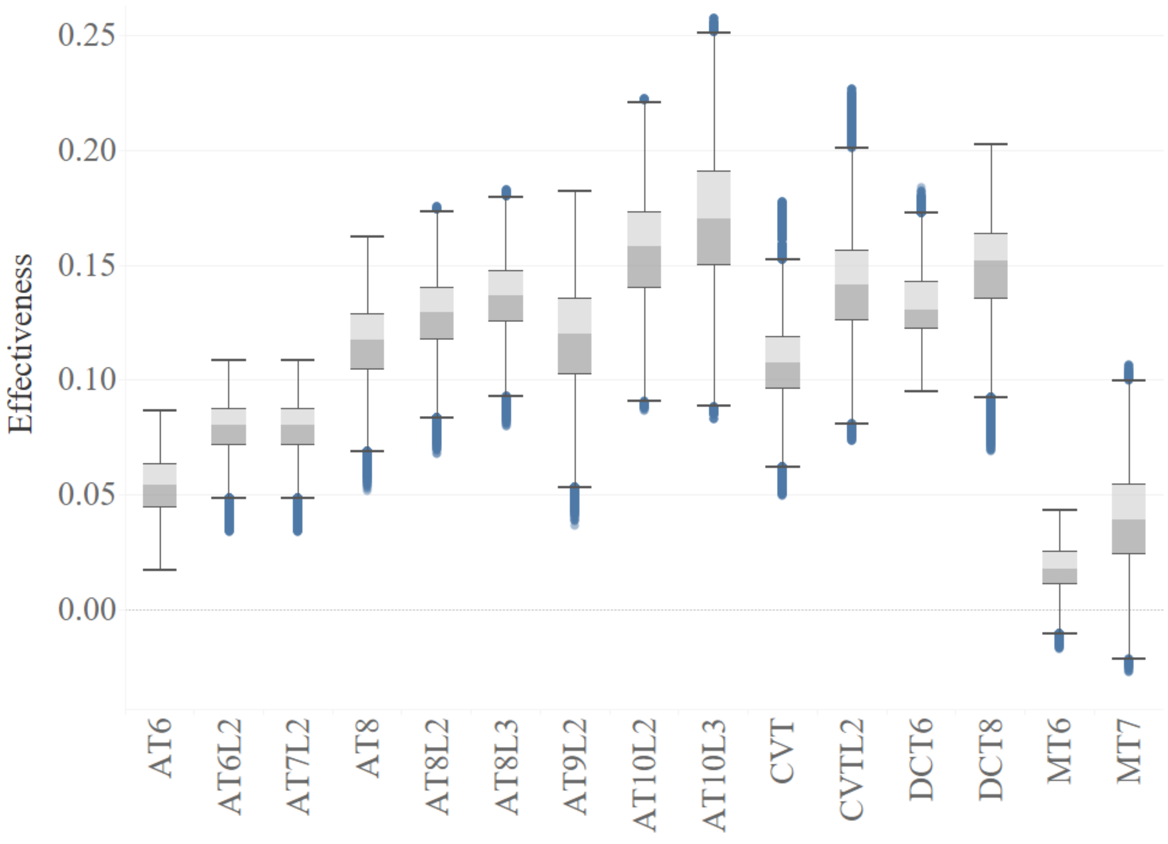

Figure 3-9 – Transmission Technologies Effectiveness Values for all Vehicle Technology Classes[283]

We comprehensively simulate 18 transmission technologies using the Autonomie tool. Each transmission is modeled with defined gear ratios, gear efficiencies, gear spans, and unique shift logic for the configuration. The following sections discuss specific shift logic employed in the Autonomie modeling.

3.2.6.1 Shift Logic

Transmission shifting logic has a significant impact on vehicle energy consumption. Argonne models shift logic in Autonomie to maximize powertrain efficiency while maintaining acceptable drive quality. The logic used in the Autonomie full vehicle modeling relies on two components: (1) the shifting controller, which provides the logic to select appropriate gears during simulation; and (2) the shifting initializer, an algorithm that defines shifting maps (*i.e.*, values of the parameters of the shifting controller) specific to the selected set of modeled vehicle characteristics and modeled powertrain components.[284]

3.2.6.1.1 Shifting Controller

The shift controller is the logic that governs shifting behavior during simulated operation. Inputs from the model inform the shift controller performance. The inputs include the specific engine

[283] The data used to create this figure can be found in the FE_1 Improvements file.
[284] Autonomie model documentation, Chapter 4.4.5.

and transmission and instantaneous conditions in the simulation. The model adjusts shifting logic based on engine characteristics to maximize the advantages of the engine technology. Instantaneous conditions include values such as vehicle speed, driver demand, and a shifting map unique to the full vehicle configuration.[285]

3.2.6.1.2 Shifting Initializer

The shifting initializer is an algorithm that defines shifting maps (*i.e.*, values of the parameters of the shifting controller) specific to the selected set of modeled vehicle characteristics and modeled powertrain components. The shifting initializer is run for every unique combination of vehicle technologies modeled in the Autonomie tool and is an input to the full vehicle simulation. The shifting initializer creates a shifting map that optimizes fuel economy performance for the powertrain and road load combination within the constraints of performance neutrality.[286,287]

3.2.7 Transmission Costs

The CAFE Model uses both cost and effectiveness in selecting technology updates during the compliance simulation. We use information from sponsored research, CBI, and the National Academy of Sciences to determine direct manufacturing costs (DMCs) for fuel saving technologies.[288] We apply a learning factor and RPE to the DMC to determine the total overall cost of the technology for a given model year (*i.e.*, an absolute cost). The full list of transmission technology costs across all model years, in 2018 dollars, can be found in Technologies input file. Chapter 2.6 discusses how we apply the RPE and learning curves to technology DMCs.

This analysis uses absolute costs instead of relative costs, which were used in prior rulemaking analyses. We use absolute costs to ensure the full cost of the transmission is removed when the model applies electrification technologies. This analysis models the cost of adoption of BEV technology by first removing the costs associated with existing powertrain systems, then applying the BEV system costs. An interested reader can still determine relative costs by comparing the absolute costs for the initial technology combination to the new technology combination.

3.2.8 Automatic Transmissions

We use automatic transmission DMCs from recommended relative costs discussed in the NAS 2015 report and NAS-cited studies. Table 3-49 shows the cost for the automatic transmissions in the current analysis with learning curve and RPE adjustments applied.

DMC estimates for all automatic transmissions are based on cost estimates from Table 5.7, Table 5.9, and Table 8A.2a of the 2015 NAS report, unless noted otherwise.[289] In the cases of level

[285] *See* Autonomie model documentation, Chapter 4.4.5, for more information on the shifting controller.
[286] *See* Chapter 2.4.5 for more information on performance neutrality.
[287] *See* Autonomie model documentation, Chapter 4.4.5.2, for more information on the shifting initializer algorithm.
[288] FEV prepared several cost analysis studies for EPA on subjects ranging from advanced 8-speed transmissions to belt alternator starter, or start/stop systems. NHTSA contracted Electricore, EDAG, and Southwest Research for teardown studies evaluating mass reduction and transmissions. The 2015 NAS report on fuel economy technologies for light-duty vehicles also evaluated the agencies' technology costs developed based on these teardown studies.
[289] 2015 NAS report, at p. 189, pp. 298–99.

two (L2) and level three (L3) transmissions, when not already included in the cost estimate, we add the costs for HEG level 2 or level 3 technologies to the base transmission cost.

The AT9 technology DMCs are based on estimates from Table 8A.2a of the 2015 NAS report.[290] The NAS-reported AT9 cost is relative to the AT8 and does not account for the cost of the HEG technology. In our analysis, the AT9 is only equipped with level 2 HEG technology. Therefore, we calculate the costs for the AT9L2 by adding the cost estimate for one additional gear to the AT8L2 cost.[291]

For AT10 technologies, we use DMCs from Table 8A.2a of the 2015 NAS report.[292] The NAS AT10 cost is relative to the AT8 and does not account for the cost of HEG technology. For the current analysis, the AT10 is only equipped with either level 2 or level 3 HEG technology. The costs for the AT10L2 reflect adding two more gears to the AT8L2. The costs for the AT10L3 reflect adding level 3 HEG technology to AT10L2.

Table 3-49 – Summary of Absolute Automatic Transmission Technology Costs for Automatic Transmissions, including Learning Effects and Retail Price Equivalent for the Current Analysis

Name	Technology Pathway	C-2017	C-2021	C-2025	C-2029
AT5	Automatic Transmission	$ 2,085.30	$ 2,085.30	$ 2,085.30	$ 2,085.30
AT6	Automatic Transmission	$ 2,063.19	$ 2,063.19	$ 2,063.19	$ 2,063.19
AT6L2	Automatic Transmission	$ 2,397.50	$ 2,323.16	$ 2,303.65	$ 2,294.85
AT7L2	Automatic Transmission	$ 2,351.16	$ 2,292.16	$ 2,276.53	$ 2,269.53
AT8	Automatic Transmission	$ 2,195.51	$ 2,195.32	$ 2,195.18	$ 2,195.15
AT8L2	Automatic Transmission	$ 2,530.24	$ 2,431.30	$ 2,405.33	$ 2,393.61
AT8L3	Automatic Transmission	$ 2,787.99	$ 2,631.74	$ 2,590.74	$ 2,572.25
AT9L2	Automatic Transmission	$ 2,659.49	$ 2,531.80	$ 2,498.29	$ 2,483.17
AT10L2	Automatic Transmission	$ 2,659.49	$ 2,531.80	$ 2,498.29	$ 2,483.17
AT10L3	Automatic Transmission	$ 2,917.97	$ 2,737.81	$ 2,684.21	$ 2,662.29

3.2.9 Continuously Variable Transmissions

Table 3 shows CVT costs with learning curve and RPE adjustments. The DMC for CVT and CVTL2 use data from the 2015 NAS report Table 8A.2a.[293]

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290 2015 NAS report, at pp. 29899.
291 2015 NAS report, at pp. 298–99.
292 2015 NAS report, at pp. 298–99.
293 2015 NAS report, at pp. 298–99.

Table 3-50 – Summary of Absolute Transmission Costs for Continuously Variable Transmissions, including Learning Effects and Retail Price Equivalent for the Current Analysis

Name	Technology Pathway	C-2017	C-2021	C-2025	C-2029
CVT	CVT	$ 2,341.87	$ 2,330.48	$ 2,322.63	$ 2316.55
CVTL2	CVT	$ 2,534.64	$ 2,514.69	$ 2,500.94	$ 2,490.29

3.2.10 Dual Clutch Transmissions

Table 3-50 shows the absolute cost for DCTs with learning curve and RPE adjustments. The DMC for the DCTs use data from the 2015 NAS report Table 8A.2a.[294]

Table 3-50 – Summary of Absolute Transmission Costs for Dual-Clutch Transmissions, including Learning Effects and Retail Price Equivalent for the Current Analysis

Name	Technology Pathway	C-2017	C-2021	C-2025	C-2029
DCT6	Sequential Transmission	$ 2,115.92	$ 2,115.88	$ 2,115.84	$ 2,115.84
DCT8	Sequential Transmission	$ 2,654.56	$ 2,653.75	$ 2,653.15	$ 2,653.02

3.2.11 Manual Transmissions

Table 3-51 shows the absolute costs for the MTs with learning curve and RPE adjustments. The costs for MTs are based on previous rulemaking values that have seen no significant change since established.[295]

Table 3-51 – Summary of Absolute Transmission Costs for Manual Transmissions, including Learning Effects and Retail Price Equivalent for the Current Analysis

Name	Technology Pathway	C-2017	C-2021	C-2025	C-2029
MT5	Manual Transmission	$ 1,563.97	$ 1,563.97	$ 1,563.97	$ 1,563.97
MT6	Manual Transmission	$ 1,939.24	$ 1,925.76	$ 1,917.08	$ 1,911.82
MT7	Manual Transmission	$ 2,357.13	$ 2,186.30	$ 2,100.64	$ 2,044.10

3.3 Electric Paths

The electric paths include a large set of technologies that share the common element of using electrical power for certain vehicle functions that were traditionally powered mechanically by engine power. Electrification technologies thus can range from electrification of specific accessories (for example, electric power steering to reduce engine loads by eliminating parasitic losses) to electrification of the entire powertrain (as in the case of a battery electric vehicle).

[294] 2015 NAS report, at pp. 298-99.
[295] Final Rulemaking for 2017-2025 Light-Duty Vehicle Greenhouse Gas Emission Standards and Corporate Average Fuel Economy Standards, EPA-420-R-12-901 (August 2012), at pp. 3–111.

The electrified vehicles in this analysis have a partly or fully electrified powertrain. Beginning with the fewest electrification components, mild and micro hybrids typically only provide engine on/off functions with minimal electrical assist. The micro hybrid technology we use in this analysis is 12V start-stop (SS12V), and the mild hybrid technology we use in this analysis is a 48V belt integrated starter generator (BISG).

Hybrid electric vehicles (HEVs) use electrical components and a battery to manage power flows and assist the engine for improved efficiency and/or performance. In many cases, HEVs can also support a limited amount of all-electric propulsion. The HEVs (also referred to as strong hybrids) that we include in this analysis include both power-split (SHEVPS) and parallel (SHEVP2) architectures.

Plug-in hybrid electric vehicles (PHEVs) have a primarily electric powertrain and use a combination of batteries and an engine for propulsion energy. We include PHEVs with an AER of 20 and 50 miles in the analysis, to encompass the range of PHEV AER in the market.

BEVs have an all-electric powertrain and use only batteries for propulsion energy. We include BEVs with ranges of 200, 300, 400, and 500 miles in the analysis. Finally, fuel cell electric vehicles (FCEVs) are another form of electrified vehicle that have a fully electric powertrain. FCEVs use a fuel cell system to convert the hydrogen fuel into electrical energy.

Table 3-52 below shows an overview of these electrified technologies and their designations in the analysis. Like other technologies in this analysis, these technologies are not representative of any specific manufacturer's design or architecture, but encompass the range of effectiveness and cost for these types of powertrains in the rulemaking timeframe. For example, the BEV200 efficiency and cost is not supposed to represent exactly a Tesla Model 3 or a Nissan Leaf.

Table 3-52 – Overview of Electrification Technologies Used in This Analysis

Electric System	Technologies
Micro-Hybrid*	12V start-stop
Mild-Hybrid**	48V BISG
Strong Hybrid	SHEVPS and SHEVP2
PHEV***	PHEV20, PHEV50
BEV	BEV200, BEV300, BEV400, and BEV500
FCEV	Fuel cell
*This system does not have electrical assist or regeneration braking capabilities. **Mild Hybrid is a BISG in this analysis and it is an engine mounted belt integrated starter generator. ***PHEVs in this analysis include both power split (PS) and P2 hybrid architecture.	

The cost effectiveness of electrification technologies is based on the effectiveness and cost of the battery and non-battery components. The battery strongly influences the cost of electrified vehicles, particularly where the battery is the main source of energy for propulsion of the vehicle. Because developments in battery technology may apply to more than one category of electrified vehicles, they are discussed collectively in Chapter 3.3.5. That section details battery-related topics that directly affect the specification and costing of batteries for all types of electrified vehicles that we consider.

Non-battery electrification components also have an influence on both the effectiveness and cost of electrified vehicles. In this analysis, non-battery electrification components include propulsion components like one or more electric machines (an umbrella term that includes what are commonly known as motors, generators, and motor/generators). Electric machines commonly act as motors to provide propulsion, and/or act as generators to enable regenerative braking and the conversion of mechanical energy to electrical energy for storage in the battery.

Non-battery electrification components also include power electronics that process and route electric power between the energy storage and propulsion components. More specifically, power electronics that we include in this analysis are motor controllers, which issue complex commands to control torque and speed of the propulsion components precisely; inverters and rectifiers, which convert and manage direct current (DC) and alternating current power flows between the battery and the propulsion components; onboard battery chargers, for charging the BEV or PHEV battery from alternating current line power; and DC-to-DC converters that are sometimes needed to allow DC components of different DC voltages to work together.

In addition, onboard chargers are charging devices installed on-board electrified vehicles to allow charging from grid electrical power. Onboard chargers travel with the vehicle and are distinct from stationary charging equipment. Level 1 charging refers to charging powered by a standard household 110-120V alternating current power outlet. Level 2 charging refers to charging at 220-240V alternating current power. DC fast charging refers to systems that charge at rapid rate beyond Level 2. As discussed further below, the analysis assumes that BEVs are capable of up to 50kW charging, and we include the cost of an onboard charger in plug-in electric vehicle costs.

Each electrified vehicle architecture includes different non-battery components, in addition to different conventional vehicle technologies (*e.g.*, internal combustion engines or transmissions in the case of micro, mild, and strong hybrids and PHEVs), that influence the total cost of the vehicle. The process by which the CAFE Model prices non-battery components and adds or subtracts components as necessary to complete the powertrain architecture is discussed in Chapter 3.3.5.

The following subsections discuss how each electrification technology is defined in the CAFE Model and the electrification pathways down which a vehicle can travel in the compliance simulation. The subsections also discuss how we assign electrified vehicle technologies to vehicles in the MY 2020 analysis fleet, any limitations on electrification technology adoption, and the specific effectiveness and cost assumptions that we use in the Autonomie and CAFE Model analysis.

3.3.1 Electrification Modeling in the CAFE Model

As explained before, the CAFE modeling system defines technology pathways for grouping and establishing a logical progression of technologies on a vehicle. Technologies that share similar characteristics form cohorts that we represent and interpret within the CAFE Model as discrete entities. We lay these entities out into pathways (or paths), which the system uses to define relations of mutual exclusivity between conflicting sets of technologies.

The technologies that we include on the modeling system's three vehicle-level electrification and electric improvements paths are illustrated in Figure 3-10 below. As shown in the Electrification path, the baseline-only CONV technology is grayed out. We use this technology to denote whether a vehicle comes in with a conventional powertrain (*i.e.*, a vehicle that does not include any level of hybridization) and to allow the model to properly map to the Autonomie vehicle simulation database results. If multiple branches converge on a single technology, the subset of technologies disabled from adoption extend only up the point of convergence.

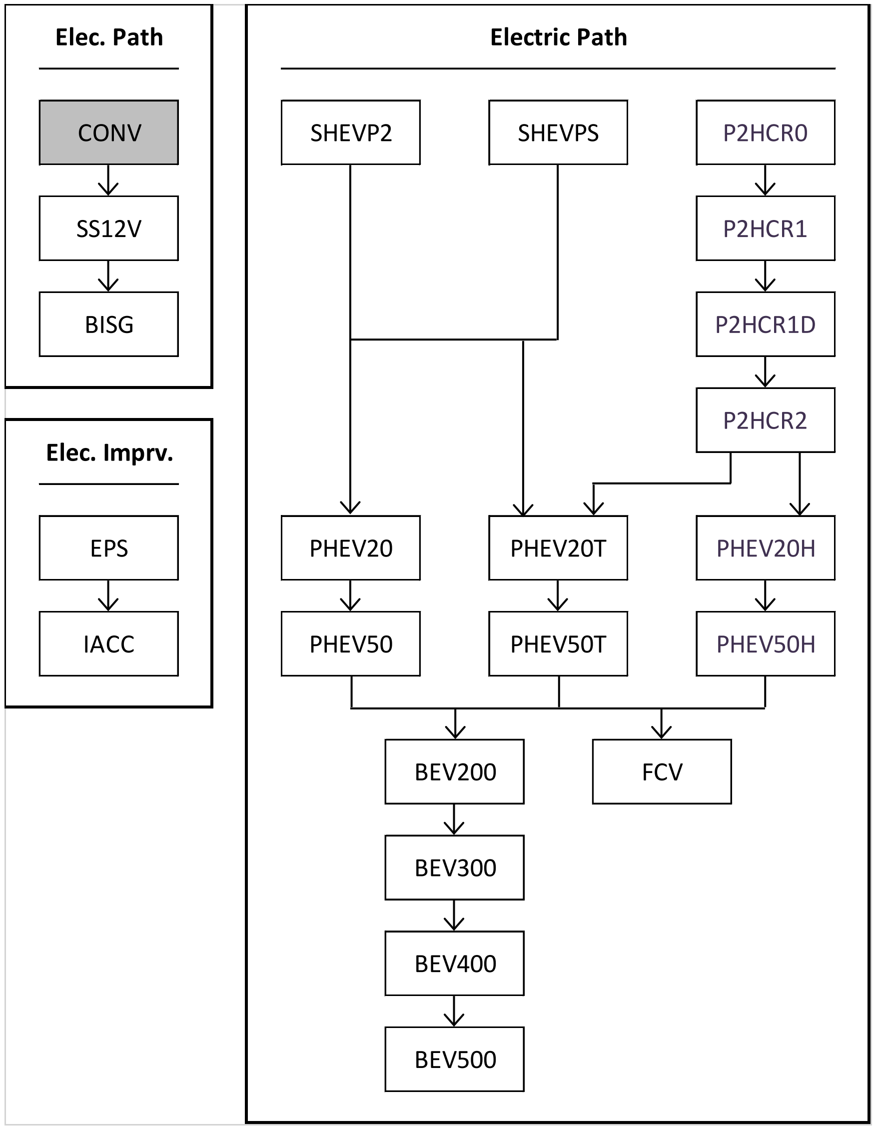

Figure 3-10 – Electrification Paths in the CAFE Model

The CAFE Model defines the technology pathway for each type of electrification grouping in a logical progression. Whenever the CAFE Model converts a vehicle model to one of the available electrified systems, modeling algorithms will update both effectiveness and costs for the vehicle. Additionally, all technologies on the different electrification paths are mutually exclusive and are evaluated in parallel. For example, the model may evaluate PHEV20 technology prior to having to apply SS12V or strong hybrid technology. We discuss the specific set of algorithms and rules further in the sections below and include more detailed discussions in the CAFE Model Documentation. The following sections discuss the specifications of each electrification technology used in the analysis.

3.3.1.1 Micro-Hybrids

12-volt stop-start (SS12V), sometimes referred to as start-stop, idle-stop, or a 12-volt micro hybrid system, is the most basic hybrid system that facilitates idle-stop capability. In this system, the integrated starter generator is coupled to the internal combustion (IC) engine. When the vehicle comes to an idle-stop the IC engine completely shuts off, and, with the help of the 12-volt battery, the engine cranks and starts again in response to throttle application or release of the brake pedal to move the vehicle. The 12-volt battery used for the start-stop system is an improved unit compared to a traditional 12-volt battery, and is capable of higher power, increased life cycle, and capable of minimizing voltage drop on restart. This technology is beneficial to reduce fuel consumption and emissions when the vehicle frequently stops, such as in city driving conditions or in stop and go traffic. SS12V can be applied to all vehicle technology classes.

3.3.1.2 Mild Hybrids

The belt integrated starter generator (BISG), sometimes referred to as a mild hybrid system or P0 hybrid, provides idle-stop capability and uses a higher voltage battery with increased energy capacity over conventional automotive batteries. These higher voltages allow the use of a smaller, more powerful and efficient electric motor/generator, which replaces the standard alternator. In BISG systems, the motor/generator couples to the engine via belt (similar to a standard alternator). In addition, these motor/generators can assist vehicle braking and recover braking energy while the vehicle slows down (regenerative braking) and in turn can propel the vehicle at the beginning of launch, allowing the engine to be restarted later. Some limited electric assist also provides improved engine efficiency during acceleration. Like the micro hybrids, BISGs can be applied to all vehicles in the analysis. We assume all mild hybrids are 48 volt systems with engine belt-driven motor/generators.

We did not include crank integrated starter generator (CISG) systems, sometimes referred to as a P1 hybrids, in the analysis.[296] A CISG typically has a 48 volt motor/generator that is mounted between the engine and the transmission in a custom housing. CISG systems avoid losses associated with BISG belt slipping, however they increase the weight of the powertrain and require more significant changes to the powertrain architecture than BISG systems. The size of the motor/generator increases the overall length of the powertrain, often causing packaging and integration issues, and making it difficult for most vehicles to adopt CISG technology. In some cases, the increased length powertrain may not fit in an existing vehicle design. In other cases, the increased size of the powertrain may interfere with other critical powertrain components such as exhaust and air inlet piping systems that must also be housed in the same space.

The model can apply mild hybrid technology to all vehicle technology classes and all conventional engine technologies except for Engine 26a (VCR). Chapter 3.3.4 discusses further details of the technology specification and effectiveness.

3.3.1.3 Strong Hybrids

A strong hybrid vehicle is a vehicle that combines two or more propulsion systems, where one uses gasoline (or diesel), and the other captures energy from the vehicle during deceleration or braking, or from the engine, and stores that energy so it may be used by the vehicle. Strong

[296] Past CAFE analyses included a CISG system that was similar to the BISG system effectiveness but was more expensive (similar to the cost presented for the system in the 2015 NAS report). The 2021 NAS report refers to all mild hybrid systems as BISG systems.

hybrids reduce fuel consumption through three major mechanisms, including (1) capturing energy during braking and some decelerations that might otherwise be lost to the braking system, and using the stored energy to provide launch assist, coasting, and propulsion during stop and go traffic conditions, (2) capturing energy from the engine under some conditions to enable the engine to operate at a more efficient operating point and by storing the energy such as by charging the battery, and (3) potentially enabling engine downsizing. The effectiveness of the strong hybrid system for improving fuel economy depends on how the above factors are balanced, and the stored energy is applied. For example, the captured energy may be used primarily to allow longer periods with the internal combustion engine off, or to supplement engine power to allow the engine to operate at more efficient conditions, potentially in combination with a downsized engine. Conversely, for some performance vehicles, hybrid technologies may be applied primarily for acceleration performance improvement without engine downsizing.

We include the following strong hybrid systems in the analysis: hybrids with "P2" parallel drivetrain architectures (SHEVP2),[297] and hybrids with power-split architectures (SHEVPS).

P2 parallel hybrids (SHEVP2) are a type of hybrid vehicle that use a transmission-integrated electric motor placed between the engine and a gearbox or CVT, with a clutch that allows decoupling of the motor/transmission from the engine. Figure 3-11 below shows the SHEVP2 configuration. Although similar to the configuration of the CISG system discussed previously, a P2 hybrid generally has a larger electric motor and battery in comparison to the CISG. Disengaging the clutch allows all-electric operation and more efficient brake-energy recovery. Engaging the clutch allows coupling of the engine and electric motor and, when combined with a transmission, reduces gear-train losses relative to power-split or 2-mode hybrid systems. P2 hybrid systems typically rely on the internal combustion engine to deliver high, sustained power levels. The system uses electric-only mode when power demands are low or moderate.

[297] Depending on the location of electric machine (motor with or without inverter), the parallel hybrid technologies are classified as P0–motor located at the primary side of the engine, P1–motor located at the flywheel side of the engine, P2–motor located between engine and transmission, P3–motor located at the transmission output, and P4–motor located on the axle.

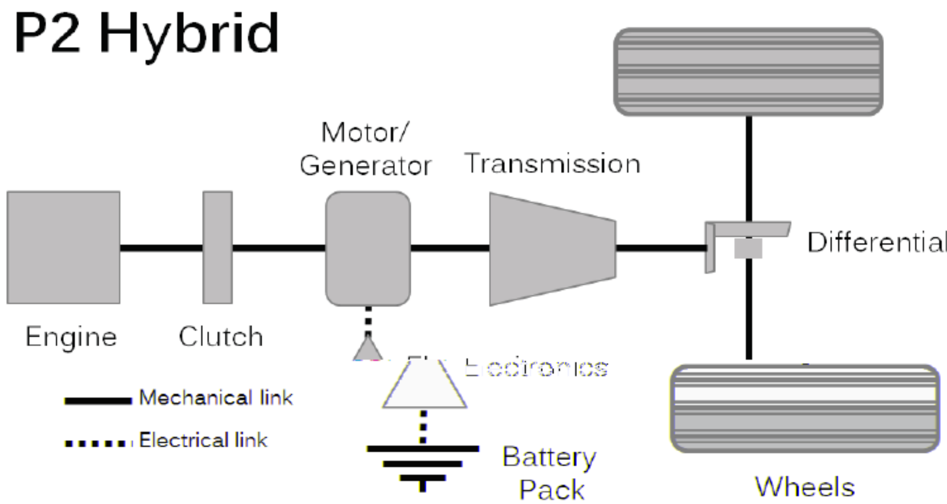

Figure 3-11 – P2 Strong Hybrid Architecture Showing the Motor/Generator Coupled to the Engine through a Clutch[298]

An important feature of the SHEVP2 system is that it can be applied in conjunction with most engine technologies. Accordingly, once a vehicle is converted to a SHEVP2 powertrain in the compliance simulation, the CAFE Model allows the vehicle to adopt the most conventional engine technologies that are cost effective, regardless of whether a conventional engine technology is less advanced than the conventional engine technology that the vehicle started with. For example, a vehicle in the MY 2020 analysis fleet that starts with a TURBO2 engine could adopt a TURBO1 engine with the SHEVP2 system, if that TURBO1 engine allows the vehicle to meet its fuel economy goal cost effectively. This is based in part on comments to past analyses that asserted that although manufacturers could adopt SHEVP2 systems into existing powertrain architectures, adopting the SHEVP2 system afforded the opportunity for the manufacturer to incorporate a less expensive conventional engine technology alongside it.

In addition, as discussed in Chapter 3.1.7, the SHEVP2 powertrain improves fuel economy, in part, by allowing the engine to spend more time operating at engine speed and load conditions that have high efficiency. The effectiveness improvement for SHEVP2 is reduced when combined with advanced engine technologies, which also improve fuel economy by broadening the range of engine speed and load conditions where the engine operates at high efficiency. In other words, there is only a minimal additional effectiveness improvement if a SHEVP2 powertrain is combined with an advanced engine, making SHEVP2 less cost effective in those cases. Including a less advanced engine technology with the SHEVP2 powertrain allows a similar efficiency improvement at a lower cost. Chapter 3.3.3 and the CAFE Model Documentation S4 also discuss this logic.

The power-split hybrid (SHEVPS) is a hybrid electric drive system that replaces the traditional transmission with a single planetary gear set (the power-split device) and a motor/generator. This motor/generator uses the engine either to charge the battery or to supply additional power to the drive motor. A second, more powerful motor/generator is connected to the vehicle's final

298 2015 NAS report, at p. 133.

drive and always turns with the wheels. The planetary gear splits engine power between the first motor/generator and the drive motor either to charge the battery or to supply power to the wheels. During vehicle launch, or when the battery SOC is high, the engine, which is not as efficient as the electric drive, is turned off and the electric motor propels the vehicle.[299] During normal driving, the engine output is used both to propel the vehicle and to generate electricity. The electricity generated can be stored in the battery and/or used to drive the electric motor. During heavy acceleration, both the engine and electric motor (by consuming battery energy) work together to propel the vehicle. When braking, the electric motor acts as a generator to convert the kinetic energy of the vehicle into electricity to charge the battery.

Figure 3-12 below shows the SHEVPS architecture with the two motor/generator design. The analysis separates the two motor/generators to appropriately size each to maintain performance, and to capture the associated costs. Chapter 3.3.4 and Chapter 3.3.5.2 include more discussion of the SHEVPS motor effectiveness and cost.

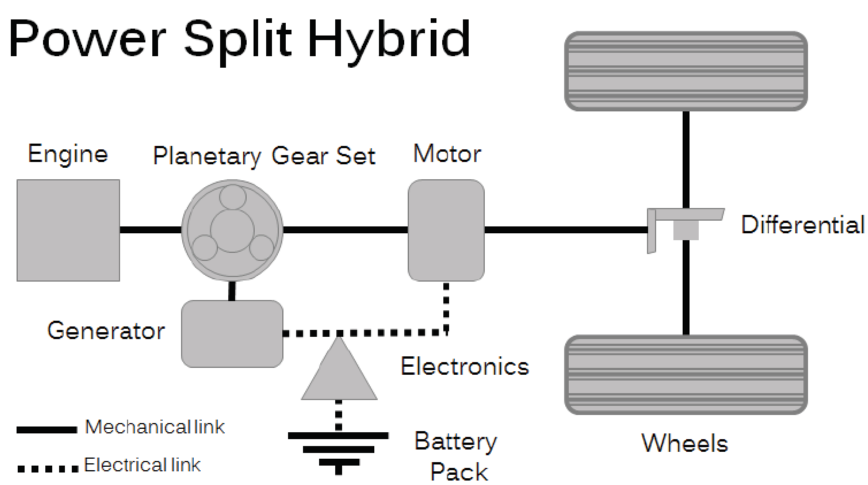

Figure 3-12 – Power Split (PS) Strong Hybrid Architecture with the Separate Generator and Motor Electrically Connected via the Battery and also via a Planetary Gear Set[300]

The parallel hybrid drivetrain, although enhanced by the electrification components, remains fundamentally similar to a conventional powertrain. In contrast, the power-split hybrid drivetrain is novel and considerably different than a conventional powertrain. Although these hybrid architectures are quite different, both types provide start-stop or idle-stop functionality, regenerative braking capability, and vehicle launch assist. A SHEVPS has a higher potential for fuel economy improvement than a SHEVP2, although its cost is also higher and engine power density is lower.[301]

[299] Autonomie model documentation, Chapter 4.13.2.
[300] 2015 NAS report, at p. 133.
[301] Kapadia, J., Kok, D., Jennings, M., Kuang, M. et al., "Powersplit or Parallel - Selecting the Right Hybrid Architecture," SAE Int. J. Alt. Power. 6(1):2017, doi:10.4271/2017-01-1154.

To expand on the hybrid powertrain configurations, Table 3-53 below shows the configuration of conventional engines and transmissions used with strong hybrids for this analysis. The SHEVPS powertrain configuration is paired with a planetary transmission (eCVT) and Atkinson engine (Eng26). This configuration is designed to maximize efficiency at the cost of reduced towing capability and real-world acceleration performance.[302] In contrast, the SHEVP2 powertrains are paired with an advanced 8-speed automatic transmissions (AT8L2) and can be paired with most conventional engines,[303] as discussed above.

Table 3-53 – Configuration of Strong Hybrid Architectures with Transmissions and Engines

CAFE Model Technologies	**Transmission Options**	**Engine Options (PC/SUV)**	**Engine Options (LT)**
SHEVPS	Planetary - eCVT	Eng 26 - Atkinson	N/A
SHEVP2[304]	AT8L2	All Engines except for VTGE and VCR	All Engines except for VTGE and VCR
See further details in Chapter 3.3.4 Electrification Effectiveness			

3.3.1.4 Plug-In Hybrids

Plug-in hybrid electric vehicles (PHEV) are hybrid electric vehicles with the means to charge their battery packs from an outside source of electricity (usually the electric grid). These vehicles have larger battery packs with more energy storage and a greater capability to be discharged than other non-plug-in hybrid electric vehicles. PHEVs also generally use a control system that allows the battery pack to be substantially depleted under electric-only or blended mechanical/electric operation and batteries that can be cycled in charge-sustaining operation at a lower SOC than non-plug-in hybrid electric vehicles. These vehicles generally have a greater AER than typical strong HEVs.

Unlike the micro, mild, and strong hybrids, PHEVs utilize two different types of fuels for energy of propulsion system; one, an onboard battery, charged by plugging the vehicle into the electrical grid, and two, a conventional engine with fuel tank for gasoline (or diesel). Depending on how these vehicles are operated, they could, in any particular mode of operation, use electricity exclusively, operate like a conventional hybrid, or operate in some combination of these two modes.

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[302] Kapadia, J., D, Kok, M. Jennings, M. Kuang, B. Masterson, R. Isaacs, A. Dona. 2017. Powersplit or Parallel - Selecting the Right Hybrid Architecture. SAE International Journal of Alternative Powertrains 6 (1): 68–76. https://doi.org/10.4271/2017-01-1154. (Accessed: February 15, 2022).

[303] We did not model SHEVP2s with VTGE (Eng23c) and VCR (Eng26a).

[304] Engine 01, 02, 03, 04, 5b, 6a, 7a, 8a, 12, 12-DEAC, 13, 14, 17, 18, 19, 20, 21, 22b, 23b, 24, 24-Deac. *See* Chapter 3.1 for these engine specifications.

For CAFE compliance, PHEV gasoline equivalent fuel economy is measured two ways per EPA regulations: first in a “charge depleting mode” with the vehicle operating on electricity with a fully charged battery, and second with the battery depleted and in a “charge sustaining mode” and the vehicle operating on gasoline. The overall fuel economy is calculated by weighting the two measured values. Through MY 2015, these two measured values were weighted equally to calculate overall PHEV fuel economy. Optionally beginning in MY 2016, and mandatory beginning in MY 2020, manufacturers use the EPA “utility factor” method for weighting the two measured values for calculating PHEV fuel economy. The “utility factor” weighting is based on the vehicle’s all electric range (AER). The utility factor method follows Society of Automotive Engineers (SAE) recommend practice J1711.[305,306,307,308] As discussed in Chapter 2.4, the Autonomie full vehicle model simulates powertrains accounting for these compliance procedures.

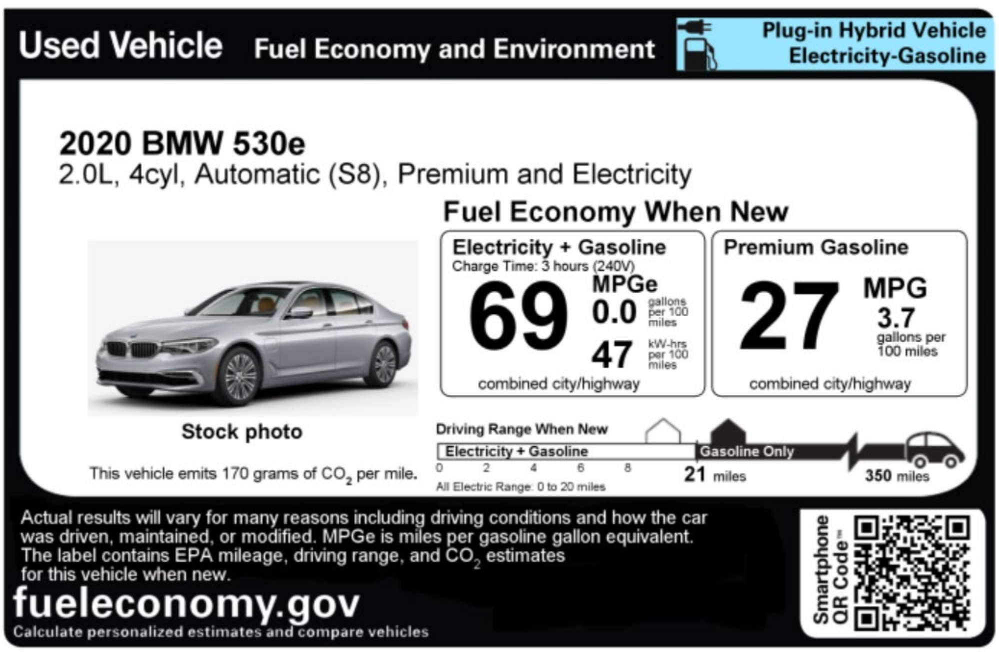

Figure 3-13 – Fuel Economy Label for the 2020 BMW 530e Plug-in Showing the Electricity and Gasoline Miles-per-Gallon Equivalent (MPGe)[309]

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[305] Guidance Document. “EPA Test Procedure for Electric Vehicles and Plug-in Hybrids.” https://fueleconomy.gov/feg/pdfs/EPA%20test%20procedure%20for%20EVs-PHEVs-11-14-2017.pdf. November 14, 2017. (Accessed: February 15, 2022).
[306] 76 Fed. Reg. 39477, 39504-39505 (Jul. 6, 2011).
[307] 40 CFR 600.116-12(b).
[308] For more detailed information on the development of this SAE utility factor approach, see http:// www.SAE.org, specifically SAE J2841 ‘‘Utility Factor Definitions for Plug-In Hybrid Electric Vehicles Using Travel Survey Data,’’ September 2010.
[309] Fueleconomy.gov. https://www.fueleconomy.gov/feg/UsedCarLabel.jsp. (Accessed: February 15, 2022).

The methodology that we use to assign fuel economy values to PHEVs in the analysis fleet also accounts for the changes in the regulations and these procedures, and we discuss them further in Chapter 2.2 and Chapter 3.3.2.

We include four PHEV architectures that reflect combinations of two levels of AER and two engine types. We use 20 miles AER and 50 miles AER to reasonably span the various AER in the market in the rulemaking time frame, and their effectiveness and cost. We use an Atkinson engine and a turbocharged downsized engine to span the variety of engines in the market.

PHEV20/PHEV20H and PHEV50/PHEV50H are essentially a SHEVPS with a larger battery and the ability to drive with the engine turned off. In the CAFE Model, the designation for "H" in PHEVxH could represent another type of engine configuration, but for this analysis we use the same effectiveness values as PHEV20 and PHEV50 to represent PHEV20H and PHEV50H, respectively. The PHEV20/PHEV20H represents a "blended-type" plug-in hybrid, which can operate in all-electric (engine off) mode only at light loads and low speeds and must blend electric motor and engine power together to propel the vehicle at medium or high loads and speeds. The PHEV50/PHEV50H represents an extended range electric vehicle (EREV), which can travel in all-electric mode even at higher speeds and loads.

PHEV20T and PHEV50T are 20 mile and 50 mile AER vehicles based on the SHEVP2 engine architecture. The PHEV versions of these architectures include larger batteries and motors to meet performance in charge sustaining mode at higher speeds and loads as well as similar performance and range in all electric mode in city driving, at higher speeds and loads. For this analysis, the CAFE Model considers these PHEVs to have an advanced 8-speed automatic transmission (AT8L2) and TURBO1 (Eng12) in the powertrain configuration. Further discussion of engine sizing, batteries, and motors for these PHEVs is discussed in Chapter 3.3.4 includes more discussion of PHEV engine sizing, batteries, and motors.

Table 3-54 below shows the different PHEV configurations that we use in this analysis.

Table 3-54 – Configuration of Plug-in Hybrid Architectures with Transmissions and Engines

CAFE Model Technologies	Transmission Options	Engine Options (PC/SUV)	Engine Options (LT)
PHEV20/PHEV20H	Planetary - eCVT	Eng 26 – Atkinson Engine	N/A
PHEV20T	AT8L2	Eng 12 - Turbo1	Eng 12 - Turbo1
PHEV50/PHEV50H	Planetary - eCVT	Eng 26 - Atkinson	N/A
PHEV50T	AT8L2	Eng 12 - Turbo1	Eng 12 - Turbo1
See further details in Chapter 3.3.4 Electrification Effectiveness			

3.3.1.5 Battery Electric Vehicles

BEVs are equipped with all-electric drive systems powered by energy-optimized batteries charged primarily by electricity from the grid. BEVs do not have a combustion engine or traditional transmission. Instead, BEVs rely on all electric powertrains, with an advanced transmission packaged with the powertrain. The range of battery electric vehicles vary by vehicle and battery pack size.

We simulate BEVs with ranges of 200, 300, 400 and 500 miles in the CAFE Model. BEV range is measured pursuant to EPA test procedures and guidance.[310] The CAFE Model assumes that BEV transmissions are unique to each vehicle (*i.e.*, the transmissions are not shared by any other vehicle) and that no further improvements are available.

A key note about the BEVs offered in this analysis is that the CAFE Model does not account for vehicle range when considering additional BEV technology adoption. That is, the CAFE Model does not have an incentive to build BEV300, 400, and 500s, because the BEV200 is just as efficient as those vehicles and counts the same toward compliance, but at a significantly lower cost because of the smaller battery. While manufacturers have been building 200-mile range BEVs, those vehicles have generally been passenger cars. Manufacturers have told us that greater range is important for meeting the needs of broader range of consumers and to increase consumer demand. More recently, there has been a trend towards manufacturers building higher range BEVs in the market, and manufacturers building crossover utility vehicle (CUV)/SUV and pickup truck BEVs. To simulate the potential relationship of BEV range to consumer demand, we include several adoption features for BEVs. These are discussed further in Chapter 3.3.3.

In Chapters 3.3.2 and 3.3.3 we discuss the analysis fleet assignments and adoption features for BEVs, how we rely on Argonne's expertise and other sources to evaluate effectiveness and performance, and how we determine costs for both the battery and non-battery components.

3.3.1.6 Fuel Cell Electric Vehicles

Similar to BEVs, fuel cell electric vehicles (FCEVs) use an all-electric drivetrain, but unlike BEVs, FCEVs do not solely rely on batteries; rather, electricity to run the FCEV electric motor is mainly generated by an onboard fuel cell system. FCEV architectures are similar to series hybrids,[311] but with the engine and generator replaced by a fuel cell. Commercially available FCEVs consume hydrogen to generate electricity for the fuel cell system, with most automakers using high pressure gaseous hydrogen storage tanks. FCEVs are currently produced in limited numbers and are available in limited geographic areas where hydrogen refueling stations are

[310] BEV electric ranges are determined per EPA guidance Document. "EPA Test Procedure for Electric Vehicles and Plug-in Hybrids." https://fueleconomy.gov/feg/pdfs/EPA%20test%20procedure%20for%20EVs-PHEVs-11-14-2017.pdf. November 14, 2017. (Accessed: February 15, 2022).

[311] Series hybrid architecture is a strong hybrid that has the engine, electric motor, and transmission in series. The engine in a series hybrid drives a generator that charges the battery.

accessible. For reference, in MY 2020, only four FCEV models were offered for sale, and since 2014 only 12,081 FCEVs have been sold.[312, 313]

For this analysis, the CAFE Model simulates a FCEV with a range of 320 miles. Any type of powertrain could adopt a FCEV powertrain; however, to account for limited market penetration and unlikely increased adoption in the rulemaking timeframe, we use technology phase-in caps to control how many FCEVs a manufacturer could build. Chapter 3.3.3 includes more discussion of FCEV adoption features.

3.3.2 Electrification Analysis Fleet Assignments

We identify electrification technologies present in the baseline fleet as the starting point for the regulatory analysis. These assignments are based on manufacturer-submitted CAFE compliance information, publicly available technical specifications, marketing brochures, articles from reputable media outlets, and data from Wards Intelligence.[314]

Table 3-55 lists every electrification technology considered in the analysis, including the acronym that we use in the documentation and input files as well as a brief description. For brevity, we refer to technologies by their acronyms in this section. Note that some electrification technologies are not eligible for assignment in the baseline; they are indicated by the gray rows in Table 3-55 and do not appear in Table 3-56.

Table 3-55 – CAFE Model Electric Paths Technologies

Technology	Description
SS12V	12-Volt Stop-Start (Micro Hybrid)
BISG	48V Belt Mounted Integrated Starter/Generator (Mild Hybrid)
SHEVP2	P2 (Parallel) Strong Hybrid/Electric Vehicle
SHEVPS	Power Split Strong Hybrid/Electric Vehicle
P2HCR0	SHEVP2 with Level 0 High Compression Ratio Engine
P2HCR1	SHEVP2 with Level 1 High Compression Ratio Engine
P2HCR1D	SHEVP2 with Level 1 High Compression Ratio Engine with Cylinder Deactivation
P2HCR2	SHEVP2 with Level 2 High Compression Ratio Engine
PHEV20	Plug-In Hybrid with 20-mile Range
PHEV50	Plug-In Hybrid with 50-mile Range
PHEV20T	PHEV20 with Turbo Engine
PHEV50T	PHEV50 with Turbo Engine
PHEV20H	PHEV20 with High Compression Ratio Engine
PHEV50H	PHEV50 with High Compression Ratio Engine

312 Argonne National Lab. "Light Duty Electric Drive Vehicles Monthly Sales Update." Energy Systems Division. https://www.anl.gov/es/light-duty-electric-drive-vehicles-monthly-sales-updates. Light Duty Electric Drive Vehicles Monthly Sales Updates _ ANL.pdf. (Accessed: February 15, 2022).
313 Market Data file: Honda Clarity, Hyundai Nexo and Nexo Blue, and Toyota Mirai.
314 "U.S. Car and Light Truck Specifications and Prices, '20 Model Year." *Wards Intelligence*, 3 Aug. 2020, wardsintelligence.informa.com/WI964244/US-Car-and-Light-Truck-Specifications-and-Prices-20-Model-Year. (Accessed: February 15, 2022).

Technology	Description
BEV200	200-mile Battery Electric Vehicle
BEV300	300-mile Battery Electric Vehicle
BEV400	400-mile Battery Electric Vehicle
BEV500	500-mile Battery Electric Vehicle
FCV	Fuel Cell Electric Vehicle

Table 3-56 gives the baseline fleet penetration rates of eligible electrification technologies. Over half the fleet has some level of electrification, with the vast majority of these being micro hybrids. BEVs represent less than 2 percent of MY 2020 baseline fleet; BEV300 is the most common BEV technology, and we observe no BEV500s.

Table 3-56 – Penetration Rate of Electrification Technologies in the MY 2020 Fleet

Electrification Technology	Sales Volume with this technology	Penetration Rate in 2020 Baseline Fleet
None	5,791,220	42.61%
SS12V	6,837,257	50.30%
BISG	258,629	1.90%
SHEVP2	6,409	0.05%
SHEVPS	378,523	2.78%
PHEV20	46,393	0.34%
PHEV20T	18,943	0.14%
PHEV50	2,392	0.02%
PHEV50T	18	0.0001%
BEV200	72,123	0.53%
BEV300	145,900	1.07%
BEV400	34,000	0.25%
BEV500	0	0%
FCV	744	0.005%

3.3.2.1 Micro and Mild Hybrids

Micro and mild hybrids refer to the presence of SS12V and BISG, respectively. We use the data sources discussed above to identify the presence of these technologies on vehicles in the fleet. We only assign micro and mild hybrid technology if we could confirm its presence with manufacturer brochures or technical specifications.

3.3.2.2 Strong Hybrids

Strong hybrid technologies include SHEVPS and SHEVP2. For a discussion of differences in architecture between these technologies, see Chapter 3.3.1.3. Note that P2HCR0, P2HCR1, P2HCR1D, and P2HCR2 are not assigned in the fleet and are only available to be applied by the model. When possible, manufacturer specifications are used to identify the strong hybrid architecture type. In the absence of more sophisticated information, we determine hybrid architecture by number of motors. We assign hybrids with one electric motor P2, and those with two PS.

3.3.2.3 Plug-In Hybrids

Plug-in hybrid technologies that we assign in the baseline fleet include PHEV20/20T and PHEV50/50T; we do not assign PHEV20H and PHEV50H in the fleet and they can only be applied by the model. We assign vehicles with an electric-only range of 40 miles or less as PHEV20; we assign those with a range above 40 miles as PHEV50. We assign vehicles as PHEV20T/50T if the engine is turbocharged (*i.e.*, if it would qualify for one of technologies on the turbo engine technology pathway).[315]

We calculate individual gasoline and electric fuel economy values as part of characterizing PHEVs in the baseline fleet. This is necessary because the certification fuel economies for PHEVs reported in compliance data are a single value that combine both types of fuel economies. To calculate each PHEV's gas fuel economy, we scale values derived from fueleconomy.gov by a factor of 1.3.[316] The scaled gas fuel economy become the final value that we use in the Market Data file.

To compute electric fuel economy, we calculate utility factors, which define the proportion of miles traveled by PHEVs using electricity according to mathematical curves defined by the SAE.[317] These curves use each vehicle's AER as the input; range values are derived from the same source as the baseline gas fuel economy values and are also scaled by a factor of 1.3. Analyst-defined utility factors or a default value of 0.5[318] are also an option for each PHEV. Of the three possible utility factors—the calculated value, the analyst-defined value, or 0.5—we applied the greatest value.

We then follow the SAE standard for calculating the utility factor-weighted electric fuel economy[319] while defining a functional relationship to calculate it from known values, which is given in Equation 3-1. Note that the equation is divided by 2.1897, the petroleum equivalency factor, because this factor is later accounted for in the model.

$$Electric\ Fuel\ Economy = \frac{(Certification\ FE) \times (Scaled\ Gas\ FE) \times (Utility\ Factor)}{(Scaled\ Gas\ FE - Certification\ FE) \times (1 - Utility\ Factor)} \times \frac{1}{2.1897}$$

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[315] *See* Chapter 3.1 for more information on turbocharged engines in the analysis.

[316] The 1.3 scalar value accounts for the adjustment procedure used by EPA when deriving fuel economy label ("window sticker") values, which are calculated by multiplying measured fuel economies by a factor of 0.7. More information can be found at https://www.fueleconomy.gov/feg/pdfs/EPA%20test%20procedure%20for%20EVs-PHEVs-11-14-2017.pdf. (Accessed: February 15, 2022).

[317] *J2841: Utility Factor Definitions for Plug-In Hybrid Electric Vehicles Using Travel Survey Data*. SAE International, 21 Sept. 2010, www.sae.org/standards/content/j2841_201009. (Accessed: February 15, 2022).

[318] A utility factor of 0.5 indicates that exactly half of a PHEV's miles traveled are on gas fuel, while the other half are on electric power.

[319] J1711: Recommended Practice for Measuring the Exhaust Emissions and Fuel Economy of Hybrid-Electric Vehicles, Including Plug-in Hybrid Vehicles. SAE International, 8 June 2010, www.sae.org/standards/content/j1711_201006. (Accessed: February 15, 2022).

Equation 3-1 – Electric Fuel Economy

This approach has some limitations. In some cases, the electric fuel economy values or utility factors appear unrealistic. This is due to the certification fuel economy values that manufacturers report in compliance data, which often already include a petroleum equivalency factor and AC or off-cycle adjustment provisions. Manufacturers are not required to report these values individually to the agencies for each vehicle. We will consider how to better collect these data moving forward.

3.3.2.4 Fuel Cell and Battery Electric Vehicles

Fuel cell and battery electric vehicle technologies include BEV200/300/400/500 and FCEV. Vehicles with all-electric powertrains that used hydrogen fuel are assigned FCEV. The BEV technologies are assigned to vehicles based on range according to the thresholds listed in Table 3-57. These range thresholds best account for vehicles' existing range capabilities while allowing room for the model to potentially apply more advanced electrification technologies.

Table 3-57 – Range Thresholds for Assigning BEV Technologies

Vehicle Electric Range [miles]	Technology Assigned
<250	BEV200
250 to 349	BEV300
350 to 449	BEV400
>450	BEV500

3.3.3 Electrification Adoption Features

We apply several adoption features to the electrification technologies. The hybrid/electric technology path logic dictates how vehicles could adopt different levels of electrification technology. Figure 3-14 shows the electrification technology pathways; these are discussed in detail in each technologies' section below. Broadly speaking, more advanced levels of hybridization or electrification supersede all prior levels, while certain technologies within each level are mutually exclusive. We model (from least to most electrified) micro hybrids, mild hybrids, strong hybrids, plug-in hybrids, and fully electric vehicles.

As discussed further below, SKIP logic—restrictions on the adoption of certain technologies—apply to plug-in (PHEV) and strong hybrid vehicles (SHEV). Some technologies on these pathways are "skipped" if a vehicle is high performance, requires high towing capabilities as a pickup truck, or belongs to certain manufacturers who have demonstrated that their future product plans will more than likely not include the technology. We expand on the specific criteria for SKIP logic for each applicable electrification technology later in this section.

This section also discusses the supersession of engines and transmissions on vehicles that adopt SHEV or PHEV powertrains. To manage the complexity of the analysis, we model these types of hybrid powertrains with several specific engines and transmissions, rather than in multiple configurations. The SHEV and PHEV cost and effectiveness values account for these specific engines and transmissions.

Finally, phase-in caps limit the adoption rates of battery electric (BEV) and fuel cell vehicles (FCV). These phase-in caps account for current market share, scalability, and reasonable consumer adoption rates of each technology. Chapter 3.3.3.4 discusses phase-in caps and the reasoning behind them in detail.

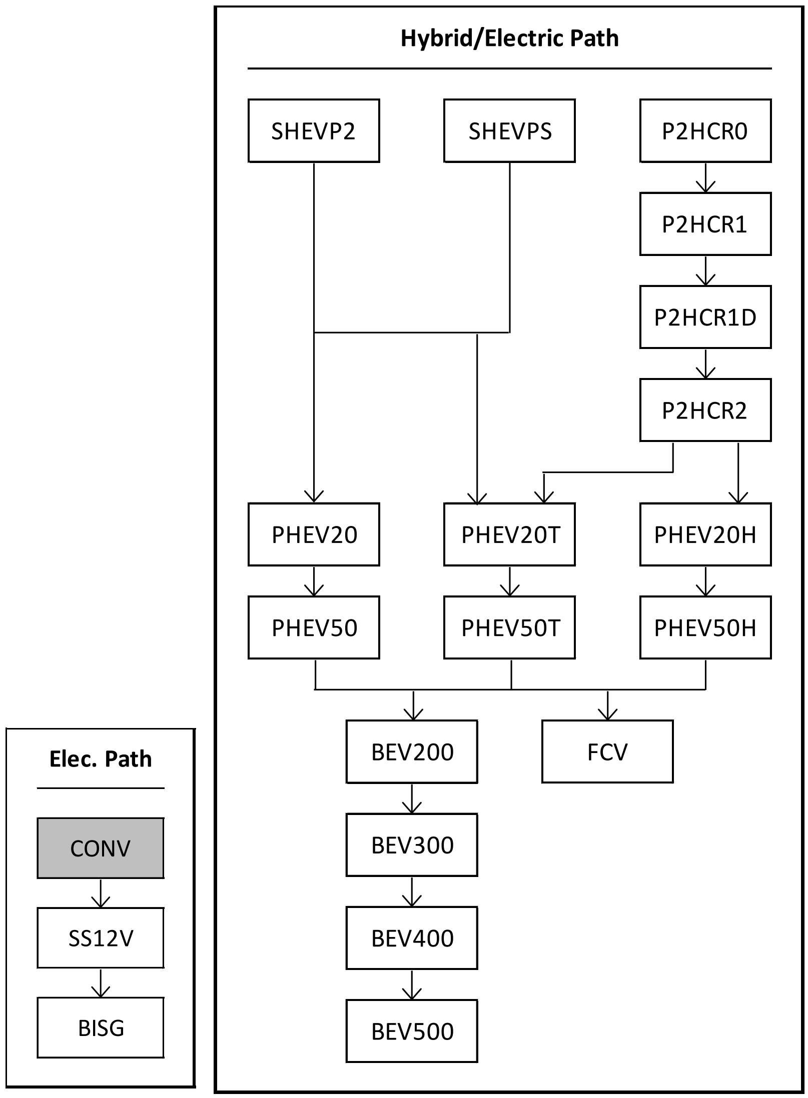

Figure 3-14 – Electrification Technology Pathways

The following sections discuss the adoption features that the model applies to each type of electrification technology.

3.3.3.1 Micro and Mild Hybrids

For this analysis, micro and mild hybridization refers to the presence of SS12V and BISG on a vehicle, respectively. The only adoption feature for these technologies is path logic, as illustrated in the lower left corner of Figure 3-14. The pathway consists of a linear progression starting with a conventional powertrain with no electrification at all, which is superseded by SS12V, which in turn is superseded by BISG. Vehicles can only adopt micro and mild hybrid technology if the vehicle did not already have a more advanced level of electrification.

3.3.3.2 Strong Hybrids

The strong hybrid technologies include SHEVP2, SHEVPS, P2HCR0, P2HCR1, P2HCR1D, and P2HCR2. The adoption features that we apply to strong hybrid technologies include path logic, powertrain substitution, and vehicle class restrictions. Per the defined technology pathways, SHEVPS, SHEVP2, and the P2HCR technologies are considered mutually exclusive. In other words, when the model applies one of these technologies, the others are immediately disabled from future application. However, all vehicles on the strong hybrid pathways can still advance to one or more of the plug-in hybrid technologies.

When the model applies any strong hybrid technology to a vehicle, the transmission technology on the vehicle is superseded. Regardless of the transmission originally present, P2 hybrids adopt an 8-speed automatic transmission (AT8L2), and PS hybrids adopt a continuously variable transmission (eCVT). When the model applies the SHEVP2 technology, the model can consider various engine options to pair with the SHEVP2 architecture according to existing engine path constraints, taking into account relative cost effectiveness. For SHEVPS technology, the existing engine is replaced with a hybrid full Atkinson cycle engine.[320]

SKIP logic is also used to constrain adoption for SHEVPS, P2HCR0, P2HCR1, and P2HCR1D. (No SKIP logic applies to SHEVP2; P2HCR2 is restricted from all vehicles in the 2020 fleet, as discussed further in Chapter 3.1) These technologies are "skipped" for vehicles with engines[321] that meet one of the following conditions:

- The engine belongs to an excluded manufacturer;[322]
- The engine belongs to a pickup truck (*i.e.*, the engine is on a vehicle assigned the "pickup" body style);
- The engine's peak horsepower is more than 405 HP; or if
- The engine is on a non-pickup vehicle, but is shared with a pickup.

The reasons for these conditions are similar to those for the SKIP logic that we apply to HCR engine technologies, discussed in more detail in Chapter 3.1.3. In the real world, pickups and performance vehicles with certain powertrain configurations cannot adopt the technologies listed

[320] Designated Eng26 in the list of engine map models used in the analysis. *See* Chapter 3.1 for more information.
[321] This refers to the engine assigned to the vehicle in the 2020 baseline fleet.
[322] Excluded manufacturers included BMW, Daimler, and Jaguar Land Rover.

above and maintain vehicle performance without redesigning the entire powertrain. SKIP logic is put in place to prevent the model from pursuing compliance pathways that are ultimately unrealistic.

3.3.3.3 Plug-In Hybrids

Plug-in hybrid (PHEV) technologies include PHEV20/20H/20T and PHEV50/50H/50T. They supersede the micro, mild, and strong hybrids, and can only be replaced by full electric technologies. Plug-in hybrid technology paths are also mutually exclusive, with the PHEV20 technologies able to progress to the PHEV50 technologies.

The engine and transmission technologies on a vehicle are superseded when PHEV technologies are applied to a vehicle. For all PHEV20T/50T plug-in technologies, the model applies an AT8L2 transmission and for all PHEV20/50 (PHEV20H/50H) plug-in technologies, the model applies an eCVT transmission. For PHEV20/50 and PHEV20H/50H, the vehicle receives a hybrid full Atkinson cycle engine.[323] For PHEV20T/50T, the vehicle receives a TURBO1 engine.[324]

SKIP logic applies to PHEV20/20H and PHEV50/50H under the same four conditions listed for the strong hybrid technologies in the previous section, for the same reasons previously discussed.

3.3.3.4 Fuel Cell and Battery Electric Vehicles

The adoption of BEVs and FCEVs is limited by both path logic and phase-in caps. BEV200/300/400/500 and FCEV are applied as end-of-path technologies that supersede previous levels of electrification.

The main adoption feature applicable to BEVs and FCEVs is phase-in caps, which are defined in the CAFE Model input files as percentages that represent the maximum rate of increase in penetration rate for a given technology. They are accompanied by a phase-in start year, which determines the first year the phase-in cap applies. Together, the phase-in cap and start year determine the maximum penetration rate for a given technology in a given year; the maximum penetration rate equals the phase-in cap times the number of years elapsed since the phase-in start year. Note that phase-in caps *do not* inherently dictate how much a technology is applied by the model. Rather, they represent how much of the fleet *could* have a given technology by a given year. Because BEV200 costs less and has higher effectiveness values[325] than other advanced electrification technologies, the model will have vehicles adopt it first, until it is restricted by the phase-in cap.

Table 3-58 shows the phase-in caps, phase-in year, and maximum penetration rate through 2050 for BEV and FCEV technologies. For comparison, we also list the actual penetration rate of each technology in the 2020 baseline fleet in the fourth column from the left.

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[323] Designated Eng26 in the list of engine map models used in the analysis. *See* Chapter 3.1 for more information.
[324] Designated Eng12 in the list of engine map models used in the analysis. *See* Chapter 3.1 for more information.
[325] This is because BEV200 uses fewer batteries and weighs less than BEVs with greater ranges.

Table 3-58 – Phase-In Caps for Fuel Cell and Battery Electric Vehicle Technologies

Technology Name	Phase-In Cap	Phase-In Start Year	Actual Penetration Rate in 2020 (Baseline Fleet)	Maximum Penetration Rate in 2020	Maximum Penetration Rate in 2025	Maximum Penetration Rate in 2030	Maximum Penetration Rate in 2035	Maximum Penetration Rate in 2040	Maximum Penetration Rate in 2045	Maximum Penetration Rate in 2050
BEV200	0.09%	1998	0.53%	1.98%	2.43%	2.88%	3.33%	3.78%	4.23%	4.68%
BEV300	0.70%	2009	1.07%	7.70%	11.20%	14.70%	18.20%	21.70%	25.20%	28.70%
BEV400	1.25%	2016	0.25%	5.00%	11.25%	17.50%	23.75%	30.00%	36.25%	42.50%
BEV500	4.25%	2021	-	-	17.00%	38.25%	59.50%	80.75%	102.00%	123.25%
FCV	0.018%	2016	0.005%	0.072%	0.162%	0.252%	0.342%	0.432%	0.522%	0.612%

The BEV200 phase-in cap is informed by manufacturers' tendency to move away from low-range vehicle offerings, in part because of potential consumer hesitancy to adopt this technology. In some cases, the advertised range on most electric vehicles may not reflect the actual real world range in cold and hot ambient conditions and real-world driving conditions, affecting the utility of these lower range vehicles.[326] Many manufacturers have told us that the portion of consumers willing to accept a vehicle with our lowest range model is small, with manufacturers targeting range values above 250 miles.[327,328]

Furthermore, the average BEV range has steadily increased over the past decade,[329] perhaps in part as batteries become more cost effective. EPA observed in its 2021 Automotive Trends Report that "the average range of new EVs has climbed substantially. In model year 2020, the average new EV is projected to have a 286-mile range, or about four times the range of an average EV in 2011. This difference is largely attributable to higher production of new EVs with much longer ranges."[330] Based on the cited examples and basis described in this section, the maximum growth rate for BEV200 in the model is set accordingly low to less than 0.1 percent per year. While this rate is significantly lower than that of the other BEV technologies, the BEV200 phase-in cap allows the penetration rate of low-range BEVs to grow by a multiple of what is currently observed in the market.

For BEV300, 400, and 500, phase-in caps are intended to conservatively reflect potential challenges in the scalability of BEV manufacturing, and implementing BEV technology on many vehicle configurations, including larger vehicles. In the short term, the penetration of BEVs is

[326] AAA. "AAA Electric Vehicle Range Testing." February 2019. https://www.aaa.com/AAA/common/AAR/files/AAA-Electric-Vehicle-Range-Testing-Report.pdf. (Accessed: February 15, 2022).
[327] For example, in February 2021, Tesla, the United States' highest-selling BEV manufacturer, discontinued the Standard Range Model Y because its range did not meet the company's "standard of excellence."
[328] Baldwin, Roberto. "Tesla Model Y Standard Range Discontinued; CEO Musk Tweets Explanation." Car and Driver, 30 Apr. 2021, www.caranddriver.com/news/a35602581/elon-musk-model-y-discontinued-explanation. (Accessed: February 15, 2022).
[329] 2021 EPA Automotive Trends Report, at p. 56, figure 4.17.
[330] 2021 EPA Automotive Trends Report, at p. 58.

largely limited by battery availability.[331] For example, Tesla is not yet producing electric vans because of cell production constraints, and it remains a bottleneck in the company's expansion into new product lines.[332] Incorporating battery packs that provide greater amounts of electric range into vehicles also poses its own engineering challenges. Heavy batteries and large packs may be difficult to integrate for many vehicle configurations and require structural vehicle modifications. Pickup trucks and large SUVs in particular require higher levels of energy as the number of passengers and/or payload increases, for towing and other high-torque applications. We use the BEV400 and 500 phase-in caps to reflect these transitional challenges.

The phase-in cap for FCEVs is assigned based on existing market share as well as historical trends in FCEV production. FCEV production share in the past five years has been extremely low, and we set the phase-in cap accordingly.[333] As with BEV200, however, the phase-in cap still allows for the market share of FCEVs to grow several times over.

3.3.4 Electrification Effectiveness

For this analysis, we consider a range of electrification technologies which, when modeled, result in varying levels of effectiveness at reducing fuel consumption. As discussed above, the modeled electrification technologies include micro hybrids, mild hybrids, two different strong hybrids, two different plug-in hybrids with two separate all electric ranges, full battery electric vehicles and FCEVs. Each electrification technology consists of many complex sub-systems with unique component characteristics and operational modes. As discussed further below, the systems that contribute to the effectiveness of an electrified powertrain in the analysis include the vehicle's battery, electric motors, power electronics, and accessory loads. We discuss the procedures for modeling each of these sub-systems below, and in Chapter 2.4, and the Autonomie model documentation.

Argonne uses data from their AMTL to develop Autonomie's electrified powertrain models. The modeled powertrains are not intended to represent any specific manufacturer's architecture but are intended to act as surrogates predicting representative levels of effectiveness for each electrification technology.

As we discuss in Chapter 2.4, certain technologies' effectiveness for reducing fuel consumption requires optimization through the appropriate sizing of the powertrain. Autonomie uses sizing control algorithms based on data collected from vehicle benchmarking,[334] and sized the modeled electrification components based on the performance neutrality considerations discussed above. This analysis iteratively minimizes the size of the powertrain components to maximize efficiency while enabling the vehicle to meet multiple performance criteria. The Autonomie simulations use a series of resizing algorithms that contain "loops," such as the acceleration performance loop (0-60 mph), which automatically adjust the size of certain powertrain components until a

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[331] *See, e.g.*, Cohen, Ariel. "Manufacturers Are Struggling To Supply Electric Vehicles With Batteries." Forbes, Forbes Magazine, 25 March 2020, www.forbes.com/sites/arielcohen/2020/03/25/manufacturers-are-struggling-to-supply-electric-vehicles-with-batteries. (Accessed: February 15, 2022).
[332] Hyatt, Kyle. "Tesla Will Build an Electric Van Eventually, Elon Musk Says." Roadshow, CNET, 28 Jan. 2021, https://www.cnet.com/roadshow/news/tesla-electric-van-elon-musk. (Accessed: February 15, 2022).
[333] 2021 EPA Automotive Trends Report, at p. 56, figure 4.14.
[334] Autonomie model documentation, Chapter 8.3.

criterion, like the 0-60 mph acceleration time, is met. As the algorithms examine different performance or operational criteria that must be met, no single criterion can degrade; once a resizing algorithm completes, all criteria will be met, and some may be exceeded as a necessary consequence of meeting others.

As discussed in Chapter 2.4, Autonomie applies different powertrain sizing algorithms depending on the type of vehicle considered because different types of vehicles not only contain different powertrain components to be optimized, but they must also operate in different driving modes. While the conventional powertrain sizing algorithm must consider only the power of the engine, the more complex algorithm for electrified powertrains must simultaneously consider multiple factors, which could include the engine power, electric machine power, battery power, and battery capacity. Also, while the resizing algorithm for all vehicles must satisfy the same performance criteria, the algorithm for some electric powertrains must also allow those electrified vehicles to operate in certain driving cycles, like the US06 cycle, without assistance of the combustion engine, and ensure the electric motor/generator and battery can handle the vehicle's regenerative braking power, all-electric mode operation, and intended range of travel.

To establish the effectiveness of the technology packages, Autonomie simulates the vehicles' performance on compliance test cycles, as discussed in Chapter 2.4.[335,336,337] For vehicles with conventional powertrains and micro hybrids, Autonomie simulates the vehicles using the 2-cycle test procedures and guidelines.[338] For mild HEVs, strong HEVs, and FCEVs, Autonomie simulates the same 2-cycle test, with the addition of repeating the drive cycles until the final SOC is approximately the same as the initial SOC, a process described in SAE J1711. For PHEVs, Autonomie simulates vehicles performing the test cycles per guidance provided in SAE J1711.[339] For BEVs and FCEVs, Autonomie simulates vehicles performing the test cycles per guidance provided in SAE J1634.[340]

The range of effectiveness for the electrification technologies in this analysis is a result of the interactions between the components listed above and how the modeled vehicle operates on its respective test cycle. This range of values will result in some modeled effectiveness values being close to real-world measured values, and some modeled values that will depart from measured values, depending on the level of similarity between the modeled hardware configuration and the real-world hardware and software configurations. This modeling approach comports with the National Academy of Science 2015 recommendation to use full vehicle modeling supported by application of lumped improvements at the sub-model level.[341] The

[335] EPA, "How Vehicles are Tested." https://www.fueleconomy.gov/feg/how_tested.shtml. (Accessed: February 15, 2022).
[336] Autonomie model documentation, Chapter 6.
[337] EPA Guidance Letter. "EPA Test Procedures for Electric Vehicles and Plug-in Hybrids." Nov. 14, 2017. https://www.fueleconomy.gov/feg/pdfs/EPA%20test%20procedure%20for%20EVs-PHEVs-11-14-2017.pdf. (Accessed: February 15, 2022).
[338] 40 CFR part 600.
[339] PHEV testing is broken into several phases based on SAE J1711. charge-sustaining on the city and HWFET cycle, and charge-depleting on the city and HWFET cycles.
[340] SAE J1634. "Battery Electric Vehicle Energy Consumption and Range Test Procedure." July 12, 2017.
[341] 2015 NAS report, at 292.

approach allows the isolation of technology effects in the analysis supporting an accurate assessment.

The range of effectiveness values for the electrification technologies, for all ten vehicle technology classes, is shown in Figure 3-15 below. In the graph, the box shows the inner quartile range (IQR) of the effectiveness values and whiskers extend out 1.5 x IQR.[342] The blue dots show values outside these bounds.

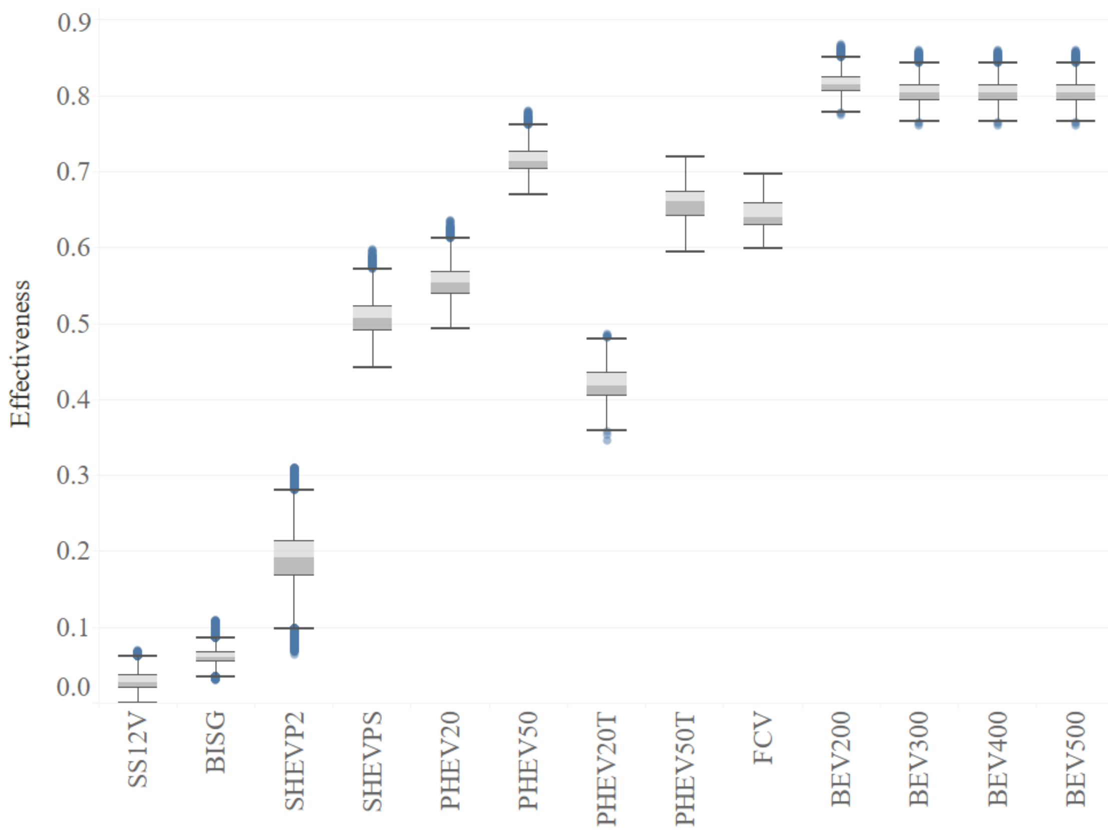

Figure 3-15 – Electrification Technology Effectiveness Values for All the Vehicle Technology Classes[343]

The following sections discuss the data that we use to model each electrification component, including the batteries, electric motors, power electronics, and accessories, and the Autonomie models that we use to simulate the effectiveness of each electrified powertrain technology on its respective test cycle.

342 The IQR is the interquartile range – the difference between the upper quartile and the lower quartile. Each whisker shows the data points between that range.
343 The data used to create this figure can be found the FE_1 Improvements file.

3.3.4.1 Batteries, Electric Motors, Power Electronics, and Accessories

Autonomie determines the effectiveness of each electrified powertrain type by modeling the basic components, or building blocks, for each powertrain, and then combining the components modularly to determine the overall efficiency of the entire powertrain. The basic building blocks that comprise an electrified powertrain in the analysis include the battery, electric motors, power electronics, and accessory loads. Autonomie identifies components for each electrified powertrain type, and then interlinks those components to create a powertrain architecture. Autonomie then models each electrified powertrain architecture and provides an effectiveness value for each architecture. For example, Autonomie determines a BEV's overall efficiency by considering the efficiencies of the battery, the electric traction drive system (the electric machine and power electronics) and mechanical power transmission devices. Or, for a SHEVP2, Autonomie combines a very similar set of components to model the electric portion of the hybrid powertrain, and then also includes the combustion engine and related power for transmission components.

For this analysis, Autonomie employs a set of electric motor efficiency maps created by Oak Ridge National Laboratory (ORNL): one for a traction motor and an inverter, the other for a motor/generator and inverter.[344] Autonomie also uses test data validations from technical publications to determine the peak efficiency of BEVs and FCEVs. The electric motor efficiency maps, created from production vehicles as shown in Table 3-59 below, represent electric motor efficiency as a function of torque and motor RPM. These efficiency maps provide nominal and maximum speeds, as well as a maximum torque curve. Argonne uses the maps to determine the efficiency characteristics of the motors but scales them such that their peak efficiency value corresponds to the latest state of the art technologies for different electrified powertrains. Specifically, Argonne scales the maps to have total system peak efficiencies ranging from 96-98 percent depending on the powertrain type.[345] The maps also include some of the losses due to power transfer through the electric machine.[346] Table 3-59 shows the electric machine efficiency map sources for the different powertrain configurations that we use in this analysis.

Table 3-59 – Electric Machine Efficiency Map Sources for Different Powertrain Configurations

Powertrain Type	Source of Efficiency Map for Motor1 (Traction Motor) + Inverter	Source of Efficiency Map for Motor2 (Motor/Generator) + Inverter
SS12V, BISG	Camry EM1 data from ORNL	
SHEVP2	Sonata HEV data from ORNL	
SHEVPS, PHEV20	Camry EM1 data from ORNL	Camry EM2 Data from ORNL
PHEV50	Camry EM1 data from ORNL	Sonata HEV Data from ORNL

[344] Oak Ridge National Laboratory (2008). Evaluation of the 2007 Toyota Camry Hybrid Synergy Drive System. Submitted to the U.S. Department of Energy; Oak Ridge National Laboratory (2011). Annual Progress Report for the Power Electronics and Electric Machinery Program.
[345] *See* Autonomie model documentation, Chapter 5.6.2.
[346] *See* Autonomie model documentation, Chapters 4.7 and 5.6.

BEV and FCEV[347]	Chevrolet Bolt EM data from SAE paper	

Beyond the powertrain components, Autonomie also considers electric accessory devices that consume energy and affect overall vehicle effectiveness, such as headlights, radiator fans, wiper motors, engine control units (ECU), transmission control unit (TCU), cooling systems, and safety systems. In real-world driving, the electrical accessory load on the powertrain varies depending on the how the driver uses certain features and the condition in which the vehicle is operating, such as for night driving or hot weather driving. However, for regulatory test cycles related to fuel economy, the electrical load is repeatable because the fuel economy regulations control for these factors, as discussed in Chapter 2.4.[348] Accessory loads during test cycles do vary by powertrain type and vehicle technology class, since distinctly different powertrain components and vehicle masses will consume different amounts of energy.

The baseline fleet consists of different vehicle types with varying accessory electrical power demand. For instance, vehicles with different motor and battery sizes will require different capacities of electric cooling pumps and fans to manage component temperatures. Autonomie has built-in models that can simulate these varying sub-system electrical loads. However, for this analysis, we use a fixed (by vehicle technology class and powertrain type), constant power draw to represent the effect of these accessory loads on the powertrain on the 2-cycle test. We intend and expect that fixed accessory load values will, on average, have similar impacts on effectiveness as found on actual manufacturers' systems. This process is in line with the past analyses.[349,350] For this analysis, we aggregate electrical accessory load modeling assumptions for the different powertrain types and classes from data from the Draft TAR, EPA Proposed Determination,[351] CBI from manufacturers,[352] research and development data from DOE's

[347] Burak Ozpineci, Oak Ridge National Laboratory Annual Progress Report for the Power Electronics and Electric Motors Program, ORNL/SPR-2014/532, https://info.ornl.gov/sites/publications/Files/Pub52422.pdf, November 2014. (Accessed: February 15, 2022). (For FCVs, we used data from the Nissan Leaf).
[348] NHTSA Benchmarking, "Laboratory Testing of a 2017 Ford F-150 3.5 V6 EcoBoost with a 10-speed transmission." DOT HS 812 520.
[349] Draft Technical Assessment Report (July 2016), Chapter 5.
[350] EPA Proposed Determination TSD (November 2016), at pp. 2–270.
[351] EPA Proposed Determination TSD (November 2016), at pp. 2–270.
[352] Alliance of Automobile Manufacturers Comments on Draft TAR, at p. 30.

Vehicle Technologies Office,[353,354,355] and DOT-sponsored vehicle benchmarking studies completed by Argonne's AMTL.[356] These assumptions are provided below in Table 3-60.[357]

Table 3-60 – Accessory Load Assumptions in Watts by Vehicle Class and Powertrain Type

Vehicle Class	Performance Category	Accessory Load (Watts) by Vehicle Powertrain Type		
		Conventional	HEVs	PHEVs and BEVs
Compact	Base	250	275	375
Compact	Premium	300	375	475
Midsize	Base	250	275	375
Midsize	Premium	300	375	475
Small SUV	Base	300	325	425
Small SUV	Premium	300	375	475
Midsize SUV	Base	300	325	425
Midsize SUV	Premium	350	375	475
Pickup	Base	300	325	425
Pickup	Premium	300	375	475

The following sections discuss how the assumptions for each powertrain type are simulated across the test cycle to meet modeling and performance requirements.

[353] DOE VTO Power Electronics Research and Development. https://www.energy.gov/eere/vehicles/vehicle-technologies-office-electric-drive-systems. (Accessed: February 15, 2022).
[354] Argonne National Laboratory, Advanced Mobility Technology Laboratory (AMTL). https://www.anl.gov/es/advanced-mobility-technology-laboratory. (Accessed February 15, 2022).
[355] DOE's lab years are ten years ahead of manufacturers' potential production intent (*e.g.*, 2020 Lab Year is MY 2030).
[356] Stutenberg, K., Kim, N., Russo, D. M., Islam, E., Kim, K., Lohse-Busch, H., Rousseau, A., Vijayagopal, R. (2021, July). Vehicle technology assessment, model development, and validation of a 2018 Honda Accord LX with a 1.5L I4 and continuously variable transmission (Report No. DOT HS 813 159). National Highway Traffic Safety Administration., Stutenberg, K., Kim, N., Russo, D. M., Islam, E., Kim, K., Lohse-Busch, H., Rousseau, A., & Vijayagopal, R. (2021, July). Vehicle technology assessment, model development and validation of a 2018 Toyota Camry XLE with a 2.5L I4 and 8-speed automatic transmission (Report No. DOT HS 813 160). National Highway Traffic Safety Administration., Stutenberg, K., Kim, N., Russo, D. M., Islam, E., Lohse-Busch, H., Rousseau, A., & Vijayagopal, R. (2021, July). Vehicle technology assessment, model development, and validation of a 2019 Acura MDX Sport Hybrid (Report No. DOT HS 813 161). National Highway Traffic Safety Administration., Jehlik, F., Kim, N., Islam, E., Lohse-Busch, H., Rousseau, A., Stutenberg, K., & Vijayagopal, R. (2021, July). Vehicle technology assessment, model development, and validation of a 2019 Infiniti QX50 (Report No. DOT HS 813 162). National Highway Traffic Safety Administration., Lohse-Busch, H., Stutenberg, K., Ilieve, S., & Duoba, M. (2018, July). Laboratory testing of a 2017 Ford F-150 3.5L V6 EcoBoost with a 10-speed transmission (Report No. DOT HS 812 520). Washington, DC: National Highway Traffic Safety Administration., Lohse-Busch, H., Stutenberg, K., Ilieve, S., & Duoba, M. (2018, July). Laboratory testing of a 2017 Ford F-150 3.5L V6 EcoBoost with a 10-speed transmission (Report No. DOT HS 812 520). Washington, DC: National Highway Traffic Safety Administration.
[357] *See* ANL - Summary of Main Component Performance Assumptions_NPRM_022021, ANL - All Assumptions_Summary_NPRM_022021.xlsx.

3.3.4.2 Micro Hybrids

Autonomie represents a micro hybrid system using SS12V technology. The SS12V system in this analysis does not provide any brake energy recovery. The effectiveness improvement from SS12V systems is attributable to the amount of fuel saved during the engine idling period on the 2-cycle test. Although the SS12V system only provides minimal benefit on the 2-cycle test,[358] the fuel economy improvement from SS12V systems is also credited in the analysis through the application of off-cycle FCIVs. For further discussion of the SS12V system models, see the Autonomie model documentation.[359]

Micro hybrid systems normally do not provide propulsion assist, so this technology has little to no impact on the vehicle performance metrics. Thus, in this analysis, Autonomie does not resize the powertrain when a vehicle adopts a micro hybrid system because with or without the micro hybrid system, the combustion engine size must be retained to maintain performance metrics such as acceleration.

3.3.4.3 Mild Hybrids

The mild hybrid system in Autonomie is a 48V BISG.[360] The main focus of mild hybrid vehicles is to provide idle-stop and capture some regenerative braking energy, and although they also can provide some assistance to the engine during the initial propelling of the vehicle, this is done to improve efficiency and does not significantly improve acceleration performance. With BISG mild hybrids, the electric machine is linked to the engine through a belt, and thus the potential power assistance is usually limited. In this analysis a BISG uses a 10 kW motor/generator paired with a 403 watt-hour battery pack to better align with BISG systems emerging in the marketplace.[361] The specification of this system is provided in the Autonomie summary assumptions files.[362]

Like the modeled micro hybrid system, the effectiveness improvement from the mild hybrid system is attributable to the amount of fuel saved during the engine idling period on the 2-cycle test, and additional fuel economy benefits are credited through the application of off-cycle FCIVs. Also similar to the mild hybrid system, Autonomie does not resize the vehicle powertrain with the addition of the 48V BISG technology. However, the BISG system model allows limited assist to propel the vehicle and limited regenerative braking.

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[358] The regulatory two-cycle test only contains 18 percent vehicle idling, which is not always representative of real-world operation. *See* EPA Detailed Test Information, https://www.fueleconomy.gov/feg/fe_test_schedules.shtml. (Accessed: February 15, 2022).
[359] *See* Autonomie model documentation, Chapters 4.6, 4.7 and 4.13.
[360] These systems are 48V Direct Current (DC) electrical systems.
[361] *See, e.g.*, Bosch 48V battery, https://www.bosch-mobility-solutions.com/en/solutions/batteries/48v-battery/; A123 Systems 48V battery, http://www.a123systems.com/automotive/products/systems/48v-battery/; K.C. Colwell, *The 2019 Ram 1500 eTorque Brings Some Hybrid Tech, If Little Performance Gain, to Pickups*, Car and Driver (March 14, 2019), https://www.caranddriver.com/reviews/a22815325/2019-ram-1500-etorque-hybrid-pickup-drive. (Accessed: February 15, 2022).
[362] *See* ANL - Summary of Main Component Performance Assumptions_NPRM_022021, ANL - All Assumptions_Summary_NPRM_022021.xlsx, and ANL_BatPac_Lookup_tables_Feb2021v2.xlsx.

3.3.4.4 Strong Hybrids

As discussed earlier, this analysis considers two types of strong hybrid technology, a power-split hybrid (SHEVPS) architecture and a P2 hybrid (SHEVP2) architecture. The SHEVPS model in Autonomie includes a power-split device, two electric machines, and an engine, and allows for various interactions between these components. The SHEVP2 model in Autonomie is based on the pre-transmission (P2) configuration where the electric motor is placed between the engine and transmission for direct flow of power to the wheels. The vehicle is propelled either by the combustion engine, electric motor, or both simultaneously, but the speed/efficiency region of operation for SHEVP2s under any engine/motor combination is ultimately dictated by the transmission gearing and speed. A detailed discussion of the SHEVPS and SHEVP2 modeling and validation are provided in the Autonomie model documentation.[363] Autonomie full vehicle models representing the strong hybrids are based on vehicle test data from vehicle benchmarking.

As discussed previously in this section, power-split hybrids utilize a full-time Atkinson mode engine, two electric machines, and a planetary gear set transmission along with a battery pack to propel the vehicle. The smaller motor/generator (EM1) is used to control the engine speed and the engine is used to either charge the battery or to supply additional electric power to the second "drive" motor. The more powerful drive motor/generator (EM2) is permanently connected to the vehicle's final drive and always turns with the wheels. The Autonomie SHEVPS model and controls are based on a few high-level characteristics of real-world strong hybrid power-split systems that drive how the components are sized to meet performance metrics. For example:

- In the initial vehicle launch, when SOC is stable, the electric motor is the only propulsion system; and
- In normal city driving, the engine could both propel the vehicle and through the generator/motor charge the battery.

The SHEVPS resizing algorithm makes an initial estimate of the size of the engine, battery, and electric motors. The initial estimates for the combustion engine and EM2 sizes are based on the peak power required for acceleration performance and the continuous power required for gradeability performance. The initial estimates for the battery and EM1 power are based on the maximum regenerative braking power. With these initial size estimates, the algorithm computes the vehicle mass, and runs simulations to determine if 0-60 and 50-80 mph acceleration performance is acceptable. If acceleration is not satisfactory (too fast or too slow), the algorithm iteratively adjusts the sizes of the engine, motors, and battery, and runs simulations until a minimum powertrain size is found that meets all performance requirements. With each iteration, the engine, battery, and motor characteristics are also updated for gradeability performance and regeneration, if necessary. Figure 3-16 below shows the general steps of the SHEVPS sizing algorithm. Detailed descriptions are available in the Autonomie model documentation.

[363] Autonomie model documentation, Chapters 4.13, 4.16, and 6.

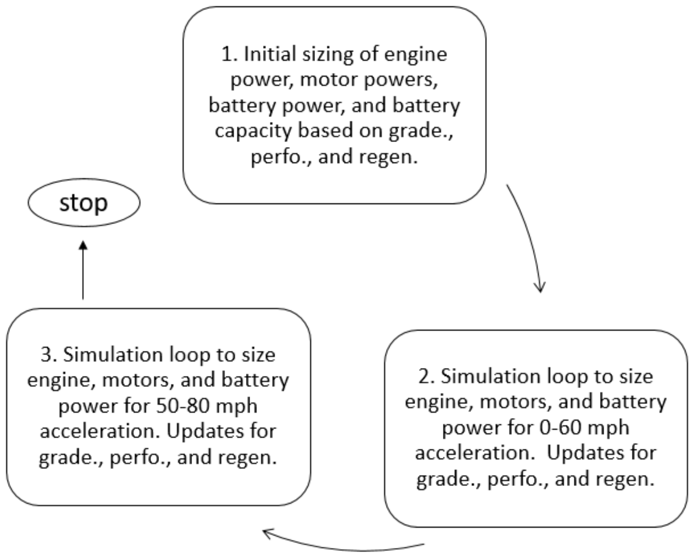

Figure 3-16 – Simplified SHEVPS Sizing Algorithm in Autonomie

The SHEVP2 uses a combustion engine and a multi-speed transmission-integrated electric motor (EM1). As discussed earlier, this SHEVP2 allows most engines and an advanced eight speed transmission to integrate with an electric motor. To minimize the number of Autonomie simulations for combinations of engines and transmissions for all ten vehicle classes,[364] we use the AT8L2 as the only transmission that can be integrated with SHEVP2. As manufacturers continue to increase gear counts from the common five and six speed gears and improve transmission internals, this improvement is carried into the SHEVP2 architecture. In MY 2020, about 50 percent of the fleet had transmissions with seven gears or higher.[365] Additionally, the higher-geared eight speed automatic transmission enables the maximization of engine efficiency by allowing the engine to operate in the more efficient region as compared to a lower geared transmission. These benefits are further discussed in Chapter 3.2.

As with SHEVPS, the SHEVP2 resizing algorithm starts by estimating the size of the engine, battery, and electric motor based on performance criteria or an estimated regenerative braking power, and then by calculating the associated vehicle mass. The algorithm then uses a simulation loop to find a more precise value of regenerative braking power generated in the UDDS "city driving" cycle and adjusts the electric motor size and vehicle mass accordingly. Next, the algorithm uses simulation loops to optimize the engine, motor, and battery sizes in relation to acceleration performance criteria. If the acceleration criteria require downsizing the powertrain, the electric motor size is not reduced as this would not be suitable to handle regenerative braking power. If the acceleration criteria cause the electric motor to increase in size, the algorithm then returns to the regenerative braking loop and subsequently all other loops until all components are optimized. Figure 3-17 below shows a simplified sizing algorithm for SHEVP2s.

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[364] For this analysis, there are 1,103,760 simulation results for all ten vehicles classes. That number does not include the simulations associated with sizing of components for different powertrains.
[365] *See* Chapter 3.2 for a more detailed breakdown of transmission penetration rates.

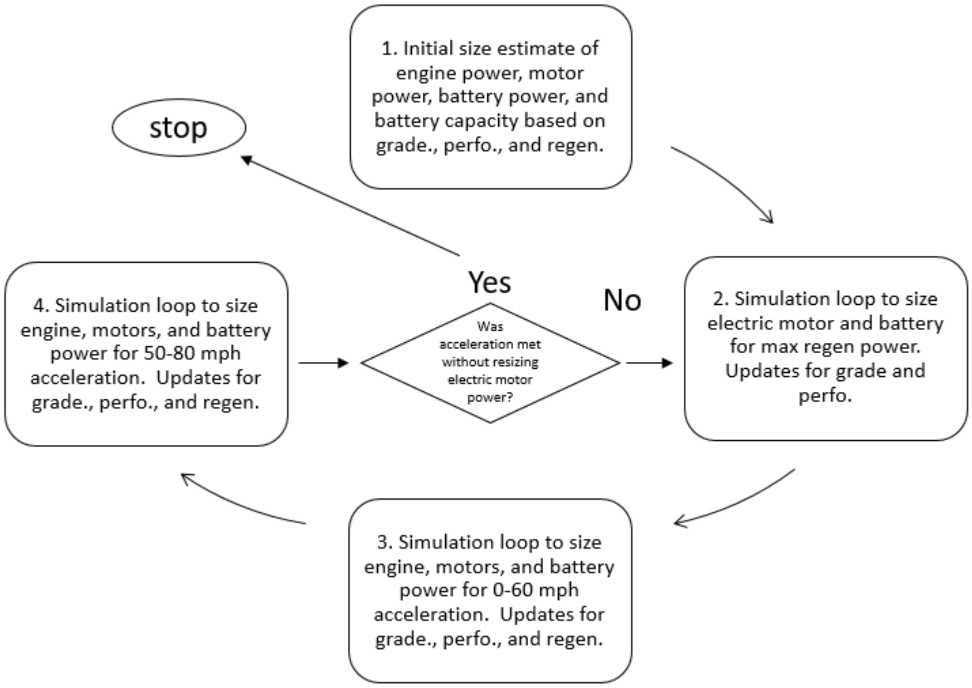

Figure 3-17 – Simplified SHEVP2 Sizing Algorithm in Autonomie

To maintain performance neutrality, the acceleration optimization loops in the SHEVP2 algorithm differ between the non-performance vehicle class and the performance class. For performance classes, Autonomie does not resize the powertrain to avoid reducing the performance in SHEVP2 hybrids compared to the same vehicle with a conventional powertrain. This mimics the observed marketplace trend in which parallel hybrid models tend to retain a similar engine size as the non-hybrid models bearing the same nameplate. For non-performance classes, SHEVP2 powertrains allow engine downsizing. This algorithm is discussed in the Autonomie model documentation with a more detailed flow chart of the closed loop design.[366]

In addition, we limit adoption of some advanced engine technologies with strong hybrids in cases where the electrification technology would have little effectiveness benefit beyond the benefit of the advanced engine system but would substantially increase costs. Specifically, we do not model strong hybrid technologies with VCR engines (eng26a) and eBoost engines (eng23c). We believe that manufacturers would not consider these combinations because the combination of electrification and advanced engine technologies are not as cost-effective as other technologies.

3.3.4.5 Plug-in Hybrids

The effectiveness of the PHEV systems is dependent on both the vehicle's battery pack size and range, in addition to the other fuel economy-improving technologies on the vehicle (*e.g.*, aerodynamic and mass reduction technologies).

[366] Autonomie model documentation, Chapter 8.3.3.

As discussed earlier in Chapter 3.3.1, Autonomie follows EPA regulatory guidance using the SAE J1711 test procedure to model the incremental effectiveness of adding PHEV technology to a vehicle. The procedure from this guidance is divided into several phases that model charge sustaining, charge depleting, and cold weighting calculations for different test cycles. This is described in detail in the Autonomie model documentation.[367]

The resizing algorithm for PHEVs, similar to strong HEVs, considers the power needed for acceleration performance and all-electric mode operation (compared to regenerative braking for strong HEVs); the PHEV resizing algorithms use these metrics for an initial estimation of engine, motor(s) and battery powers, and battery capacity. The initial mass of the vehicle is then computed, including the weight for a larger battery pack and charging components.[368] However, since PHEVs offer expanded electric driving capacity, their resizing algorithm must also yield a powertrain with the ability to achieve certain driving cycles and range in electric only mode, in which the engine remains off for all or most the operation. The analysis sizes the PHEV electric motor and battery power so that the vehicle can complete either the city cycle (UDDS) or US06 (aggressive, high speed) driving cycle in electric mode, and the battery energy storage capacity to achieve the specified AER on the 2-cycle tests on the basis of adjusted energy values.[369,370]

For this analysis, we classify PHEVs into four technology levels, as discussed previously: (1) PHEV20 indicating a vehicle with an AER of 20 miles and powertrain system based on SHEVPS hybrid architecture; (2) PHEV50 indicating a vehicle with an AER of 50 miles and powertrain system based on SHEVPS hybrid architecture; (3) PHEV20T indicating a vehicle with an AER of 20 miles and powertrain system based on SHEVP2 hybrid architecture; and (4) PHEV50T indicating a vehicle with AER of 50 miles and powertrain system based on SHEVP2 hybrid architecture.

The PHEV20, PHEV20T, PHEV50, and PHEV50T resizing algorithms are functionally equal, and differ only in the type of electric mode driving cycle simulated in each (UDDS for PHEV20/20T, or US06 for PHEV50/50T). These algorithms simulate the driving cycles in an iterative loop to determine the size of the electric motors and the battery required to complete the cycles. In the case of PHEV20 and PHEV20T, the power of the electric motors and battery must be sized to propel the vehicle through the UDDS cycle in "charge-depleting (CD) mode"; in this mode, the electric machine alone propels the vehicle except during high power demands, at which point the engine may turn on and provide propulsion assistance. The PHEV50 and PHEV50T motor(s) and battery must be sized to power the vehicle through the US06 cycle in "electric vehicle (EV) mode," where the engine is always off. Then, all PHEV algorithms adjust the battery capacity, or vehicle range, by ensuring the battery energy content is sufficient to complete a simulated UDDS + Highway Fuel Economy Test (HWFET) combined driving cycle, based on EPA-adjusted energy consumption. Finally, the algorithm sizes the engine, electric motor(s), and battery powers accordingly to meet 0-60 and 50-80 mph acceleration targets. All loops are repeated until the acceleration targets are met without needing to resize the electric

[367] Autonomie model documentation, Chapter 6.
[368] Autonomie model documentation, Chapter 8.3.
[369] Battery sizing and the definition of the combined 2-cycle test's AER is discussed in detail in Chapter 6 of the Autonomie model documentation.
[370] Argonne has incorporated SAE J1711, Recommend Practice for Measuring Exhaust Emissions and Fuel Economy of Hybrid-Electric Vehicles, Including Plug-In Hybrid Vehicles, into the Autonomie modeling.

motors, at which point the resizing algorithm finishes. Figure 3-18 below shows the general steps of the PHEV sizing algorithm. Detailed steps can be seen in the Autonomie model documentation.[371]

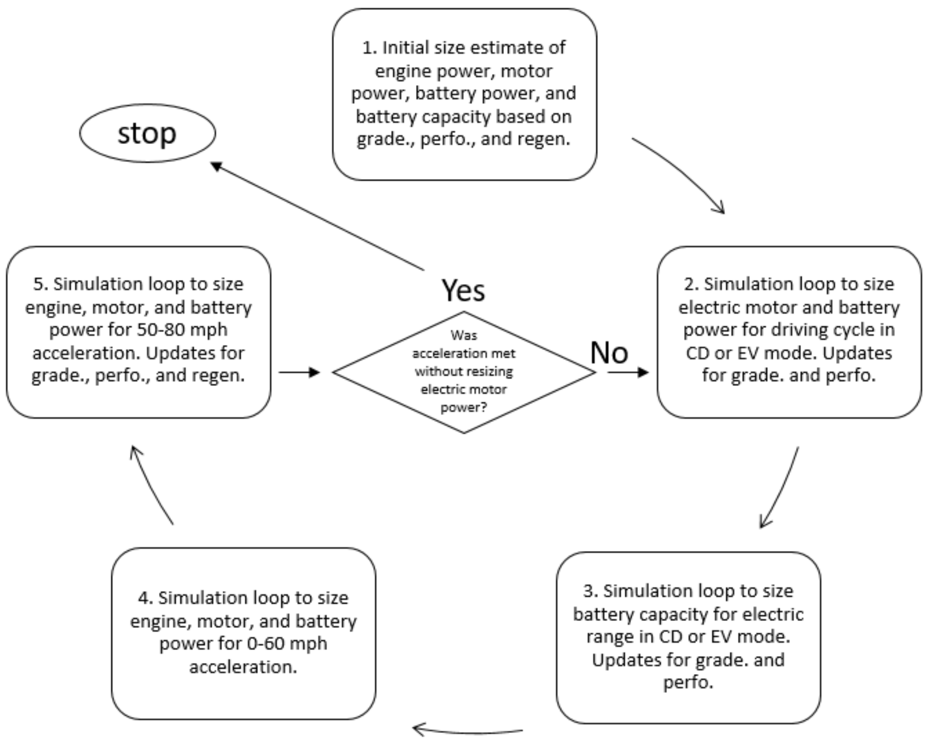

Figure 3-18 – Simplified PHEV Sizing Algorithm in Autonomie

Table 3-61 below shows a summary of PHEV components and denotes if they are eligible to be resized in the Autonomie sizing algorithm. As discussed earlier, the Autonomie sizing algorithm is automated and any change in one of the component checks in the steps shown in Figure 3-18 requires the components to be revaluated and sized appropriately.

Table 3-61 – Summary of Components that Could Resize as Part of PHEV Sizing Algorithm

	IC Engine	Electric Motor	Battery Power	Battery Capacity
PHEV20	Inherited from sized conventional vehicle and resized	Resized	Resized	Resized
PHEV50	Inherited from sized conventional vehicle and resized	Resized	Resized	Resized

371 Autonomie model documentation, Chapter 8.3.4-8.3.6.

PHEV20T	Inherited from sized conventional vehicle and not resized	Resized	Resized	Resized
PHEV50T	Inherited from sized conventional vehicle and not resized	Resized	Resized	Resized

3.3.4.6 Battery Electric Vehicles

The effectiveness of BEVs is dependent on the efficiency of the components that transfer power from the battery to the driven wheels. These components include the battery, electric machine, power electronics, and mechanical gearing. For this analysis, we use efficiency maps from production vehicles to calculate electric machine efficiency and scale the electric machine efficiency such that the peak efficiency value corresponds to the latest state-of-the-art technologies. The range of a BEV in the analysis depends on the vehicle's class and the battery pack size.

An important note about Autonomie's BEV model is that it does not simulate any one manufacturer's technology, architecture, battery pack, thermal, or SOC control strategies. Those BEV characteristics are unique for each manufacturer's vehicle models. And, like many other parts of this analysis, these technology models in Autonomie are discrete representative designs. Accordingly, the absolute MPGe from Autonomie could vary significantly compared to production vehicles in the market in the rulemaking time frame.[372]

Another important note about BEVs in this analysis is that the effectiveness of a BEV built in the CAFE Model is independent of the effectiveness of the conventional powertrain it replaces. As vehicles adopt BEV technology, the CAFE Model uses the Autonomie databases to determine the added incremental efficiency that will bring a specific vehicle up to the appropriate fuel economy level that allows the manufacturer's fleet to achieve compliance. Since the CAFE Model considers a variety of vehicle types with differing powertrain types, vehicle technology classes, performance criteria, and physical properties (curb weight, etc.), each with a different overall effectiveness, the efficiency increment needed to achieve BEV effectiveness will vary with each case. The effectiveness used in the CAFE Model represents the difference between the performance of the full vehicle models' simulations—the full vehicle model representing the baseline vehicle and the full vehicle model representing the end-state—with all additional fuel economy improving technology applied, as we discuss in Chapter 2.4.

As we discuss in Chapter 3.3.1, Autonomie follows EPA regulatory guidance using the SAE J1634 test procedure to determine incremental effectiveness for BEVs in the CAFE Model analysis. The procedure from this guidance uses the multi-cycle test (MCT) method from SAE

[372] Paul Seredynski (2010-12-21). "Decoding Electric Car MPG: With Kilowatt-Hours, Small Is Beautiful". Edmunds.com. Retrieved 2011-02-17. https://www.edmunds.com/fuel-economy/decoding-electric-car-mpg.html. (Accessed: February 15, 2022).

J1634. Autonomie's BEV model starts with the battery at full charge or maximum SOC, and simulates the vehicle on the MCT until the battery is empty or has reached a minimum SOC.[373]

The resizing algorithm for BEVs is functionally the same as the PHEV algorithm, however, BEVs do not use a combustion engine, and thus the BEV algorithm does not include this component. The model calculates initial estimates of motor and battery powers based on acceleration performance, gradeability performance, and vehicle range. Then, the algorithm successively runs four simulation loops to finetune the powertrain size to ensure that all performance and operational criteria are maintained. First, the BEV motor and battery are sized to power the vehicle through the US06 cycle. Next, the battery capacity is adjusted to ensure the energy content is sufficient to complete a simulated UDDS+HWFET combined driving cycle, based on EPA adjustment factors to represent sticker values, and to meet the vehicle range requirement. Finally, the electric motor and battery powers are sized to meet 0-60 and 50-80 mph acceleration targets. If either acceleration simulation loop results in a change to the electric motor size, the algorithm repeats all simulation loops. The algorithm finishes once the acceleration targets are met without resizing the electric motors. Figure 3-19 below shows a simplified sizing algorithm for BEVs.

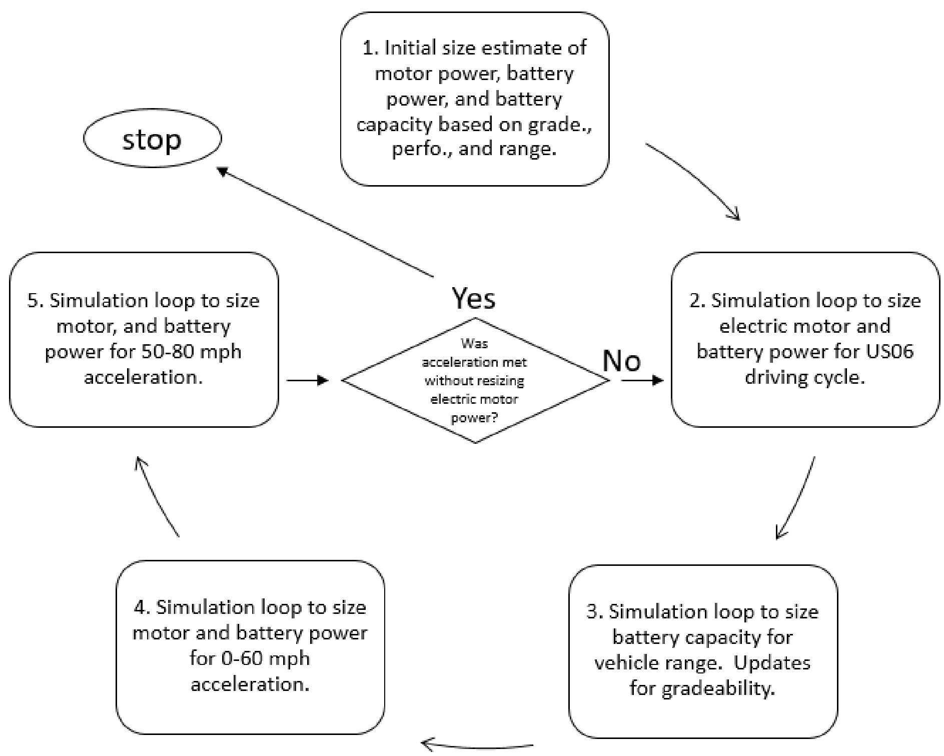

Figure 3-19 – Simplified BEV Sizing Algorithm in Autonomie

For further detailed discussion of how Autonomie simulates BEVs, see the Autonomie model documentation.[374]

[373] The minimum and maximum SOC for BEVs in this analysis is 5 to 95 percent.
[374] Autonomie model documentation, Chapters 4.6, 4.7, 4.13, 4.14, and 5.8.

3.3.4.7 Fuel Cell Electric Vehicles

The fuel-cell system in the analysis is modeled to represent hydrogen consumption as a function of the produced power, assuming normal-temperature operating conditions with a peak system efficiency of 64 percent. The system's specific power is 860 W/kg. The hydrogen storage technology selected is a high-pressure tank with a specific weight of 0.04 kg H_2/kg, sized to provide a 320-mile range on the 2-cycle tests on the basis of adjusted energy values.

The sizing algorithm for FCEVs is similar to PHEVs and BEVs, but is adapted for the specific components of a FCEV powertrain: the electric motor, fuel-cell, hydrogen (H_2) fuel tank, and battery pack. During very low power operation, the battery pack alone powers the motor/wheels, depleting the battery charge. At moderate driving loads, the fuel cell provides electrical power (generated by consuming stored H_2) to the motor and also to charge the battery. Under heavy loads, both the fuel cell and battery deliver electric power to the motor.

To begin the FCEV sizing algorithm, the model calculates initial estimates of motor, fuel cell, and battery powers based on criteria for acceleration, gradeability, and vehicle range. The algorithm successively runs four simulation loops to finetune powertrain size, ensuring that all performance and operational criteria are maintained. First, the FCV motor and battery are sized to power the vehicle through the US06 cycle. Next, the model adjusts the on-board mass of H_2 fuel, as well as the fuel tank mass, to ensure the vehicle can complete a simulated 2-cycle test and meet the range requirement. Finally, the algorithm sizes the electric motor and fuel cell powers accordingly to meet 0-60 and 50-80 mph acceleration targets. If either acceleration simulation loop results in a change to the electric motor size, the algorithm repeats all simulation loops. Once the acceleration targets are met without resizing the electric motor, the algorithm completes. Figure 3-20 below shows a simplified sizing algorithm for FCVs.

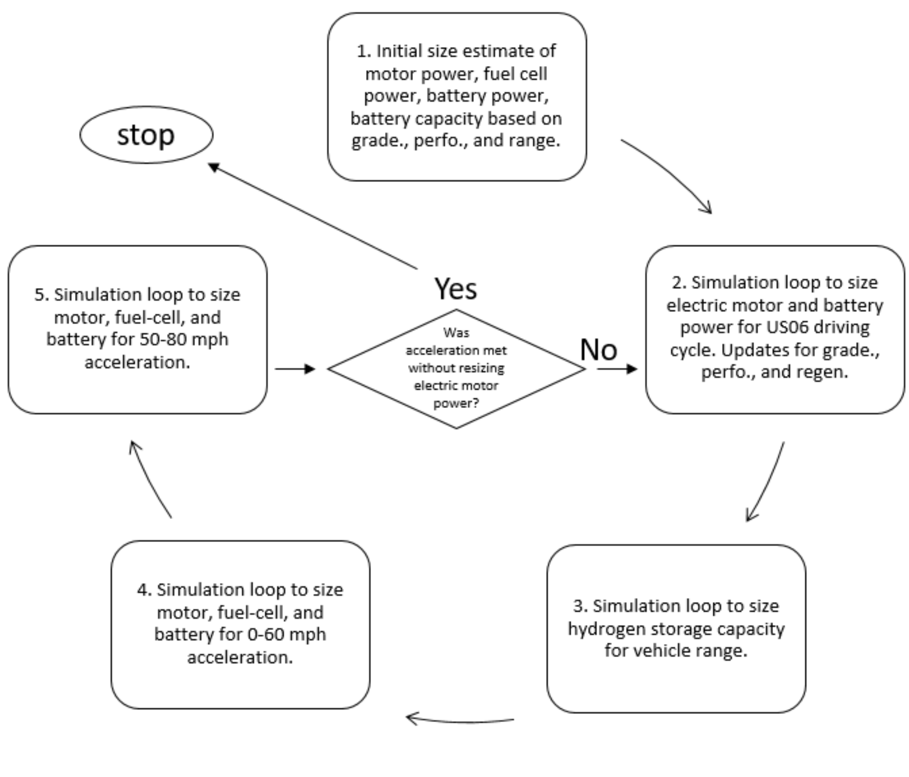

Figure 3-20 – Simplified Fuel Cell Vehicle Sizing Algorithm

3.3.5 Electrification Costs

The total cost to electrify a vehicle in this analysis is based on the battery the vehicle requires, the non-battery electrification component costs the vehicle requires, and the traditional powertrain components that must be added or removed from the vehicle to build the electrified powertrain.

3.3.5.1 Battery Pack Modeling

We work collaboratively with the experts at Argonne National Laboratory to generate battery costs using BatPaC, which is a model designed to calculate the cost of a vehicle battery for a specified battery power, energy, and type. Argonne uses BatPaC to create lookup tables for battery cost and mass that the Autonomie simulations reference when a vehicle receives an electrified powertrain. The BatPaC battery cost estimates are generated for a base year, in this case for MY 2020. Accordingly, the BatPaC inputs fairly characterize the state of the market in MY 2020, including with a widely-utilized cell chemistry, average estimated battery pack production volume per plant, and plant efficiency (*i.e.*, plant cell yield). For two specific electrified vehicle applications, BEV400 and BEV500, we do not use BatPaC to generate battery pack costs. Rather, we scale the BatPaC-generated BEV300 costs to match the range of BEV400 and BEV500 vehicles to compute a direct manufacturing cost for those vehicles' batteries.

To reflect how we expect batteries could lower in cost over the timeframe considered in the analysis, we apply a learning rate to the direct manufacturing cost. Broadly, the learning rate that we apply to batteries reflects middle-of-the-road year-over-year improvements until MY 2032, and then the learning rates incrementally become shallower as battery technology is expected to mature in MY 2033 and beyond. We performed additional analysis with BatPaC to confirm that these learning rates are reasonable for this analysis, and this is described in detail below.

The following sections discuss Argonne's process for generating battery pack direct manufacturing costs, our scaling for BEV400 and BEV500 costs, and the learning rate for battery pack costs.

3.3.5.1.1 Battery Pack Costs from BatPaC

BatPaC is a software designed for policymakers and researchers interested in estimating the manufacturing cost of lithium-ion batteries for electric drive vehicles.[375] The model provides data needed to design and build a battery pack, such as dimensions of the cell, estimate of materials, and manufacturing cost, with the manufacturing costs based on a "baseline plant" designed for a battery of intermediate size and production scale. A user can configure BatPaC with alternative chemistries, charging constraints, battery configurations, production volumes, and cost factors for other battery designs by customizing these parameters in the modeling tool. BatPaC calculations are based on a generic pack design that reasonably represents the weight and

[375] BatPaC: Battery Manufacturing Cost Estimation, Argonne National Laboratory, https://www.anl.gov/tcp/batpac-battery-manufacturing-cost-estimation. (Accessed: February 15, 2022).

manufacturing cost of batteries deployed commercially. The advantage of using this approach is the ability to model a wide range of commercial design specifications for various classes of vehicles.

For this analysis, we use BatPaC version 4.0 (October 2020 release) to estimate the battery cost for electrification technologies.[376] Similar to past rulemaking analyses, running individual BatPaC simulations for each full vehicle simulation requiring an electrified powertrain would have been computationally intensive and impractical, given that approximately 750,000 simulated vehicles out of the 1.1 million total simulated vehicles have an electrified powertrain. Accordingly, Argonne staff builds "lookup tables" with BatPaC to provide battery pack manufacturing costs, battery pack weights, and battery pack cell capacities for vehicles modeled in the large-scale simulation runs.

Figure 3-21 illustrates the inputs generated in Autonomie to create the BatPaC-based lookup tables, and the outputs characterized in the BatPaC-based lookup tables that are used to provide estimates referenced in this analysis. The peak power requirement or total energy requirement from the Autonomie simulations is used as an input to the BatPaC model, and outputs from the model include cost, mass, pack capacity, and voltage.

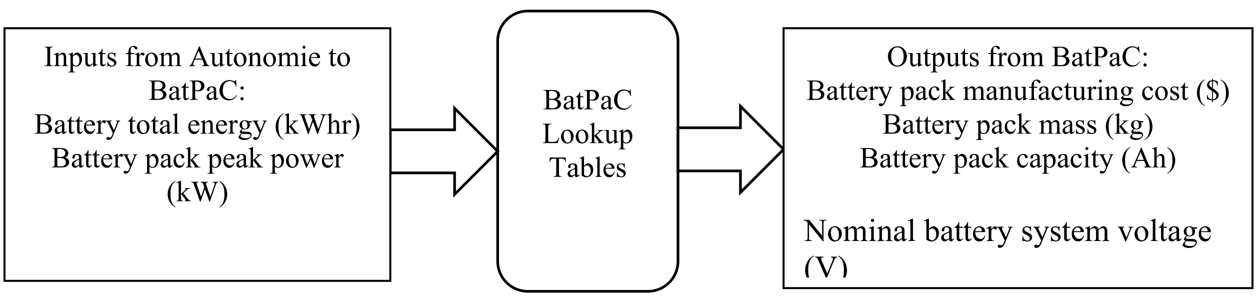

Figure 3-21 – Flowchart Showing How Autonomie Calls BatPaC Look-up Tables

While manufacturers' battery pack specifications are highly heterogeneous in the real world, we endeavor to develop battery pack costs that fairly encompass the cost of battery packs for vehicles in each technology class with a direct manufacturing cost (DMC) base year of MY 2020. As detailed in the BatPaC model documentation, the costs of materials, labor, and capital equipment in the model are based upon Argonne's estimates of 2018 values, "[t]hus, if BatPaC is used to calculate the current costs of batteries at current production levels (say 30,000 all-electric (BEV) packs per year) we expect it to provide good estimates of current battery prices to OEMs. Estimates done for ten years in the future should be at production levels of 100,000 to 500,000

[376] Nelson, Paul A., Ahmed, Shabbir, Gallagher, Kevin G., and Dees, Dennis W. Modeling the Performance and Cost of Lithium-Ion Batteries for Electric-Drive Vehicles, Third Edition (ANL/CSE-19/2), available at https://publications.anl.gov/anlpubs/2019/03/150624.pdf. (Accessed: February 15, 2022). To request the BatPaC model used in this analysis, submit the request using the instructions at https://www.anl.gov/cse/batpac-model-software. (Accessed: February 15, 2022).

units per year, which will result in lower pack prices because of the assumed increase in the degree of plant automation."[377]

We used vehicle teardown reports to determine commonly-utilized battery pack chemistries for each modeled electrification technology. In addition, we looked at vehicle sales volumes in MY 2020 to determine a reasonable base production volume assumption. The Autonomie model documentation details other specific assumptions that Argonne uses to simulate battery packs and their associated costs for the full vehicle simulation modeling, including updates to the battery management unit costs, and the range of power and energy requirements used to bound the lookup tables.[378] We discuss specific considerations for three notable BatPaC specifications – battery cell chemistry, plant production volume, and cell yield – in turn, below.

Applying learning curves to the battery pack DMC in subsequent analysis years lowers the cost such that the cost of a battery pack in any future model year could be representative of the cost to manufacture a battery pack, regardless of potentially diverse parameters such as cell chemistry, cell format (*e.g.*, cylindrical, prismatic, or pouch), or production volume. Our assumptions for battery pack learning curves are discussed in detail following the discussion of BatPaC inputs and assumptions.

3.3.5.1.1.1 Battery Cell Chemistry

We use three different cell chemistries to establish initial battery pack costs.[379] We select cell chemistries based on the type of electrified powertrain. To determine which chemistries reasonably represent manufacturer's packs for different vehicle types in MY 2020, we and Argonne survey industry trends, current and future battery cell chemistry, and vehicles in the A2Mac1 database, a widely-used industry database that has component level information of the vehicles in the marketplace,[380] in addition to other reports. The Autonomie model documentation includes more detail about the reports referenced for this analysis.[381] Table 3-62 shows the battery chemistries that we use by electrification technology for this analysis.

Table 3-62 – Battery Chemistries Assumed by Applications

Electrification Technology	Battery Chemistry
Micro HEV	AGM
Mild HEV	LFP
HEV	NMC622
PHEV	NMC622
BEV	NMC622

[377] *Id*. at pp. 1-2.
[378] Autonomie model documentation, Chapter 5.9.
[379] As discussed below, a cost reduction is built into the battery pack learning curve that assumes potential changes to battery chemistry in later years.
[380] A2Mac1: Automotive Benchmarking. (Proprietary data). Retrieved from https://portal.a2mac1.com/. (Accessed: February 15, 2022).
[381] Autonomie model documentation, Chapter 5.9.

As we discuss further in Chapter 3.3.5 below, we use a lower cost SS12V (micro HEV) battery based on absorbed-glass-mat (AGM) chemistry for this analysis, which is more widely used in the industry. The cost is fixed across vehicle classes, and we did not develop this cost in BatPaC. For mild HEVs we use the LFP-G[382] chemistry because power and energy requirements for mild hybrids are very low, the charge and discharge cycles are high, and the battery raw materials are much less expensive than a nickel manganese cobalt (NMC)-based cell chemistry.

We use NMC622-G for all other electrified vehicle technology initial battery pack cost calculations.[383] We recognize there is ongoing research and development in several battery chemistry options that may have the potential to reduce costs and increase battery capacity. However, in this analysis, we account for the potential cost savings for *future* battery cell chemistries in the learning rate cost reduction. As discussed above, the battery chemistry we use is intended to reasonably represent what is in use in MY 2020, the DMC base year for our BatPaC calculations. As discussed further in the Autonomie model documentation, Argonne references battery cell teardown analysis reports from the A2Mac1 database and Total Battery Consulting to evaluate different assumptions for the different modeled electrification technologies. Of the five fully electrified vehicles surveyed for this analysis, four of those vehicles use NMC622, and one uses NMC532-G.[384]

Stakeholders had commented to the 2020 final rule that batteries using NMC811 chemistry had either recently come into the market or was imminently coming into the market, and therefore we should have selected NMC811 as the appropriate chemistry for modeling battery pack costs. Similar to the other technologies considered in this analysis, we endeavor to use technology that is a reasonable representation of what the industry could achieve in the model year or years under consideration, in this case the base DMC year of 2020, as discussed above. At the time of this current analysis, the referenced A2Mac1 teardown reports and other reports provide the best available information about the range of battery chemistries actually employed in the industry. At the time of writing, we have still not found examples of NMC811 in commercial application across the industry in a way that we believe selecting NMC811 would have represented industry average performance in MY 2020. As discussed in Chapter 3.3.5.1.4, we did analyze the potential future cost of NMC811 in the composite learning curve generated to ensure the battery learning curve projections are reasonable.

3.3.5.1.1.2 Battery Plant Production Volume

In practice, a single battery plant can produce different battery packs with either different cell chemistries or with the same cell chemistries with different power, energy, and thermal strategies (for example, with the Hyundai Kona and Hyundai Ioniq, see Table 3-64 below). However, in BatPaC, a battery plant is assumed to manufacture and assemble a specific battery pack design, and all cost estimates are based on one single battery plant manufacturing only that specific battery pack. For example, if a manufacturer has more than one EV and each uses a specific battery pack design, a BatPaC user would include manufacturing volume assumptions for each

[382] Lithium Iron Phosphate ($LiFePO_4$).
[383] Lithium Nickel Manganese Cobalt Oxide ($LiNiMnCoO_2$).
[384] Autonomie model documentation, Chapter 5.9.2.3.

design separately to represent each plant producing each specific battery pack. As a consequence, we examine battery pack designs for vehicles sold in MY 2020 to determine a reasonable manufacturing plant production volume assumption. We consider each assembly line and material processing designed for a specific battery pack and for a specific EV as an individual battery plant. Since battery technologies are still evolving, it is likely to be some time before battery cells can be treated as commodity where in the specific numbers of cells are used for varying battery pack requirements and everything else remains the same. Table 3-63 shows the assumed baseline battery manufacturing plant production volume for this analysis.

Table 3-63 – Battery Manufacturing Plant Production Volume Assumption for Different Electrification Technologies

Technology	Production Volume
Mild Hybrid	100,000
HEV	100,000
PHEV20	25,000
PHEV50	25,000
BEV200	25,000
BEV300	25,000

Similar to the 2020 final rule, we use BEV sales as a starting point to analyze potential base modeled battery manufacturing plant production volume assumptions, as actual production data for specific battery manufacturing plants are extremely hard to obtain. We associate the production volume of individual battery packs designed for specific BEVs to the sales volume of those specific BEVs because, as explained above, BatPaC assumes that each battery plant produces a specific battery pack design.

We observe battery pack designs for BEVs sold both in the U.S and globally. Manufacturers design BEVs to suit local or regional duty cycles, customer preferences, affordability, supply constraints, and local laws. As a consequence, BEVs sold in the United States may have different performance metrics and battery technology compared to same BEV sold in other parts of the world. For example, the U.S. Tesla Model 3 and Model Y battery packs use a lithium nickel cobalt aluminum oxide (NCA)-based cell,[385] and the same vehicles for sale in China use LFP-G-based packs.[386] Even though the battery packs are built for the same vehicle model, the battery packs will likely have different costs due to the different cell chemistries.[387] In addition to cost differences due to different chemistries, the total battery capacity, battery pack design, vehicle range, battery pack mass, charge and discharge cycles, end of life, and other parameters differ across markets. As a result, we consider U.S. sales and not global sales when estimating battery pack production volume.

[385] Nickel Manganese Cobalt Aluminum.
[386] *See* Electric Vehicle Database, Tesla Model 3 Standard Range Plus LFP, https://ev-database.uk/car/1320/Tesla-Model-3-Standard-Range-Plus-LFP. (Accessed: February 15, 2022).
[387] For example, BatPaC estimates the cost of LFP-G to be 15 to 20 percent cheaper than a similarly sized NCA-based cell chemistry battery pack.

Table 3-64 shows the production volume, cell size, cell format and available battery pack information for MY 2020 EVs sold in the United States, using sales volume data from the MY 2020 Market Data file used in this analysis (sales volumes for all models aggregated by nameplate). Review of Table 3-64 shows there is no standardization of the cell size, total energy, or the pack size across different vehicle manufacturers, or even between different BEVs under the same manufacturer.[388] Each battery pack is custom designed and sized to account for vehicle performance, vehicle class, and packaging space. Therefore, to align with the BatPaC assumption that a plant would only produce battery packs of one specific design, using sales volume data for each nameplate, because each nameplate uses a different battery pack design, provided a reasonable baseline. As seen in Table 3-64, averaging MY 2020 BEV production volume results in an average production volume of 16,995, which is lower than our assumption of 25,000 units for the plant.

In selecting a battery pack manufacturing volume estimate that would be representative for an industry-wide assessment, we sought to accurately account for both the production volumes and representative practices of the industry. Ongoing reductions in battery cost based on increasing manufacturing volumes in future model years is discussed in Chapter 3.3.5.1.4.

Table 3-64 – MY 2020 BEVs by Cell Type and Production Volume

Vehicle	Cell Type	MY 2020 Production Volume	Number of cells in battery pack	No. of cells in each module	Total no. of modules	Cell size (millimeters)	Total Energy (kWh)
Porsche Taycan	Pouch	4,394	396	12	33		79.2
Audi e-tron	Pouch	793	432	12	36	326 x 96 x 11	95
Chevrolet Bolt	Pouch	28,197	288	24 (2 modules) + 30 (8 modules)	10	261 x 97 x 13	60
Hyundai Kona	Pouch	6,003	288	180 (5modlues) + 30 (8 modules)	10	263 x 93 x 14	64
Hyundai Ioniq	Pouch	2,300	180	30	6		39
Jaguar I-Pace	Pouch	1,858	432	12	36	286 x 98 x 11.4	90
Nissan Leaf	Pouch	11,558	196	8	24	261 x 216 x 7.91	40
Daimler EQC	Pouch	258	384	48, 72	2, 6		80
BMW i3	Prismatic	1,529	96	12	8	174 x 45 x 126	40

[388] *See* Gustavo Henrique Ruffo, Tesla Model Y Battery Pack Is Different From Model 3: Check Out How It Differs, Inside EVs (April 23, 2020), https://insideevs.com/news/414440/tesla-model-y-battery-different-model-3s/; Kyle Field, Tesla Model 3 Battery Pack & Battery Cell Teardown Highlights Performance Improvements, Clean Technica (January 28, 2019), https://cleantechnica.com/2019/01/28/tesla-model-3-battery-pack-cell-teardown-highlights-performance-improvements. (Accessed: February 15, 2022). For example, while both the Tesla Model 3 and Model Y use the same cylindrical cell format 2170, the battery pack is not identical. There are a number of differences in the battery pack used in the Model Y, such as a protective cover for fuses, caps on the safety switch for high voltage terminals, foam pack around outside edge of battery pack, among other differences. Similarly, in the Model S/X, the battery pack uses a serpentine cooling system that routes cooling fluids through the battery pack, whereas in the Model 3, the cooling system is a manifold base that has dedicated cooling channels between each row of cells. Model X has dual motors as standard equipment and hence energy (kWh) unlocked from the battery pack is more than Model S.

Mini Cooper	Pouch	468					42
Kia Niro	Pouch	965	294	27 (2 modules) + 30 (8 modules)	10	98 x 301 x 14.7	39
Tesla Model S	Cylindrical 18650	14,000	6,216	84	74	18 diameter x 65	60
Tesla Model X	Cylindrical 18650	20,000	6,216	84	74	18 diameter x 65	70
Tesla Model 3	Cylindrical 2170	106,000	2,976	96	31	21 diameter x 65	50
Tesla Model Y	Cylindrical 2170	56,000	2,976	96	31	21 diameter x 65	75
Total		254,323					
Average		16,955					

Subsequent to the publication of the proposed rule for MYs 2024-2026, DOE released a report titled “Lithium-ion Battery Supply Chain for E-Drive Vehicles in the United States: 2010-2020.”[389] One table in the report shows the battery cell manufacturer, battery pack manufacturer, battery size (total energy), and production volume for several vehicle makes and models.[390] This table is similar to our Table 3-64, above, but has added information for the battery cell manufacturer and the battery pack manufacturer. The table in the report shows that the battery cell manufacturer is not always the battery pack manufacturer, and as shown in Table 3-64, a battery pack is unique for each BEV. As stated above, each battery pack is custom designed to meet performance characteristics, such as initial launch speed, passing speed, range, cold weather performance, thermal management, both battery and occupant safety, packaging, and cost, among other characteristics. Further, the report shows the average BEV production volume for model years 2018 to 2020 is 12,235, which is considerably less than 25,000 units assumed for a plant and a lower estimate than our 16,995 average presented above.

DOE’s report also provides battery cell and battery pack manufacturing capacity across different countries. For the BEVs sold in the United States, a considerable portion of the battery pack is manufactured and assembled in the United States, with the next major battery pack manufacturers supplying the U.S. fleet being Germany, Japan, and South Korea.[391] The report indicated the progression of battery pack production capacity in the U.S in GWh over time. Based on DOE’s estimates of production capacity, we can estimate that there is an approximate difference in pack production of 25,000 packs between years.[392] This updated production data

[389] Lithium-Ion Battery Supply Chain for E-Drive Vehicles in the United States: 2010-2020, ANL/ESD-21/3

[390] Table B-1 (page 66 of the report: Lithium-Ion Battery Supply Chain for E-Drive Vehicles in the United States: 2010-2020). This table shows all BEVs from 2010-2020, including the BEVs that are no longer in production. For our analysis, only the models from 2018-2020 that are in production are considered.

[391] Figure ES-1 in the report titled “Lithium-Ion Battery Supply Chain for E-Drive Vehicles in the United States: 2010-2020.”

[392] The numbers in the column under U.S. is plotted and linear curve fit is generated. The equation for the linear curve fit is used to calculate average battery pack production capacity. The values were converted from GWh to kWh and then divided by 75kWh to generate number of battery packs (one battery pack equal to one vehicle). The differences in the production volume between the years were calculated to arrive at 23,380.

from DOE provides another reference point for our 25,000-unit per plant production volume estimate.

3.3.5.1.1.3 Cell Yield Assumptions

Manufacturing plant efficiency is another parameter important to estimate battery pack costs. BatPaC version 4.0 defines manufacturing plant efficiency in terms of cell yield, or the number of cells that are usable out of the total number of cells that the plant produces.[393] An advanced and mature battery manufacturing plant can be expected to produce greater than 95 percent good cells, and a cell yield of 95 percent is suggested as a default value in BatPaC as a forward-looking estimate. Because battery pack technology and battery pack manufacturing processes are proprietary, however, the data on plant efficiencies are not widely reported. We continue to use the 95 percent value for this analysis and will explore acquiring additional data on cell yield for future analyses.

3.3.5.1.2 BEV400 and 500 Battery Pack Costs

New for the NPRM and carried into this analysis are the BEV400 and BEV500 technologies. We initially examined using BatPaC to model the cost and weight of battery packs for BEV400 and BEV500s, however, initial values from the model could not be validated and were based on assumptions for smaller sized battery packs. The initial results provided cost and weight estimates for BEV400 battery packs out of alignment with current examples of BEV400s in the market, and there are currently no examples of BEV500 battery packs in the market against which to validate the pack results.

As a result, we use a modified form of an analogous estimate to determine the longer-range battery pack costs. To generate the costs for BEV400 and BEV500 battery packs, we scale the BatPaC-generated costs for BEV300s proportional to the range for BEV400 and BEV500 vehicles. Simply put, the initial costs for the BEV400 battery pack equal 4/3 times the cost of the BEV300 battery, and the initial costs for a BEV500 battery pack equal 5/3 times the cost of the BEV300 battery. The analogous initial costs then have the same learning curve applied, as discussed in Chapter 3.3.5.1.4, to determine costs in future model years.

3.3.5.1.3 Battery Pack Direct Manufacturing Costs

The following tables show battery pack costs for HEV, PHEV20, PHEV50, BEV200 and BEV300 for all vehicle technology classes. The tables shown here demonstrate how the cost per kWh varies with the size of the battery pack. While the overall cost of a battery pack will go up for higher kWh battery packs, the cost per kWh goes down. This represents the cost of hardware that is needed in all battery packs, but is deferred across more kWh in larger packs, which reduces the per kWh cost.

The full range of BatPaC-generated battery direct manufacturing costs is located in ANL_BatPac_Lookup_tables_Feb2021v2.xlsx. Note that these charts represent the direct

[393] Cells might not be usable because of, for example, manufacturing defects, among other reasons.

manufacturing cost using a dollar per kWh metric; battery absolute costs used in the analysis by technology key can be found in the Battery Cost file.

Table 3-65 – HEV Battery Pack Costs - Compact to Midsize

$/kW at Pack Level (Total Energy) for Compact to Midsize Vehicle Technology Class													
HEV		Energy, kWh											
		0.9	1.0	1.2	1.4	1.6	1.8	2.0	2.2	2.4	2.6	2.8	3.0
Power, kW	10.0	$105	$106	$108	$110	$112	$114	$116	$117	$119	$121	$123	$124
	20.0	$55	$56	$57	$58	$59	$59	$60	$61	$62	$63	$64	$65
	30.0	$39	$39	$39	$40	$41	$41	$42	$42	$43	$44	$44	$45
	40.0	$31	$31	$31	$31	$32	$32	$33	$33	$34	$34	$34	$35
	60.0				$23	$23	$23	$24	$24	$24	$24	$25	$25
	80.0						$19	$19	$19	$19	$20	$20	$20
	100.0								$17	$17	$17	$17	$17

Table 3-66 – HEV Battery Pack Costs - SUV to Pickup

$/kW at Pack Level (Total Energy) for SUV to Pickup Vehicle Technology Class													
HEV		Energy, kWh											
		0.9	1.0	1.2	1.4	1.6	1.8	2.0	2.2	2.4	2.6	2.8	3.0
Power, kW	10.0	$123	$124	$126	$128	$130	$132	$134	$135	$137	$139	$141	$142
	20.0	$64	$64	$65	$66	$67	$68	$69	$70	$71	$71	$72	$73
	30.0	$44	$44	$45	$45	$46	$47	$47	$48	$48	$49	$50	$50
	40.0	$34	$35	$35	$35	$36	$36	$37	$37	$37	$38	$38	$39
	60.0			$25	$25	$25	$26	$26	$26	$26	$27	$27	$27
	80.0						$20	$21	$21	$21	$21	$21	$21
	100.0								$18	$18	$18	$18	$18

Table 3-67 – Battery Costs for PHEV20 – Compact to Midsize

$/kW at Pack Level (Total Energy) for Compact to Midsize Vehicle Technology Class				
PHEV20		Energy, kWh		
		5.0	10.0	20.0
Power, kW	30.0	$518	$321	$219
	40.0	$522	$323	$219
	60.0	$531	$326	$221
	80.0	$560	$329	$222

$/kW at Pack Level (Total Energy) for Compact to Midsize Vehicle Technology Class				
PHEV20		Energy, kWh		
		5.0	10.0	20.0
	100.0	$574	$334	$224
	120.0	$589	$340	$226
	140.0	$614	$352	$227
	160.0	$641	$362	$229
	200.0		$383	$233
	240.0		$402	$242
	280.0		$427	$250

Table 3-68 – Battery Packs costs for PHEV20 – SUV to Pickup

$/kWh at Pack Level (Total Energy) for SUV to Pickup Vehicle Technology Class				
PHEV20		Energy, kWh		
		5.0	10.0	20.0
Power, kW	30.0	$562	$339	$228
	40.0	$565	$340	$228
	60.0	$573	$343	$230
	80.0	$592	$346	$231
	100.0	$605	$349	$232
	120.0	$619	$361	$234
	140.0	$642	$366	$235
	160.0	$668	$375	$237
	200.0		$395	$240
	240.0		$413	$248
	280.0		$437	$255

Table 3-69 – Battery Pack Costs for PHEV50 – Compact to Midsize

$/kWh at Pack Level (Total Energy) for Compact to Midsize Vehicle Technology Class							
PHEV50		Energy, kWh					
		10.0	20.0	30.0	40.0	50.0	60.0
Power, kW	60.0	$419	$266	$213	$186	$169	$158
	80.0	$423	$268	$214	$187	$170	$158
	100.0	$426	$269	$215	$187	$170	$159
	120.0	$431	$271	$216	$188	$171	$159

$/kWh at Pack Level (Total Energy) for Compact to Midsize Vehicle Technology Class							
PHEV50		Energy, kWh					
		10.0	20.0	30.0	40.0	50.0	60.0
	140.0	$437	$272	$216	$189	$171	$160
	160.0	$446	$274	$217	$189	$172	$160
	200.0	$467	$278	$220	$191	$173	$161
	240.0	$485	$284	$222	$192	$174	$162
	280.0	$508	$291	$224	$194	$175	$163

Table 3-70 – Battery Packs Costs for PHEV50 – SUV to Pickup

$/kWh at Pack Level (Total Energy) for SUV to Pickup Vehicle Technology Class							
PHEV50		Energy, kWh					
		10.0	20.0	30.0	40.0	50.0	60.0
Power, kW	60.0	$425	$269	$215	$187	$170	$159
	80.0	$428	$271	$216	$188	$171	$159
	100.0	$431	$272	$216	$189	$171	$160
	120.0	$436	$273	$217	$189	$172	$160
	140.0	$442	$275	$218	$190	$172	$161
	160.0	$451	$276	$219	$191	$173	$161
	200.0	$471	$280	$221	$192	$174	$162
	240.0	$489	$286	$223	$193	$175	$163
	280.0	$512	$293	$226	$195	$176	$164

Table 3-71 – Battery Packs Costs for BEV200 – Compact to Midsize

$/kWh at Pack Level (Total Energy) for Compact to Midsize Vehicle Technology Class					
BEV200		Energy, kWh			
		30.0	50.0	70.0	90.0
Power, kW	20.0	$231	$178	$155	$140
	40.0	$233	$179	$155	$141
	60.0	$234	$180	$156	$141
	80.0	$235	$181	$156	$142
	100.0	$237	$182	$157	$142
	120.0	$238	$182	$157	$143
	140.0	$240	$183	$158	$143
	160.0	$241	$184	$159	$143
	180.0	$243	$185	$159	$144
	200.0	$244	$186	$160	$144
	240.0	$248	$188	$161	$145

Table 3-72 – Battery Packs Costs for BEV200 – SUV to Pickup

$/kWh at Pack Level (Total Energy) for SUV to Pick up Vehicle Technology Class						
BEV200		Energy, kWh				
		30.0	50.0	70.0	90.0	120.0
Power, kW	20.0	$244	$186	$160	$145	$131
	40.0	$245	$187	$161	$145	$132
	60.0	$246	$188	$161	$146	$132
	80.0	$248	$188	$162	$146	$132
	100.0	$249	$189	$162	$146	$132
	120.0	$250	$190	$163	$147	$133
	140.0	$251	$190	$163	$147	$133
	160.0	$252	$191	$164	$147	$133
	180.0	$254	$192	$164	$148	$134
	200.0	$255	$193	$165	$148	$134
	240.0	$258	$194	$166	$149	$134
	280.0	$261	$196	$167	$150	$135
	320.0	$267	$197	$168	$151	$136

$/kWh at Pack Level (Total Energy) for SUV to Pick up Vehicle Technology Class						
BEV200		Energy, kWh				
		30.0	50.0	70.0	90.0	120.0
	400.0	$280	$201	$170	$152	$137

Table 3-73 – Battery Packs Costs for BEV300 – Compact to Midsize

$/kWh at Pack Level (Total Energy) for Compact to Midsize Vehicle Technology Class						
BEV300		Energy, kWh				
		30.0	50.0	70.0	90.0	120.0
Power, kW	20.0	$244	$186	$160	$145	$131
	40.0	$245	$187	$161	$145	$132
	60.0	$246	$188	$161	$146	$132
	80.0	$248	$188	$162	$146	$132
	100.0	$249	$189	$162	$146	$132
	120.0	$250	$190	$163	$147	$133
	140.0	$251	$190	$163	$147	$133
	160.0	$252	$191	$164	$147	$133
	180.0	$254	$192	$164	$148	$134
	200.0	$255	$193	$165	$148	$134
	240.0	$258	$194	$166	$149	$134

Table 3-74 – Battery Packs Costs for BEV300 – SUV to Pickup

$/kWh at Pack Level (Total Energy) for SUV to Pickup Vehicle Technology Class								
BEV300		Energy, kWh						
		30.0	50.0	70.0	90.0	120.0	140.0	160.0
Power, kW	20.0	$252	$191	$164	$148	$133	$127	$122
	40.0	$253	$192	$164	$148	$133	$127	$122
	60.0	$254	$193	$165	$148	$134	$127	$122
	80.0	$255	$193	$165	$149	$134	$127	$122
	100.0	$257	$194	$166	$149	$134	$128	$122
	120.0	$258	$194	$166	$149	$134	$128	$123
	140.0	$259	$195	$167	$150	$135	$128	$123
	160.0	$260	$196	$167	$150	$135	$128	$123
	180.0	$261	$196	$167	$151	$135	$129	$123
	200.0	$262	$197	$168	$151	$135	$129	$123
	240.0	$265	$198	$169	$152	$136	$129	$124
	280.0	$268	$200	$170	$152	$136	$130	$124
	320.0	$273	$201	$171	$153	$137	$130	$125
	400.0	$286	$204	$173	$155	$138	$131	$125

3.3.5.1.4 Battery Pack Learning Curves

A battery pack constitutes 20 percent to 30 percent of the vehicle curb weight and up to one third the cost of battery electric vehicles.[394] As a consequence of the rapid changes in battery materials, production, and other factors, there is inherent uncertainty in estimating the cost of future battery packs.

We continue to use the battery learning curves developed using BatPaC for the 2018 NPRM and 2020 final rule.[395] For the 2018 NPRM, we had used BatPaC v3.0 to model costs for a range of battery production volume inputs. The range of production volumes were selected to represent estimated volumes of production for MY 2015, MY 2020, MY 2025. We identified the change in cost for the estimated changes in production volumes linked to model years and used this rate to develop learning curves out to MY 2032. For MYs 2033 to 2050, we scaled down the learning rate in steps based on literature values and market research. We discussed in the 2020 final rule that this learning curve was intended to be agnostic to future advances in battery chemistry, production volume necessary to achieve economies of scale, or energy density of the battery pack.[396]

[394] Based on review of BEV vehicle curb weight, battery pack mass, and cost information from the A2Mac1 database.
[395] *See* 85 Fed. Reg. 24174, 24510 (Apr. 30, 2020).
[396] *Id*.

We determined this approach was a reasonable method for developing representative learning curves for manufacturing technologies that are currently rapidly changing and uncertain. However, based on stakeholder feedback to the 2020 final rule, we reexamined these learning curves in the NPRM. The learning curve analysis uses a similar approach as the previous learning curve analysis but with updated modeling tools and inputs. The learning curve analysis generates a composite learning curve using BatPaC v4.0 (October 2020 release) and accounts for a range of potential parameters. The analysis discussed in this section did not result in a change to the 2018 NPRM and 2020 final rule learning curve, but confirmed that the ~4.5 percent year over year reduction in battery costs for model years through 2032 reasonably represents a potential future pathway for electric vehicle battery development.

The analysis uses BatPaC to model the input parameters described above – plant production volume, battery chemistry, and cell yield – and their effect on battery cost. While there are a range of parameters that can ultimately influence battery manufacturing cost, including other vehicle improvements (*e.g.*, mass reduction technology, aerodynamic improvements, or tire rolling resistance improvements all effect the size and energy of a battery required to propel a vehicle where all else is equal) and the availability of materials required to manufacture the battery, we believe these parameters have a meaningful influence on the total cost of a battery pack.[397]

We use these parameters to determine a composite learning curve. The composite learning curve here is a blended learning curve that accounts for our best estimate of changes, over time, in production volume, cell chemistry, and plant efficiency. We use the composite learning curve developed here to estimate future battery pack direct manufacturing costs and compare those future costs to estimated future costs from various other sources.

We use the following assumptions as a base for the composite battery learning curve analysis. These assumptions are selected based on existing commercially available technologies and anticipated increases in production volume, and serve as a data "snapshot" representative of the battery technology advancements anticipated in the rulemaking timeframe:

1. The base year production volume assumption is 25,000 battery pack units manufactured in a plant. As explained in Chapter 3.3.5.1.1.2, we use a production volume of 25,000 units in the base year 2020 based on BEV sales in MY 2020. We believe it is reasonable to use sales as a proxy for production volume, as battery packs are generally uniquely designed for each vehicle and likely need unique production lines for each design.

2. Production volume increases linearly in steps of 25,000 units per battery pack design per year per plant. This assumption is based on an analysis of Tesla's historical ramp up of battery pack production. We look at Tesla's U.S. sales volume data for MYs 2012-2017 to determine the rate of increase that a manufacturer could achieve for battery

[397] The cost of raw material also has a meaningful influence on the future cost of the battery pack. As the production volume goes up, the demand for battery critical raw materials also goes up, which has an offsetting impact on the efficiency gains achieved through economies of scale, improved plant efficiency, and advanced battery cell chemistries. We do not consider future battery raw material price fluctuations for this analysis, however that may be an area for further exploration in future analyses. Comments on materials prices are discussed in Section III.D.3.e Electrification Costs of the preamble.

manufacturing year over year.[398] Although Tesla's sales data for MYs 2012-2017 does not increase in a linear fashion, linearizing the data shows an approximately 25,000 unit year over year increase.

3. The cost reduction that results from a production volume increase is only relative to the previous production volume.

4. The ~4.5 percent year over year learning rate is applicable until MY 2032. The learning rates for post-MY 2033 are the same as those used in the 2020 final rule.[399]

5. We anticipate cell chemistry improvements will happen sometime during the middle or later part of this decade. For this analysis we limit the battery cell chemistry selection to NMC622-G and NMC811-G. We acknowledge there are cell chemistries currently being researched that reduce or eliminate cobalt or change the electrolyte from liquid to solid; however, at this time we do not have sufficient data to estimate cost for those advanced battery cell chemistries. Therefore, we assume that for near term (2024-2027) and midterm (2027-2032) cost projection, lithium ion NMC will continue to be the predominant battery cell chemistry.

6. We limit maximum production to 200,000 units per battery pack design, per year, per plant. This assumption is based on the Tesla Gigafactory theoretical maximum capacity of 35 GWh, where there are 2 production lines running for 2 different types of BEVs: one production line of 200,000 units manufacturing a 75 kWh battery pack (similar to the Model 3 with 200 plus mile range) and a second production line of 200,000 units manufacturing an 85 kWh battery pack (similar to the Model Y with 300 plus mile range). The total capacity of the plant would be 32 GWh.

7. We assume a high level of uncertainty in this learning curve analysis and characterize the uncertainties with a sensitivity analysis.

We begin the learning curve analysis by comparing the DMC of battery packs for each battery cell chemistry as a function of production volume for BEV200 vehicles.[400] We assume a baseline production volume of 25,000 units and successive production volume increases are modeled in 25,000 unit increments. The increase in production volumes represent expected increases in production volume each year beyond the base year. See Table 3-75 for the total battery pack costs as a function of production volume for battery packs using NMC622-G cell chemistry. Table 3-76 shows the percentage cost reduction as a function of production volume

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[398] *See* CAFE Public Information Center, Tesla Manufacturer Performance Report, https://one.nhtsa.gov/cafe_pic/cafe_pic_home.htm. (Accessed: February 15, 2022).

[399] For MY 2033 - MY 2035, the learning rate slows from 4.5 percent per year to 4.0 percent per year as production volume reaches 200,000 plus units per year. For MY 2036 - MY 2039, we anticipate a much lower learning rate of 2.0 percent per year as battery technology starts to approach some level of maturity and cost stability and for MY 2039 - MY 2044, the learning rate further slows down to 1.5 percent per year, and finally for MY 2044 - MY 2050, the learning rate is just around 0.3 percent. The rate of reduction in learning rate for the out years from MY 2036 is based on similar learning rate reduction for other commodity fuel saving technology components such as automatic transmissions.

[400] Battery sizes vary based on the other technologies on the vehicle; the tables below assume a vehicle with MR0, ROLL0, and AERO0.

for battery packs using NMC622-G cell chemistry. The DMCs shows that as production volume increases, there is a decrease in battery pack cost.

We assume, across industry, that different battery manufacturing plants are functioning at unique points within the production volume range considered in this learning curve analysis, and each plant is increasing the production volume in subsequent years. In Table 3-76, we calculate the average cost reduction across all vehicle classes to be 3.3 percent year over year as a function of production volume. We average to linearize the cost reduction across all manufacturers and create a value representative of cost reductions for the whole industry, which includes plants first starting at ~25,000 battery packs per year and plants that are already near ~200,000 battery packs per year. For example, battery manufacturing plant A is producing 50,000 units per year and increases production to 75,000 units, achieving a 4.7 percent reduction in cost. Similarly, battery plant B goes from producing 125,000 units to 150,000 units per year, achieving a 1.9 percent reduction in cost. The industry average in this example (considering only 2 plants) would be 3.3 percent. In reality, there are many more plants with different rates of production, however we believe that the resulting overall average cost decrease based on production volume alone of 3.3 percent is reasonable.

The same production volume analysis is repeated using the NMC811-G battery chemistry. The analysis with the new chemistry also shows an overall average cost reduction of 3.3 percent year over year, based on increased production volume. The BatPaC simulation results are shown in Table 3-77 and Table 3-78.

In the second step, the cost reductions when battery cell chemistry changes from NMC622-G to NMC811-G for different levels of production volume are determined and shown in Table 3-79. The change in chemistry results in an average 5.2 percent cost reduction.

Table 3-75 – Battery Pack Direct Manufacturing Cost (DMC) as a Function of Production Volume for BEV200, Non-performance Vehicles, Using NMC622-G as Battery Cell Chemistry

BEV 200 (Non-Performance), Cell Chemistry NMC622-G, Cell Yield 95%[401]									
Year	Production Volume	Compact Car 60 kWh Battery Pack		Medium Car 65 kWh Battery Pack		Medium SUV 82 kWh Battery Pack		Pickup 95 kWh Battery Pack	
		Total Cost	$/kWh	Total Cost	$/kWh	Total Cost	$/kWh	Total Cost	$/kWh
Base Year	25,000	$10,060	$167[402]	$10,581	$163	$12,509	$153	$13,862	$146
Base year +1	50,000	$9,188	$153	$9,683	$149	$11,475	$140	$12,759	$134
Base year + 2	75,000	$8,756	$146	$9,237	$142	$10,959	$134	$12,207	$128
Base year + 3	100,000	$8,478	$141	$8,949	$138	$10,626	$130	$11,850	$125
Base year + 4	125,000	$8,276	$138	$8,742	$134	$10,385	$127	$11,591	$122
Base year + 5	150,000	$8,121	$135	$8,581	$132	$10,198	$124	$11,391	$120
Base year + 6	175,000	$7,995	$133	$8,451	$130	$10,047	$123	$11,228	$118
Base year + 7	200,000	$7,890	$132	$8,342	$128	$9,920	$121	$11,092	$117

Table 3-76 – Percentage Cost Reduction as a Function of Production Volume for BEV200, Non-performance Vehicles, Using NMC622-G as Battery Cell Chemistry

BEV 200 (Non-Performance), Cell Chemistry NMC622-G, Cell Yield 95%					
Year	Production Volume	Compact Car 60 kWh Battery Pack	Medium Car 65 kWh Battery Pack	Medium SUV 82 kWh Battery Pack	Pickup 95 kWh Battery Pack
Base year	25,000	-	-	-	-

[401] The numbers here reflect $/kWh at the pack level and not at the cell level. The total cost of the pack for pickups is higher relative to another vehicle class. Since bigger packs have more cells, the number of cells in production have to increase in proportion to the number of packs, and due to economies of scale achieved for higher number of battery packs, cell cost as measured in $/kWh.

[402] Battery Pack cost in $/kWh, Total Cost/Battery Energy Rating, $10,060/60 = $168/kWh for NMC622-G, Cell Yield of 95 Percent and Production Volume=25,000.

BEV 200 (Non-Performance), Cell Chemistry NMC622-G, Cell Yield 95%					
Year	Production Volume	Compact Car 60 kWh Battery Pack	Medium Car 65 kWh Battery Pack	Medium SUV 82 kWh Battery Pack	Pickup 95 kWh Battery Pack
Base Year + 1	50,000	-8.7%	-8.5%	-8.3%	-8.0%
Base Year + 2	75,000	-4.7%	-4.6%	-4.5%	-4.3%
Base Year + 3	100,000	-3.2%	-3.1%	-3.0%	-2.9%
Base Year + 4	125,000	-2.4%	-2.3%	-2.3%	-2.2%
Base Year + 5	150,000	-1.9%	-1.8%	-1.8%	-1.7%
Base Year + 6	175,000	-1.6%	-1.5%	-1.5%	-1.4%
Base Year + 7	200,000	-1.3%	-1.3%	-1.3%	-1.2%
Average		-3.4%	-3.3%	-3.2%	-3.1%
Average across all vehicle technology class		-3.3%			

Table 3-77 – Battery Pack DMC as a Function of Production Volume for BEV200, Non-performance Using NMC811-G as Battery Cell Chemistry

BEV 200 (Non-Performance), Cell Chemistry NMC811-G, Cell Yield 95%									
Year	Production Volume	Compact Car 60 kWh Battery Pack		Medium Car 65 kWh Battery Pack		Medium SUV 82 kWh Battery Pack		Pickup 95 kWh Battery Pack	
		Total Cost	$/kWh	Total Cost	$/kWh	Total Cost	$/kWh	Total Cost	$/kWh
Base year	25,000	$9,595	$160	$10,062	$155	$11,899	$145	$13,165	$139
Base year + 1	50,000	$8,749	$146	$9,191	$141	$10,896	$133	$12,098	$127
Base year + 2	75,000	$8,329	$139	$8,758	$135	$10,396	$127	$11,565	$122
Base year + 3	100,000	$8,060	$134	$8,480	$130	$10,074	$123	$11,220	$118
Base year + 4	125,000	$7,865	$131	$8,279	$127	$9,841	$120	$10,970	$115
Base year + 5	150,000	$7,714	$129	$8,123	$125	$9,661	$118	$10,777	$113
Base year + 6	175,000	$7,593	$127	$7,998	$123	$9,515	$116	$10,620	$112

BEV 200 (Non-Performance), Cell Chemistry NMC811-G, Cell Yield 95%									
Year	Production Volume	Compact Car 60 kWh Battery Pack		Medium Car 65 kWh Battery Pack		Medium SUV 82 kWh Battery Pack		Pickup 95 kWh Battery Pack	
		Total Cost	$/kWh	Total Cost	$/kWh	Total Cost	$/kWh	Total Cost	$/kWh
Base year +7	200,000	$7,491	$125	$7,893	$121	$9,392	$115	$10,489	$110

Table 3-78 – Percentage Cost Reduction as a Function of Production Volume for BEV200, Non-performance Using NMC811-G as Battery Cell Chemistry

BEV 200 (Non-Performance), Cell Chemistry NMC811-G, Cell Yield 95%					
	Production Volume	Compact Car 60 kWh Battery Pack	Medium Car 65 kWh Battery Pack	Medium SUV 82 kWh Battery Pack	Pickup 95 kWh Battery Pack
Base Year	25,000	-	-	-	-
Base Year + 1	50,000	-8.8%	-8.7%	-8.4%	-8.1%
Base Year + 2	75,000	-4.8%	-4.7%	-4.6%	-4.4%
Base Year + 3	100,000	-3.2%	-3.2%	-3.1%	-3.0%
Base Year + 4	125,000	-2.4%	-2.4%	-2.3%	-2.2%
Base Year + 5	150,000	-1.9%	-1.9%	-1.8%	-1.8%
Base Year + 6	175,000	-1.6%	-1.5%	-1.5%	-1.5%
Base Year + 7	200,000	-1.3%	-1.3%	-1.3%	-1.2%
Average		-3.4%	-3.4%	-3.3%	-3.2%
Average across vehicle Technology class		-3.3%			

Table 3-79 – Percentage Cost Reduction due to Change in Battery Cell Chemistry (NMC622-G to NMC811-G)

BEV200 (Non-Performance), Cell Chemistry NMC622-G to NMC811-G, Cell Yield 95%					
	Production Volume	Compact Car 60 kWh Battery Pack	Medium Car 65 kWh Battery Pack	Medium SUV 82 kWh Battery Pack	Pickup 95 kWh Battery Pack
Base Year	25,000	-4.6%	-4.9%	-4.9%	-5.0%
Base Year + 1	50,000	-4.8%	-5.1%	-5.0%	-5.2%
Base Year + 2	75,000	-4.9%	-5.2%	-5.1%	-5.3%
Base Year + 3	100,000	-4.9%	-5.2%	-5.2%	-5.3%
Base Year + 4	125,000	-5.0%	-5.3%	-5.2%	-5.4%
Base Year + 5	150,000	-5.0%	-5.3%	-5.3%	-5.4%
Base Year + 6	175,000	-5.0%	-5.4%	-5.3%	-5.4%
Base Year + 7	200,000	-5.1%	-5.4%	-5.3%	-5.4%
Average		-4.9%	-5.2%	-5.2%	-5.3%
Average across vehicle Technology classes		-5.2%			

After considering cell chemistry, we compute the total cost of the battery pack as a function of manufacturing cell yield values. Cell yield is a measure of plant efficiency for manufacturing battery packs. A higher cell yield means more efficient use of raw materials, processing of raw materials, energy, floor space, machinery, labor, and other inputs, which result in lower costs. A lower cell yield means some of the inputs are not efficiently used, which means more raw materials, energy, labor, and other inputs are used to produce same number of battery packs, resulting in higher battery pack costs. Table 3-75 above shows battery pack costs for NMC622-G with cell yield of 95 percent, and Table 3-80 and Table 3-81 show battery pack cost with a cell yield input of 90 percent and 85 percent, respectively, for NMC622-G.

Table 3-80 – Total Battery Pack Cost for Cell Yield of 90 Percent

90% Cell Yield; BEV 200 Non-Performance, Cell Chemistry NMC622-G								
Production Volume	Compact Car (60 kwh)		Medium Car (65 kwh)		Medium SUV (82 kwh)		Pickup (95 kwh)	
	Total Cost	$/kWh	Total Cost	$/kWh	Total Cost	$/kWh	Total Cost	$/kWh
25,000	$10,389	$173	$10,929	$168	$12,933	$158	$14,339	$151
50,000	$9,492	$158	$10,005	$154	$11,868	$145	$13,202	$139
75,000	$9,046	$151	$9,544	$147	$11,335	$138	$12,632	$133
100,000	$8,759	$146	$9,248	$142	$10,992	$134	$12,264	$129
125,000	$8,551	$143	$9,034	$139	$10,743	$131	$11,997	$126
150,000	$8,391	$140	$8,868	$136	$10,550	$129	$11,789	$124
175,000	$8,261	$138	$8,773	$135	$10,393	$127	$11,621	$122
200,000	$8,153	$136	$8,621	$133	$10,263	$125	$11,480	$121

Table 3-81 – Total Battery Pack Cost for Cell Yield of 85 Percent

85% Cell Yield; BEV 200 Non-Performance, Cell Chemistry NMC622-G								
	Compact Car (60 kwh)		Medium Car (65 kwh)		Medium SUV (82 kwh)		Pickup (95 kwh)	
Production Volume	Total Cost	$/kWh	Total Cost	$/kWh	Total Cost	$/kWh	Total Cost	$/kWh
25,000	$10,755	$179	$11,317	$174	$13,405	$163	$14,869	$157
50,000	$9,828	$164	$10,362	$159	$12,304	$150	$13,694	$144
75,000	$9,368	$156	$9,887	$152	$11,753	$143	$13,105	$138
100,000	$9,071	$151	$9,580	$147	$11,398	$139	$12,724	$134
125,000	$8,857	$148	$9,359	$144	$11,141	$136	$12,447	$131
150,000	$8,691	$145	$9,187	$141	$10,941	$133	$12,223	$129
175,000	$8,556	$143	$9,048	$139	$10,779	$131	$12,058	$127
200,000	$8,444	$141	$8,932	$137	$10,644	$130	$11,913	$125

When comparing the total cost of a battery pack manufactured at a plant with a cell yield of 95 percent to a cell yield of 90 percent, there is on average an increase in cost by 3.4 percent. Similarly, when comparing the total cost of a battery pack produced in a plant with a cell yield of 90 percent to a pack produced in a plant with a cell yield of 85 percent, there is an average 3.6 percent increase in cost. This demonstrates that for every 5 percent decrease in cell yield, there is approximately a 3.5 percent increase in battery pack cost.

Table 3-82 summarizes the individual effects of selected factors that affect the cost of battery packs: (a) production volume, (b) battery cell chemistry and (c) cell yield. The individual values determined provide an indication of the possible range a composite learning curve should fall within.

Table 3-82 – Summary List of Factors Affecting Battery Pack Cost Considered for Developing Learning Curve

Factors which Influence the Battery Cost Learning Curve	
Average cost reduction from increasing production volume	-3.26%
Average cost reduction due to change in battery chemistry	-5.15%
Average cost reduction due improved plant efficiency (cell yield)	-3.5%

Table 3-83 shows the factor values used to estimate an average battery pack composite cost reduction, over time. The table includes cost reductions due to changes in cell chemistry and an increase in production volume over time. We believe that during the rulemaking time frame, the industry will continue to use NMC622-G as the predominant battery cell chemistry but will transition to more advanced cell chemistries like NMC811-G. Actual cell yield in the industry may be lower, but we have assumed a cell yield of 95 percent regardless of cell chemistry. Table 3-84 shows the progressive percent battery pack cost reduction for the costs shown in Table 3-83 as the simulated factors change across model years. Averaging the percent cost reduction across the simulated model years and vehicle technology classes results in a 4.49 percent year over year cost reduction.

Table 3-83 – Values Used to Estimate Battery Cost Reduction Over Time

BEV200 (Non-Performance)											
Model Year	Battery Chemistry	Cell Yield	Production Volume	Compact Car 60 kWh Battery		Medium Car 65 kWh Battery		Medium SUV 82 kWh Battery		Pickup 95 kWh Battery	
				Total Cost	$/kWh	Total Cost	$/kWh	Total Cost	$/kWh	Total Cost	$/kWh
Base Year	NMC622	95%	25,000	$10,060	$168	$10,581	$163	$12,509	$153	$13,862	$146
Base Year + 1	NMC622	95%	75,000	$8,756	$146	$9,237	$142	$10,959	$134	$12,207	$128
Base Year + 2	NMC622	95%	100,000	$8,478	$141	$8,949	$138	$10,626	$130	$11,850	$125
Base Year + 3	NMC811	95%	100,000	$8,060	$139	$8,480	$135	$10,074	$127	$11,220	$122
Base Year + 4	NMC811	95%	125,000	$7,865	$131	$8,279	$127	$9,841	$120	$10,970	$115
Base Year + 5	NMC811	95%	150,000	$7,714	$129	$8,123	$125	$9,661	$118	$10,777	$113
Base Year + 6	NMC811	95%	175,000	$7,571	$126	$7,975	$123	$9,488	$116	$10,592	$111

Table 3-84 – Percentage Reduction in Battery Costs from Composite Values Used to Estimate Battery Cost Reduction Over Time

BEV200 (Non-Performance)							
Model Year	**Battery Chemistry**	**Cell Yield**	**Production Volume**	**Compact Car 60 kWh Battery**	**Medium Car 65 kWh Battery**	**Medium SUV 82 kWh Battery**	**Pickup 95 kWh Battery**
Base Year	NMC622-G	95%	25000	-	-	-	-
Base Year + 1	NMC622-G	95%	75000	-12.96%	-12.70%	-12.39%	-11.94%
Base Year + 2	NMC622-G	95%	100000	-3.17%	-3.12%	-3.04%	-2.92%
Base Year + 3	NMC811-G	95%	100000	-4.93%	-5.24%	-5.19%	-5.32%
Base Year + 4	NMC811-G	95%	125000	-2.42%	-2.37%	-2.31%	-2.23%
Base Year + 5	NMC811-G	95%	150000	-1.92%	-1.88%	-1.83%	-1.76%
Base Year + 6	NMC811-G	95%	175,000	-2.89%	-1.82%	-1.79%	-1.72%
Average				-4.72%	-4.52%	-4.43%	-4.31%
Average across all vehicle classes				-4.49%			

Using the calculated 4.49 percent average annual cost reduction, we constructed a linearized battery pack cost reduction curve, shown in Figure 3-22, showing the cost reduction year over year. The costs shown in Figure 3-22 are a $/kWh direct manufacturing cost estimate for a compact vehicle with a 60 kWh battery pack with no road load technology applied (*i.e.*, MR0, ROLL0, and AERO0).

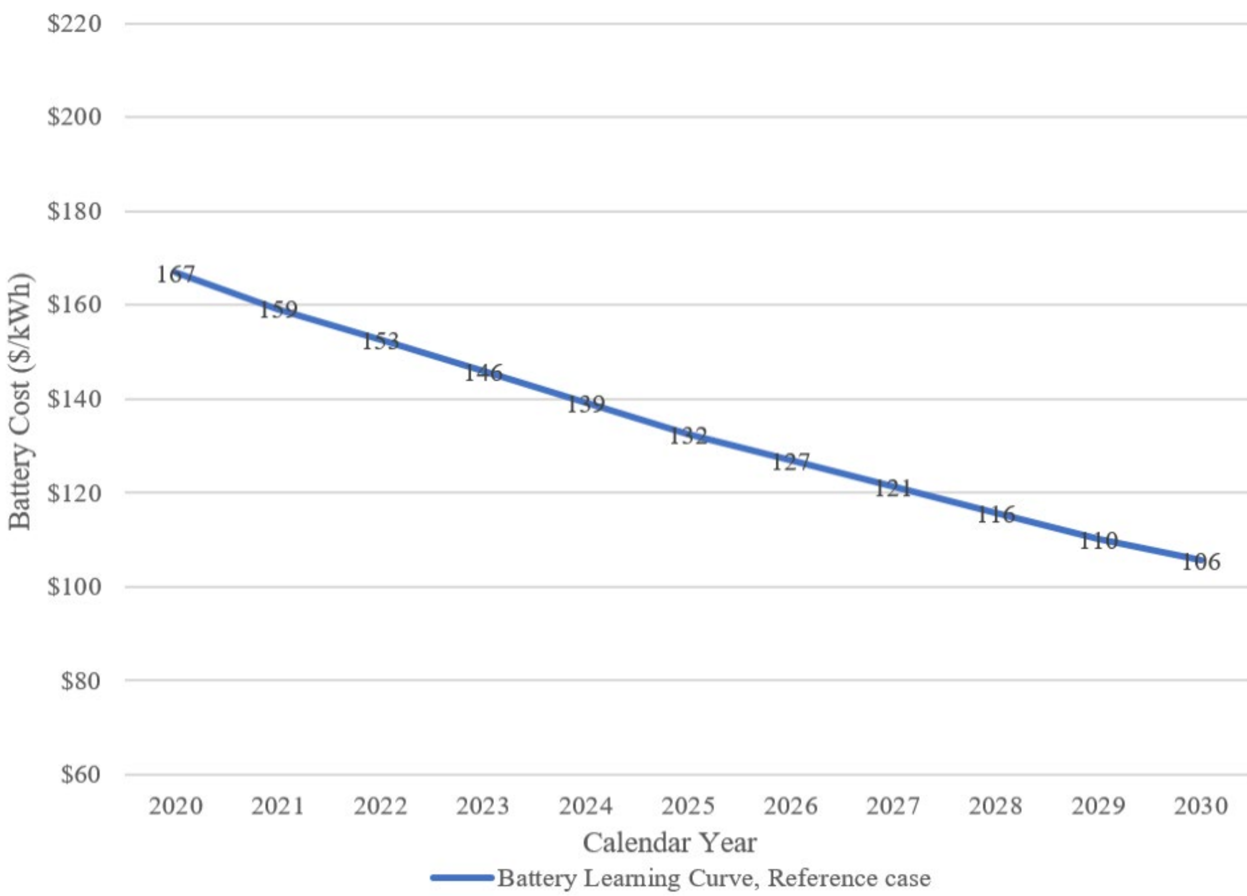

Figure 3-22 – Battery Learning Curve

Table 3-85 below shows a comparison of battery cost estimates from this analysis and other sources. Note that the costs presented in this table represent the cost to manufacture the battery pack, *i.e.*, the direct manufacturing cost, and not the cost of the pack to the OEM. The sources used to create this table did not uniformly distinguish a DMC source year, so some values vary slightly based on inflation.

Table 3-85 – Battery Cost Estimates from Other Sources ($/kWh)

	2018-2020[403]	2025	2030	2045
UBS[404]	$188	$136		
BCG[405]		$137	$117	
ICCT[406]	$175-177	$104	$64-73	
BNEF EV Outlook 2019 [407,408]	$176[409]	$87	$62	
Massachusetts Institute of Technology (MIT)[410]	$193	$146	$127[411]	
DOE VTO[412] – based on usable energy	$170	$125	$98	$80
2021 NAS Report[413]		$115	$80	
NHTSA Estimate from BatPaC version 4.0 (Oct 2020)	$167[414]	$132	$106	$77

Each individual report uses a certain set of assumptions to arrive at a rate of cost reduction. Among all the different cost estimates, Bloomberg New Energy Finance (BNEF) has the most aggressive year-over-year cost reductions, based on the historical battery cost learning rate of 18

403 Sources generally provided estimates for 2018 or 2020.

404 Hummel et al., UBS Evidence Lab Electric Car Teardown – Disruption Ahead?, UBS (May 18, 2017), https://neo.ubs.com/shared/d1ZTxnvF2k. (Accessed: February 15, 2022).

405 Mosquet et al., The Electric Car Tipping Point, BCG (Jan. 11, 2018), https://www.bcg.com/publications/2018/electric-car-tipping-point.aspx. (Accessed: February 15, 2022). This study provided cell cost estimates that the agencies converted to pack cost estimates using a multiplier of 1.3, as outlined in the Draft TAR at pp. 5–124.

406 Nic Lutsey and Michael Nicholas, Update on electric vehicle costs in the United States through 2030, ICCT (April 2, 2019), available at https://theicct.org/publications/update-US-2030-electric-vehicle-cost. (Accessed: February 15, 2022). The presented values are $/kWh pack costs for mid-range electric cars/crossovers and SUVs.

407 BNEF's projected cost for 2021 is $132/kWh and they expect battery packs to cost less than $100/kWh in 2024. See Bloomberg NEF, Battery Pack Prices Fall to an Average of $132/kWh, But Rising Commodity Prices Start to Bite (Nov. 30, 2021), https://about.bnef.com/blog/battery-pack-prices-fall-to-an-average-of-132-kwh-but-rising-commodity-prices-start-to-bite/. (Accessed: February 15, 2022).

408 McKerracher et al., Electric Vehicle Outlook 2019 – Free Interactive Report, Bloomberg New Energy Finance (May 2019), https://about.bnef.com/electric-vehicle-outlook. (Accessed: February 15, 2022).

409 Logan Goldie-Scot, A Behind the Scenes Take on Lithium-ion Battery Prices, Bloomberg New Energy Finance (March 5, 2019), https://about.bnef.com/blog/behind-scenes-take-lithium-ion-battery-prices. (Accessed: February 15, 2022). BNEF projected the pack costs in 2018$ for 2018 as $176, and used the same value in the Electric Vehicle Outlook 2019 to describe pack cost levels "today."

410 MIT Energy Initiative. 2019. *Insights into Future Mobility*. Cambridge, MA: MIT Energy Initiative. Available at http://energy.mit.edu/insightsintofuturemobility. (Accessed: February 15, 2022).

411 *Id*, at p. 78. MIT estimates $124/kWh in 2030 in 2019$. Converting $124/kWh results in $127/kWh in 2030 in 2018$.

412 Islam, E., Kim, N., Moawad, A., Rousseau, A., "A Large-Scale Vehicle Simulation Study To Quantify Benefits & Analysis of U.S. Department of Energy VTO & FCTO R&D Goals." Report to U.S. Department of Energy. Contract ANL/ESD-19/10 (forthcoming).

413 2021 NAS report, at pp. 5–142.

414 The $/kWh direct manufacturing cost estimate presented here is for a compact vehicle with a 60kWh battery pack with no road load technology applied (MR0, ROLLl0, AERO0).

percent and their battery demand forecast.[415] Similar to other sources of cost estimates, BNEF assumes improved battery chemistry and battery density increasing greater than 200Wh/kg by 2030. In order for the battery manufacturer to achieve economies of scale, BNEF assumes a global battery manufacturing facility capable of producing battery packs for both stationary energy storage and vehicle applications.

In the MIT report, the authors use a two-stage method to develop composite battery learning curves, (1) production of active materials by mining companies and materials producers, and (2) fabrication of the battery packs by integrated battery-automotive corporations.[416] The authors state that, according to two-stage learning curve model, the rate of price reductions slows significantly between 2025-2030 as a consequence of higher contribution of active materials (NMC) costs, which are modeled to decline at a lower rate of about 3.5 percent.

This study also assumes NMC811 will be available by 2030. The National Academy of Sciences (NAS) in its 2021 report assumes a battery learning rate of 5 percent per year but does not disclose the methodology for determining this assumed learning rate.[417] The learning rate we assume for MYs through 2032 is slightly more optimistic than the MIT report learning rate, and slightly less optimistic than the 2021 NAS committee's learning rate.

The MIT report has the most conservative estimate among all the cost sources referenced in Table 3-85. The cost estimates from other sources referenced above also include assumptions about higher levels of battery pack production and higher density battery cells. Most cost estimates assume improved battery chemistry over time, such as NMC811. As discussed earlier, we determined that assuming NMC622 as the predominant battery chemistry in MY 2020, the DMC source year, was a reasonable assumption; however, the composite learning curve generated for this analysis shows that a potential shift to NMC811 in the latter half of this decade makes our direct manufacturing costs fall squarely in the middle of the range of future battery cost estimates.

Out of the reports that we surveyed,[418] the BNEF and MIT assumptions represent a range of potential future costs in later years of the studies surveyed. Using the same approach as the rest of our analysis, that our costs should represent an average achievable performance across the industry, we believe that the battery DMCs with the learning curve applied provide a reasonable representation of potential costs across the industry. Figure 3-23 shows how the linearized battery pack composite learning cost reduction compares to the other battery pack cost estimates from sources listed in Table 3-85, with our projected costs falling fairly well in the middle of the range of potential costs in future years.

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[415] Logan Goldie-Scot, A Behind the Scenes Take on Lithium-ion Battery Prices, Bloomberg New Energy Finance (March 5, 2019), https://about.bnef.com/blog/behind-scenes-take-lithium-ion-battery-prices. (Accessed: February 15, 2022).
[416] Insights into Future Mobility, at pp. 78.
[417] 2021 NAS report, at pp. 4–67.
[418] Many studies have projected future battery pack costs; however, we only selected a few commonly cited studies for additional reference in this analysis.

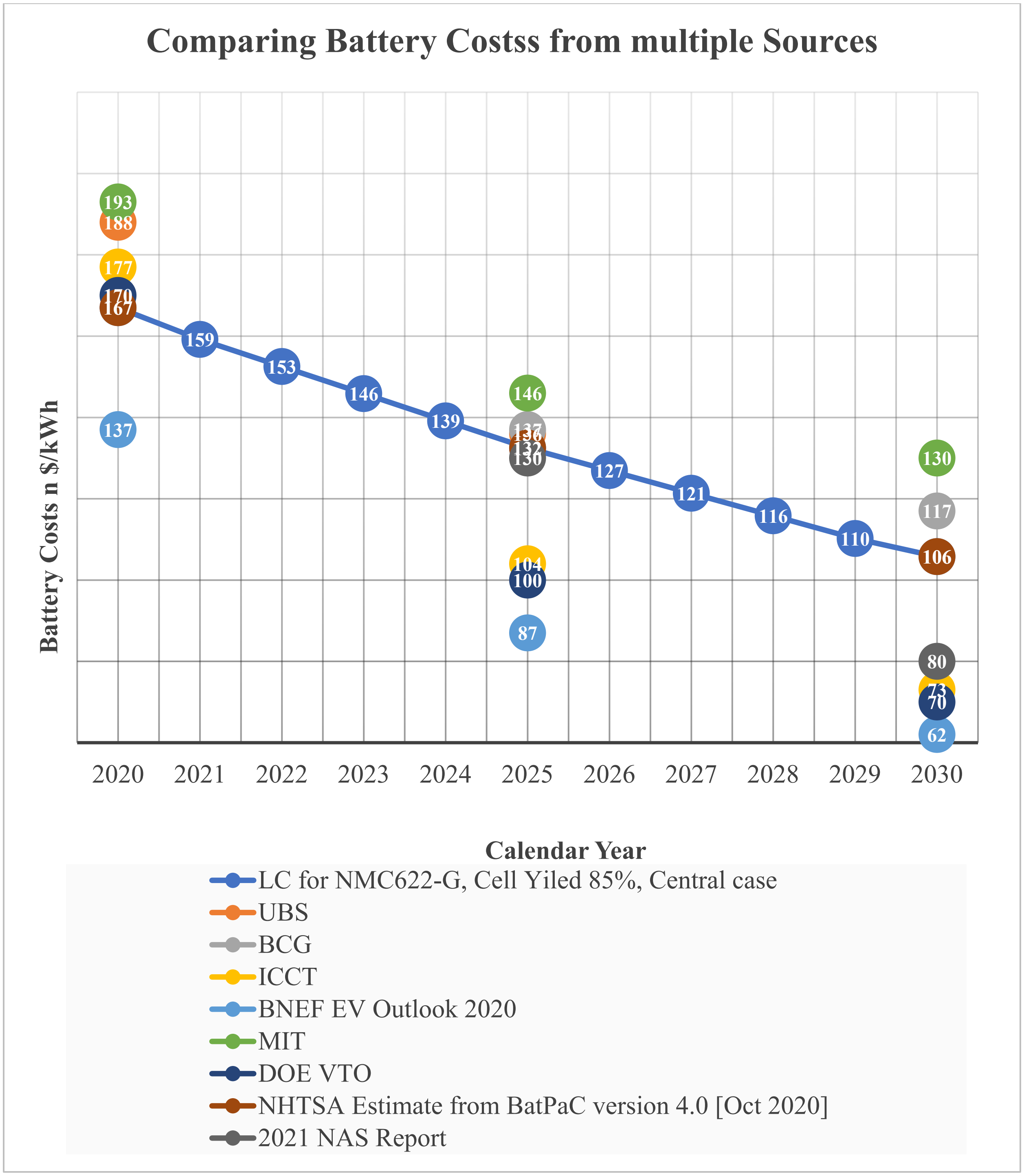

Figure 3-23 – Comparing Battery Pack Cost Estimates from Multiple Sources

As discussed above, there are inherent uncertainties in projecting future battery pack cost due to several factors. One way to bound the uncertainty in projecting battery pack cost is to perform a sensitivity analysis. We performed a sensitivity analysis for both the battery learning rate and battery DMC by varying the learning rate by plus and minus 20 percent from the reference case, and by varying the battery DMC by plus and minus 20 percent from the reference case. These results are discussed in the FRIA.

3.3.5.2 Non-Battery Electrification Component Costs

Battery components are the biggest driver of the cost of electrification; however, non-battery electrification components also add to the total cost required to electrify a vehicle. Different vehicle types have different non-battery electrification components and configurations, for instance some BEVs may have one electric motor and some BEVs may have two electric motors. In addition, some electrified vehicle types also include conventional powertrain components, like an internal combustion engine and transmission. Chapter 3.3.5.3 discusses how the battery costs, non-battery electrification component costs, and other conventional powertrain technology costs come together to create a total vehicle cost for electrified vehicles.

Beginning with the least complex electrification systems, the SS12V micro hybrid system cost in this analysis is based on one small motor and battery, and the motor is a fixed cost regardless of the engine type the system is paired with (*e.g.*, turbocharged or naturally aspirated), however the cost varies by vehicle class. We use motor costs from the 2016 Draft TAR and update the cost to 2018$.[419] The DMC for the SS12V motor for the small car, medium car, and small SUV classes is $159. The DMC for the SS12V motor for the medium SUV and pickup truck classes is $213.

Similar to the SS12V system, the 48V mild hybrid non-battery electrification component costs are fixed for all technology classes. We use the A2Mac1 database to develop a bill of materials for the BISG system, and cost the components using two sources, as explained further below. Table 3-86 lists the components that comprise the mild hybrid system, including the battery pack, and the cost of those components in the analysis.

Table 3-86 – Cost Estimate of BISG Components in 2018$

Components	DMC in 2017	RPE
Motor, Inverter & Cooling system (10kW)	$184	$276
DC to DC converter (2kW)	$184	$276
Water Pump	$43	$65
Wiring harness	$29	$44
Connecters	$10	$15
Belt pulley modifications to AC compressor	$10	$15
Auxiliary electric oil pump to transmission	$46	$69
Modifications to auxiliary brake pump	$43	$65
Brackets for motor and battery attachment	$15	$23

[419] Draft TAR, at 5–453.

Components	DMC in 2017	RPE
Total non-battery component cost	$564	$848
Battery Pack Cost (0.43kWh)[420]	$405	$608
Total system cost with battery	$969	$1,456

We use a dollar per kilowatt hour metric derived from the 2017 Electrical and Electronics Technical Team Roadmap report, discussed further below, for the motor, inverter, and cooling system, and DC-DC converter costs.[421] We use BatPaC version 4.0 (October 2020) to determine the cost of a battery pack for the 48V system.[422,423] For all other BISG component costs shown in Table 3-86, we rely on an EPA-sponsored FEV teardown of a 2013 Chevrolet Malibu ECO with eAssist.[424] FEV estimates the direct manufacturing cost of the BISG system (without batteries) to be $1,045 in 2013 dollars. This includes a cost adjustment for reduced voltage insulation. Even though the 2013 Chevrolet Malibu considered in the study used a 115V system, we determined that structural components like the motor and battery attachment brackets would translate fairly across BISG systems, regardless of voltage.

To validate these costs, we consider the 2019 Dodge Ram eTorque system retail price. Using the publicly available retail price,[425] we estimate the normalized cost of the system at $1,195 for the water-cooled system and $1,450 for the air-cooled system in 2018 dollars after the removal of an estimated RPE and learning factor. In addition, the 2015 NAS report estimates the cost range of BISG technology at $888 to $1,164 in 2010 dollars in 2025.[426] This is equivalent to a range of $1,020 to $1,337.27 in 2018 dollars in 2025. Broadly, our total BISG system cost including the battery fairly matches these estimates.

For all other electrified vehicle powertrain types, we group non-battery electrification components into four major categories: electric motors (or e-motors), power electronics (generally including the DC/DC converter, bi-directional DC/DC converter, inverter, and power distribution module), charging components (charger, charging cable, and high voltage cables), and thermal management system(s).

We further group the components into those comprising the electric traction drive system (ETDS) , and all other components. Although each manufacturer's ETDS and power electronics

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420 *See* battery_costs.csv in the docket for this action.
421 U.S. DRIVE, Electrical and Electronics Technical Team Roadmap (October 2017), https://www.energy.gov/sites/prod/files/2017/11/f39/EETT%20Roadmap%2010-27-17.pdf. (Accessed: February 15, 2022).
422 Autonomie model documentation, Chapter 5.9.4.
423 Nelson. P. A., Ahmed. S., Gallagher. K. G., Dees. D. W. EESD. CSED, ANL. Modeling the performance and Cost of Lithium-Ion Batteries for Electric-Drive Vehicles. Third Edition. ANL/CSE-19/2. https://doi.org BatPac Model Documentation Third Edition150624.pdf; Argonne. Summary of Updates/Changes in Batpac 4.0. Summary of Updates and Changes in BatPaC 4 (Oct 2020).pdf.
424 Light Duty Vehicle Technology Cost Analysis 2013 Chevrolet Malibu ECO with eAssist BAS Technology Study, FEV P311264 (Contract no. EP-C-12-014, WA 1-9).
425 "2019 Ram 1500 eTorque Pairs Pickup with Hybrid". Car and Driver (March 14, 2019), https://www.caranddriver.com/reviews/a22815325/2019-ram-1500-etorque-hybrid-pickup-drive. (Accessed: February 15, 2022).
426 2015 NAS report, at p. 305.

vary between the same electrified vehicle types and between different electrified vehicle types, we consider the ETDS for this analysis to be comprised of the e-motor and inverter, power electronics, and thermal system. Table 3-87 shows our assignments for each of the non-battery electrification components to HEVs, PHEVs, BEVs, and FCEVs in the analysis.

Table 3-87 – Non-Battery Electrification Component and Vehicle Assignment

Major Non-Battery Electrification Components	HEV	PHEV	BEV	FCEV
Electric Motor	X	X	X	X
*Electric Generator	X	X		
Power Electronics	X	X	X	X
DC/DC Converter	X	X	X	X
Charging Port & High Voltage cable	N/A	X	X	N/A
On-board Charger	N/A	X	X	N/A
Thermal System	X	X	X	X
Fuel Cell Stack	N/A	N/A	N/A	X
*only for PS strong hybrids and PS PHEVs				

When researching costs for different non-battery electrification components, we found that different reports vary in components considered and cost breakdown. This is not surprising, as vehicle manufacturers use different non-battery electrification components in different vehicle's systems, or even in the same vehicle type, depending on the application.[427,428] As detailed below, we apply costs for the major non-battery electrification components on a dollar per kilowatt hour basis. We use a $/kW cost metric for non-battery components to align with the normalized costs for a system's peak power rating as presented in U.S. DRIVE's Electrical and Electronics Technical Team Roadmap report,[429] one of the sources we use for non-battery electrification component costs. This approach captures components in some manufacturer's systems, but not all systems; however, we believe this is a reasonable metric and approach to use for this analysis given the differences in non-battery electrification component systems.

As discussed above, to estimate the cost of the ETDS, we use U.S. DRIVE's report, Electrical and Electronics Technical Team (EETT) Roadmap. The EETT Roadmap report reflects considerable work by the DOE VTO collaboratively with U.S. DRIVE, a government-industry partnership. The EETT Roadmap report estimates the 2017 manufacturing cost of a commercial on-road 100kW ETDS consisting of a single electric traction motor and inverter. The reported costs are approximately $1,800, with the cost of the electric motor accounting for $800, and

[427] For example, the MY 2020 Nissan Leaf does not have an active cooling system whereas Chevy Bolt uses an active cooling system.
[428] Argonne AMTL D3. Electric Vehicle Testing. 2021. https://www.anl.gov/es/electric-vehicle-testing. (Accessed: February 15, 2022).
[429] U.S. DRIVE, Electrical and Electronics Technical Team Roadmap (Oct. 2017), available at https://www.energy.gov/sites/prod/files/2017/11/f39/EETT%20Roadmap%2010-27-17.pdf. (Accessed: February 15, 2022).

approximately $1,000 for the inverter, equaling $18/kW for the ETDS. We compare these costs with the UBS MY 2016 Chevy Bolt teardown.[430] In the UBS report, the cost of the electrical components in the ETDS summed to $2,619 for a 150 kW (2016 Chevy Bolt nominal power) ETDS. Normalizing this cost resulted in $17.76/kW, which is in good agreement with the cost calculated from U.S. DRIVE's EETT Roadmap report.[431]

The EETT Roadmap report did not explicitly estimate the cost of other electrical equipment present in electrified powertrains, such as on-board chargers, DC to DC converters, high voltage cables, and charging cables. We rely on the UBS MY 2016 Chevy Bolt teardown report to estimate those individual costs for some categories of strong hybrid components, and all other PHEV and BEV components.

As part of our reexamination of strong hybrid costs for this analysis, discussed further in preamble Section III.D.3.e), the strong hybrid high voltage cable costs now align with the costs for high voltage cables presented in the EPA-sponsored 2011 Ford Fusion HEV teardown study.[432] We adjust the costs for high voltage cables from the 2011 Ford Fusion HEV teardown study to 2018$ and apply that to both PS and P2 strong hybrid cables.

Table 3-88 shows our cost estimates for the ETDS from the EETT Roadmap report and from the UBS MY 2016 Chevy Bolt teardown report, and the cost estimate for other electrical equipment from the same UBS report and EPA-sponsored FEV report.

Table 3-88 – Cost Estimates from the EETT Roadmap Report, UBS MY 2016 Chevy Bolt Teardown and FEV 2011 Ford Fusion HEV Teardown

Non-Battery Electrical Components	EETT Roadmap Report (2017$ in DMC Year 2017)	UBS MY 2016 Chevy Bolt Teardown (2017$ in DMC Year 2017)	Assumptions	Updated 2018$ for Analysis
ETDS	$18/kW	$17.76/kW	Based on e-motor peak power	$18.41/kW
On-Board Charger	-	$85/kW	Based on vehicle requirement (7kW for BEV, 2 kW for PHEV)	$86.96/kW
DC to DC Converter	-	$90/kW	Based on converter rated power (2kW)	$93.84/kW

[430] Hummel et al., UBS Evidence Lab Electric Car Teardown – Disruption Ahead?, UBS (May 18, 2017), https://neo.ubs.com/shared/d1wkuDlEbYPjF. (Accessed: February 15, 2022).
[431] We normalize the cost of the ETDS for the 2016 Chevy Bolt by summing the ETDS components costs and dividing by e-motor power rating (150 kW).
[432] Light Duty Technology Cost Analysis, Power-Split and P2 HEV Case Studies, EPA-420-R-11-015 (November 2011).

High Voltage Cables and Charging Cords for BEVs and PHEVs	-	$450	Fixed cost rated for 360V	$460.39
High Voltage Cables for Strong Hybrids			Fixed cost	$167.75

We convert the costs in Table 3-88 to 2018$ to align the dollar year with other costs in this analysis. Accordingly, the overall cost for non-battery electrification components in this analysis is an aggregate of the line items in Table 3-88, based on the specific electrified powertrain type.

As an example, we calculate the cost for a BEV with a 150kW motor, 7kW on-board charger, 2kW DC to DC converter, and high voltage cables as:

Total Non-Battery Electrification Component DMC = 150 kW*18.41 $/kW + 7kW*86.96 $/kW + 2kW*93.84 $/kW + $460.39 = $4018.29

Another example is a PHEV50 with 94 kW motor, 35 kW generator, 2kW on board charger, 2kW DC to DC Converter, and high voltage cables configuration:

Total Non-Battery Component DMC = 94 kW*18.41 $/kW + 35kw *18.41 $/kW + 2kW*86.96 $/kW + 2kW*93.84 $/kW + $460.39 = $3196.88

As discussed in Chapter 2.6, we adjust costs in the Technologies file to account for three variables: RPE, which is 1.5 times the direct manufacturing cost (DMC), the technology learning curve, and the adjustment of the dollar value to 2018$ for this analysis.

For the non-battery electrification component learning curves, we use cost information from Argonne's 2016 Assessment of Vehicle Sizing, Energy Consumption, and Cost through Large-Scale Simulation of Advanced Vehicle Technologies report.[433] The report provides estimated cost projections from the 2010 lab year to the 2045 lab year for individual vehicle components.[434,435] We consider the component costs used in electrified vehicles, and determine the learning curve by evaluating the year over year cost change for those components. Argonne recently published a 2020 version of the same report that included high and low cost estimates for many of the same components, that also included a learning rate.[436] Our learning estimates

433 Moawad, Ayman, Kim, Namdoo, Shidore, Neeraj, and Rousseau, Aymeric. Assessment of Vehicle Sizing, Energy Consumption and Cost Through Large Scale Simulation of Advanced Vehicle Technologies (ANL/ESD-15/28). United States (2016). Available at https://www.autonomie.net/pdfs/Report%20ANL%20ESD-1528%20-%20Assessment%20of%20Vehicle%20Sizing,%20Energy%20Consumption%20and%20Cost%20through%20Large%20Scale%20Simulation%20of%20Advanced%20Vehicle%20Technologies%20-%201603.pdf. (Accessed: February 15, 2022).

434 ANL/ESD-15/28 at p. 116.

435 DOE's lab year equates to five years after a model year, *e.g.*, DOE's 2010 lab year equates to MY 2015.

436 Islam, E., Kim, N., Moawad, A., Rousseau, A. "Energy Consumption and Cost Reduction of Future Light-Duty Vehicles through Advanced Vehicle Technologies: A Modeling Simulation Study Through 2050," Report to the US Department of Energy, Contract ANL/ESD-19/10, June 2020 https://www.autonomie.net/pdfs/ANL%20-%20Islam%20-%202020%20-%20Energy%20Consumption%20and%20Cost%20Reduction%20of%20Future%20Light-Duty%20Vehicles%20through%20Advanced%20Vehicle%20Technologies%20A%20Modeling%20Simulation%20Study%20Through%202050.pdf. (Accessed: February 15, 2022).

generated using the 2016 report fall fairly well in the middle of these two ranges, and therefore we continue to apply the learning curve estimates based on the 2016 report. There are many sources that we could have picked to develop learning curves for non-battery electrification component costs, however given the uncertainty surrounding extrapolating costs out to MY 2050, we believe these learning curves provide a reasonable estimate.

Figure 3-24, Table 3-89 and Table 3-90 show the learning rate factors for non-battery electrification components for different electrified powertrains.

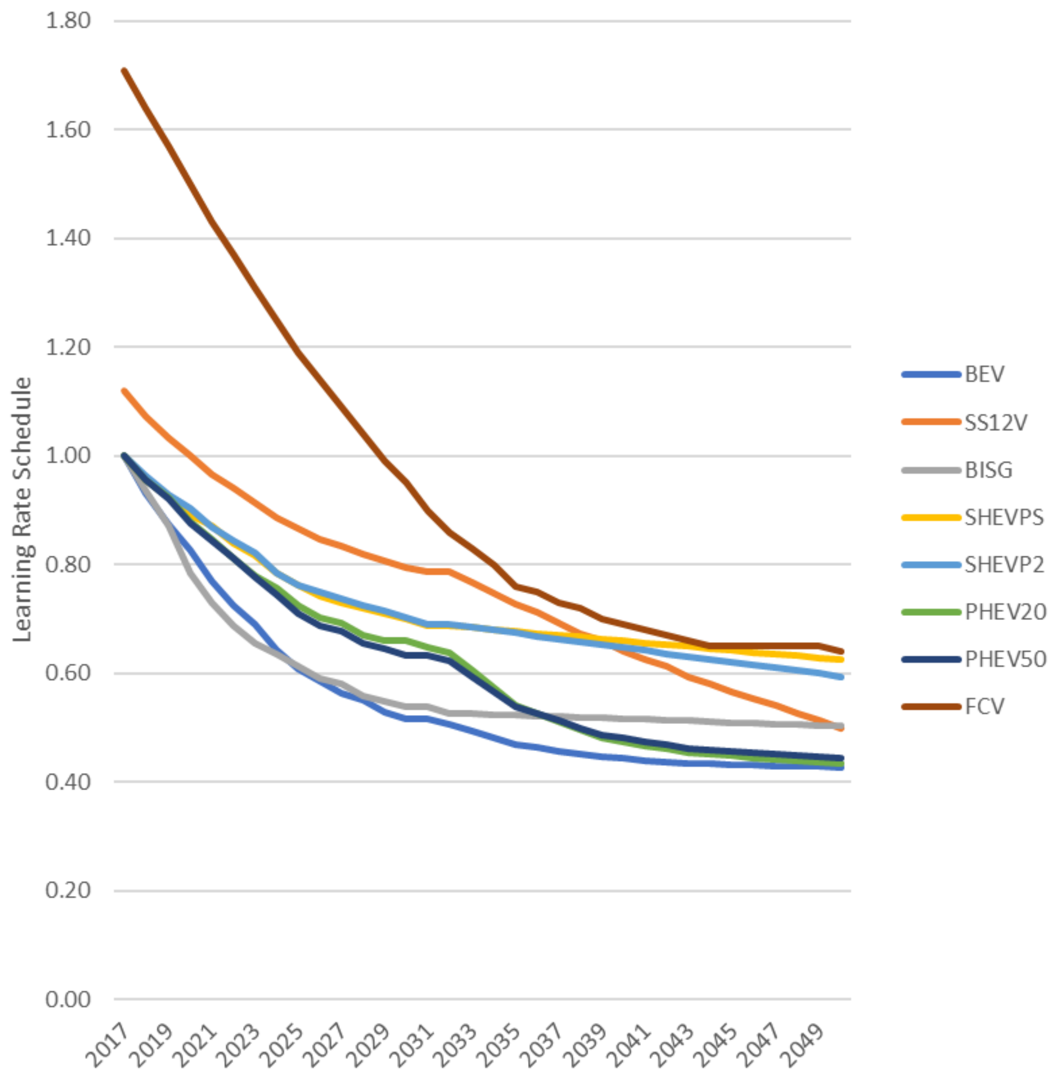

Figure 3-24 – Learning Rate Factor Used for Non-Battery Electrification Components for Electrified Powertrains

Table 3-89 – Learning Rate Factor Used for Non-Battery Electrification Components for Electrified Powertrains (MYs 2015-2032)

	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033
BEV	1.00	0.93	0.87	0.83	0.77	0.72	0.69	0.64	0.61	0.59	0.56	0.55	0.53	0.52	0.52	0.51	0.49
SS12V	1.12	1.07	1.03	1.00	0.97	0.94	0.91	0.89	0.87	0.85	0.83	0.82	0.81	0.79	0.79	0.79	0.77
BISG	1.00	0.94	0.87	0.78	0.73	0.69	0.66	0.63	0.61	0.59	0.58	0.56	0.55	0.54	0.54	0.53	0.53
SHEVPS	1.00	0.96	0.92	0.89	0.87	0.84	0.82	0.78	0.76	0.74	0.73	0.72	0.71	0.70	0.69	0.69	0.68
SHEVP2	1.00	0.96	0.93	0.90	0.87	0.85	0.82	0.79	0.76	0.75	0.74	0.73	0.71	0.70	0.69	0.69	0.69
PHEV20	1.00	0.96	0.92	0.88	0.85	0.81	0.78	0.76	0.73	0.70	0.69	0.67	0.66	0.66	0.65	0.64	0.60
PHEV50	1.00	0.96	0.92	0.88	0.84	0.81	0.78	0.74	0.71	0.69	0.68	0.66	0.64	0.63	0.63	0.62	0.59
FCV	1.71	1.64	1.57	1.50	1.43	1.37	1.31	1.25	1.19	1.14	1.09	1.04	0.99	0.95	0.90	0.86	0.83

Table 3-90 – Learning Rate Factor Used for Non-Battery Electrification Components for Electrified Powertrains (MYs 2034-2050)

	2034	**2035**	**2036**	**2037**	**2038**	**2039**	**2040**	**2041**	**2042**	**2043**	**2044**	**2045**	**2046**	**2047**	**2048**	**2049**	**2050**
BEV	0.48	0.47	0.46	0.46	0.45	0.45	0.44	0.44	0.44	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43
SS12V	1.14	1.09	1.05	1.00	0.95	0.91	0.87	0.83	0.79	0.76	0.73	0.69	0.66	0.63	0.60	0.57	1.14
BISG	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.51	0.51	0.51	0.51	0.51	0.51	0.51	0.5	0.5
SHEVPS	0.68	0.68	0.67	0.67	0.67	0.66	0.66	0.66	0.65	0.65	0.65	0.64	0.64	0.64	0.63	0.63	0.63
SHEVP2	0.68	0.67	0.67	0.66	0.66	0.65	0.65	0.64	0.64	0.63	0.63	0.62	0.62	0.61	0.6	0.6	0.59
PHEV20	0.57	0.54	0.53	0.51	0.5	0.48	0.47	0.47	0.46	0.45	0.45	0.45	0.45	0.44	0.44	0.44	0.43
PHEV50	0.57	0.54	0.53	0.51	0.5	0.49	0.48	0.47	0.47	0.46	0.46	0.46	0.46	0.45	0.45	0.45	0.45
FCV	0.80	0.76	0.75	0.73	0.72	0.70	0.69	0.68	0.67	0.66	0.65	0.65	0.65	0.65	0.65	0.65	0.64

3.3.5.3 Total Electrified Powertrain Costs

For this analysis, we calculate total electrified powertrain costs by summing individual component costs, which ensures that all technologies in an electrified powertrain appropriately contribute to the total system cost. We combine the costs associated with the internal combustion (IC) engine, transmission, electric machine(s), non-battery electrification components, and battery pack to create a full-system cost. The following sections describe how we calculate the aggregated cost of each electrified powertrain based on the detailed component costs presented in the earlier sections.

The application of the electrification costs to an existing platform follows the same basic process for each technology on the electrification path. The costs for each technology depend on the model year that the CAFE Model applies the technology. First, the model must remove costs associated with reference powertrain technologies. Next, the model applies the costs associated with the electrification technology. The costs include the cost of the engine, if applicable, transmission, electric machine(s), non-battery electrification components, and the battery pack.

The incremental costs for these electrification technologies can be found in three places: the "Engines" tab and "Vehicles" tab of the Technologies file, and the "battery_costs.csv" file, which is the database of battery costs (DMC) created using the BatPaC model. Table 3-91 shows a summary of the general components considered for each electrification technology, and where the costs of those components can be found in the CAFE Model input and model file folders.

Table 3-91 – Breakdown of the Component Costs Considered in the CAFE Analysis

Electrification Technology Type	Technologies File Vehicle Tabs	Technologies File Engine Tabs	Battery Cost File[437]
Micro Hybrid	Motor/generator	-N/A	Battery Pack[438]
Mild Hybrid	Motor/generator, DC/DC converter, other components	-N/A	Battery Pack
Strong Hybrid – P2	DC/DC converter, on-board charger, high voltage cables, e-motor, AT8L2 transmission, and power electronics	IC engine*	Battery Pack
Strong Hybrid – PS	DC/DC converter, on-board charger, high voltage cables, e-motor, eCVT transmission, and power electronics	IC engine	Battery Pack
Plug-in Hybrid (PHEV 20T/50T)	DC/DC converter, on-board charger, high voltage cables, e-motor, AT8L2 transmission, and power electronics	IC engine	Battery Pack
Plug-in Hybrid (PHEV 20/50 and 20H/50H)	DC/DC converter, on-board charger, high voltage cables, e-motor, CVTL2 transmission, and power electronics	IC engine	Battery Pack

437 The battery_costs.csv file is installed as part of the CAFE Model installation and is viewable in the model program file.
438 As discussed further in this chapter, we no longer use the BatPaC SS12V battery cost and use a cheaper AGM battery instead, and the updated cost is reflected in the battery_costs.csv file.

Electrification Technology Type	Technologies File Vehicle Tabs	Technologies File Engine Tabs	Battery Cost File[437]
BEVs	DC/DC converter, on-board charger, high voltage cables, e-motor	ETDS, see Table 3-98 for detail	Battery Pack
FCEVs	Fuel cell system, e-motor, H_2 Tank, transmission, and power electronics	-N/A	N/A

*The engine cost for a P2 Hybrid is based on engine technology used in the conventional powertrain.

The following sections discuss how the costs of each component are aggregated to create a total electrified powertrain cost.

3.3.5.3.1 Micro Hybrid Cost

As we discuss earlier in Chapter 3.3.4, SS12V technology does not provide any propulsion assistance to the vehicle, thus there is no cost associated with the SS12V system under the engine tabs of the Technologies file. In the vehicle class tabs in the Technologies file, there is a fixed cost listed for SS12V that covers the battery and non-battery components in the system.

The NPRM SS12V fixed battery pack direct manufacturing cost was $237 across all vehicle classes; however, for this analysis, as we discuss in preamble Section III.D.3.e), the SS12V battery cost now reflects the cost of a more commonly used battery chemistry. Specifically, AGM batteries are more common in SS12V systems than the Li-ion-based chemistry that we had assumed in the NPRM analysis.[439, 440, 441] The battery pack direct manufacturing costs for SS12V systems is now $113, across all vehicle classes, as shown in Table 3-92 below. This cost also more closely algins with the cost of the SS12V system presented in the 2015 NAS report.[442]

Unlike the rest of the electrification technologies, the micro hybrid system uses a shallower learning curve, as shown in Chapter 3.3.5.2. This shallow curve reflects the maturity of the technology; as we discuss in Chapter 3.3.2, 50 percent of the MY 2020 fleet utilizes a SS12V micro hybrid system.

Table 3-92 lists the cost of the SS12V system and battery for different vehicle classes. For the SS12V electrified powertrain, the Technologies file contains the cost of the non-battery components with RPE and learning, as well as learning factor for the battery for each vehicle class. The SS12V battery pack cost in the Battery Costs file now reflects the lower cost.

[439] EPA-HQ-OAR-2021-0208-0144, page 5-73.
[440] USABC, "United States Advanced Battery Consortium Battery Test Manual For 12 Volt Start/Stop Vehicles." January 2018. Revision 2. Contract DE-AC07-05ID14517.
[441] H. Tataria; O. Gross; C. Bae; B. Cunningham; J. A. Barnes; J. Deppe; J. Neubauer. "USABC Development of 12 Volt Battery for Start-Stop Application: Preprint.": 10 pp. 2015. https://www.nrel.gov/docs/fy15osti/62680.pdf. (Accessed: February 15, 2022).
[442] 2015 NAS report, at p.158.

Table 3-92 – Final Rule SS12V Total Cost for All Vehicle Classes in 2018$

	Small Car	Medium Car	Small SUV	Medium SUV	Pickup
Non-battery Component DMC in 2017	$159	$159	$159	$213	$213
Non-battery Component Cost in 2020 with RPE and Learning	$213	$213	$213	$285	$285
Battery Pack DMC in 2020	$113	$113	$113	$113	$113
Battery Pack Cost in 2020 with RPE and Learning	$170	$170	$170	$170	$170
Total System Cost in 2020	$383	$383	$383	$455	$455

3.3.5.3.2 Mild Hybrid Cost

For this analysis, we use a fixed cost for a BISG system to represent mild hybrid technology. The total cost for the BISG system is the sum of non-battery component costs from the Technologies file and the batteries from the Battery Cost file. The vehicle class tabs in the Technologies file provide a non-battery component cost that includes the DMC, RPE, and a learning factor, and a battery cost with a learning factor applied. Note that the Technologies file includes the battery cost with the learning rate applied, while the Battery Costs file provides only the battery DMC in 2020. To determine the total cost of the system for a vehicle, the vehicle technology class's technology key must align between the two files.

Table 3-93 below shows how costs are added to create the total BISG system cost. As an example, the medium car cost of $665 is from the 'MedCar' tab in 2020 in the Technologies file and includes a learning rate specific to the non-battery components, as well as RPE. The $342 is from the Battery Cost file for the same vehicle class technology key. This $342 is a DMC and is multiplied by 1.50 from the Battery Cost Learning Rates Table (columns 'AW' and onward on the 'MedCar' tab), which is the product of 1.5 RPE and a learning factor of 1 (because the base learning rate year for batteries is 2020), and that results in the total of $513. These two costs, which are both for 2020, sum to $1,178.

Table 3-93 – Example of Mild Hybrid Total Cost for Different Vehicle Classes in 2018$

	Small Car	Medium Car	Small SUV	Medium SUV	Pickup
Non-battery Component DMC in 2017	$565	$565	$565	$565	$565
Cost in 2020 with RPE and Learning	$665	$665	$665	$665	$665
Battery Pack DMC in 2020	$342	$342	$342	$342	$342
Battery Pack Cost in 2020 with RPE and Learning	$513	$513	$513	$513	$513
Total System Cost in 2020	$1,178	$1,178	$1,178	$1,178	$1,178

3.3.5.3.3 Strong Hybrid and Plug-in Hybrid Electric Vehicle Costs

In this analysis, the total cost for strong hybrids includes the electric machine, battery pack, IC engine, and transmission. Autonomie optimizes each strong hybrid powertrain for the given vehicle class by appropriately sizing each of those components.

SHEVP2 and SHEVPS have different architectures and characteristics, and in turn have different costs. We base the cost of SHEVP2 engines and transmissions on estimates discussed further in Chapter 3.1 and Chapter 3.2, respectively. The cost for SHEVP2 electric machines and battery packs are based on their sizes, and are optimized by the Autonomie sizing algorithm discussed broadly in Chapter 3.3.4 and in detail in the Autonomie model documentation.[443] SHEVPS total powertrain costs include the optimized battery pack, electric machine, a HCR1 engine, and eCVT. Like SHEVP2, electric machine and battery pack costs are dependent on their optimized size from Autonomie for different vehicle classes.

As described in Chapter 3.3.5.2, the cost of non-battery hybrid system components also includes the cost of the traction motor, motor/generators, high voltage cables and connectors, charging cord (for PHEVs), and on-board chargers. We use the cost of the AT8L2 transmission as a cost proxy for the hybrid transmission architecture in P2 hybrid systems. The costs shown here do not include the cost of the IC engine coupled to the hybrid system.

Since motor sizing varies based on road load levels, the average motor sizes act as a mid-range representation for motor ratings across all road load combinations. We use Autonomie simulations to compute the average rating for traction and generator motors across all road load combinations for SHEVPS and SHEVP2 vehicles. After calculating the average motor size, we multiply the motor size by the unit cost ($/kW) to get the overall DMC for both traction motors and generator motors as explained in Chapter 3.3.5.2. The costs shown in the following tables are 2018$ dollars.

We calculate the cost of the plug-in hybrid vehicles similar to strong hybrids. We use Autonomie to optimize plug-in-hybrid system components as explained in Chapter 3.3.4. We use these modeling results to determine costs as described in Chapters 3.3.5.1 and 3.3.5.2. As described in Chapter 3.3.4, we use one engine technology and one transmission technology per plug-in hybrid architecture type.

For PHEVs that follow SHEVP2 on the hybrid/electric architecture path as shown in Chapter 3.3.1, we base the total costs on a PHEV system paired with a TURBO1 engine. We calculate the total cost for the powertrain by summing the costs of the TURBO1 engine, an AT8L2 transmission, and the battery and non-battery electrification technology components. We calculate the total cost for PHEVs that follow SHEVPS in the hybrid/electric architecture path by summing the costs of the HCR1 engine, the CVTL2 transmission, and the sized battery pack and non-battery electrification technology components.

Table 3-94 and Table 3-95 show the overall cost of electrified powertrains for strong hybrids and PHEVs. Note that the battery cost is not broken out in a separate column in this table; however, the total electrification cost includes the cost of the battery. The total DMC of non-battery

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[443] Autonomie model documentation, Chapter 8.3.3.

electrification components includes the costs of motor and motor/generator (when applicable), DC/DC converter, cables, and on-board charger (for PHEV only). For more details of these costs refer to Chapter 3.3.5.2.

Table 3-94 – Cost Estimation for Hybrid and Plug-in Hybrid Electric Drivetrain for all Non-Performance Vehicle Technology Classes in 2020 (in 2018$)[444]

Electric Powertrain	Traction Motor calculated using Peak Power (kW)	Motor-Generator calculated using Continuous Power (kW)	Total Cost of ETDS (Motor and Inverter)	DC to DC Converter	On-board Charger	Power Distribution Cables	Total DMC of Electrical Components	Total Electrification RPE	DMC of CVT or AT8L2	RPE Cost of CVT or AT8L2	Total Electrification Cost (DMC)	Total Electification Cost (RPE) - from Tech file
Small Car– Non-Performance												
Par HEV (SHEVP2)	23.45	0	$432	$184	$0	$168	$784	$1,058	$1,655	$2,473	$2,439	$3,511
Par PHEV20 (PHEV20T)	33.89	0	$624	$184	$174	$460	$1,442	$1,904	$1,655	$2,473	$3,097	$4,334
Par PHEV50 (PHEV50T)	84.89	0	$1,563	$184	$174	$460	$2,382	$3,144	$1,655	$2,473	$4,037	$5,567
Split HEV (SHEVPS)	57.18	30.13	$1,608	$184	$0	$168	$1,960	$2616	$1,084	$1619	$3,043	$4,247
Split PHEV20 (PHEV20)	58.87	31.21	$1,659	$184	$174	$460	$2,477	$3,2670	$1,686	$2,518	$4,163	$5,775
Medium Car– Non-Performance												
Par HEV (SHEVP2)	28.01	0	$516	$184	$0	$168	$868	$1,171	$1,655	$2,473	$2,523	$3,625
Par PHEV20 (PHEV20T)	38.95	0	$717	$184	$174	$460	$1,536	$2,027	$1,655	$2,473	$3,191	$4,457
Par PHEV50 (PHEV50T)	95.21	0	$1,753	$184	$174	$460	$2,572	$3,395	$1,655	$2,473	$4,227	$5,817
Split HEV (SHEVPS)	72.62	37.61	$2,030	$184	$0	$168	$2,382	$3,180	$1,084	$1,619	$3,465	$4,812
Split PHEV20 (PHEV20)	74.66	38.92	$2,091	$184	$174	$460	$2,910	$3,841	$1,686	$2,518	$4,596	$6,345
Small SUV– Non-Performance												
Par HEV (SHEVP2)	27.34	0	$503	$184	$0	$168	$855	$1,155	$1,655	$2,473	$2,510	$3,608
Par PHEV20 (PHEV20T)	40.25	0	$741	$184	$174	$460	$1,560	$2,059	$1,655	$2,473	$3,215	$4,488
Par PHEV50 (PHEV50T)	102.41	0	$1,886	$184	$174	$460	$2,704	$3,570	$1,655	$2,473	$4,359	$5,992
Split HEV (SHEVPS)	80.07	40.68	$2,224	$184	$0	$168	$2,575	$3,438	$1,084	$1,619	$3,659	$5,071

[444] Numbers in this table are rounded.

Electric Powertrain	Traction Motor calculated using Peak Power (kW)	Motor-Generator calculated using Continuous Power (kW)	Total Cost of ETDS (Motor and Inverter)	DC to DC Converter	On-board Charger	Power Distribution Cables	Total DMC of Electrical Components	Total Electrification RPE	DMC of CVT or AT8L2	RPE Cost of CVT or AT8L2	Total Electrification Cost (DMC)	Total Electrification Cost (RPE) - from Tech file
Split PHEV20 (PHEV20)	83.15	42.15	$2,307	$184	$174	$460	$3,126	$4,126	$1,686	$2,518	$4,811	$6,630
Medium SUV– Non-Performance												
Par HEV (SHEVP2)	29.14	0	$537	$184	$0	$168	$888	$1,199	$1,655	$2,473	$2,543	$3,653
Par PHEV20 (PHEV20T)	43.32	0	$798	$184	$174	$460	$1,616	$2,133	$1,655	$2,473	$3,271	$4,563
Par PHEV50 (PHEV50T)	110.72	0	$2,039	$184	$174	$460	$2,857	$3,772	$1,655	$2,473	$4,512	$6,194
Split HEV (SHEVPS)	79.32	41.74	$2,229	$184	$0	$168	$2,581	$3,446	$1,084	$1,619	$3,665	$5,078
Split PHEV20 (PHEV20)	81.81	43.01	$2,298	$184	$174	$460	$3,117	$4,114	$1,686	$2,518	$4,803	$6,618
Pickup – Non-Performance												
Par HEV (SHEVP2)	32.59	0	$600	$184	$0	$168	$952	$1,285	$1,655	$2,473	$2,607	$3,739
Par PHEV20 (PHEV20T)	51.68	0	$952	$184	$174	$460	$1,770	$2,336	$1,655	$2,473	$3,425	$4,766
Par PHEV50 (PHEV50T)	127.92	0	$2,356	$184	$174	$460	$3,174	$4,190	$1,655	$2,473	$4,829	$6,611

Table 3-95 – Cost Estimation for Hybrid and Plug-in Hybrid Electric Drivetrain for all Performance Vehicle Technology Class in 2020 (in 2018$)[445]

Electric Powertrain	Traction Motor calculated using Peak Power (kW)	Motor-Generator calculated using Continuous Power (kW)	Total Cost of ETDS (Motor and Inverter)	DC to DC Converter	On-board Charger	Power Distribution Cables	Total DMC of Electrical Components	Total Electrification RPE	DMC of CVT or AT8L2	RPE Cost of CVT or AT8L2	Total Electrification Cost (DMC)	Total Electrification Cost (RPE) - from Tech file
Small Car– Performance												
Par HEV (SHEVP2)	25.03	0	$461	$184	$0	$168	$813	$1,097	$1,655	$2,473	$2,468	$3,550
Par PHEV20 (PHEV20T)	36	0	$663	$184	$174	$460	$1,481	$1,955	$1,655	$2,473	$3,136	$4,385
Par PHEV50 (PHEV50T)	89.03	0	$1,639	$184	$174	$460	$2,458	$3,244	$1,655	$2,473	$4,113	$5,668
Split HEV (SHEVPS)	74.95	38.75	$2,094	$184	$0	$168	$2,446	$3,265	$1,084	$1,619	$3,529	$4,897
Split PHEV20 (PHEV20)	76.51	40.15	$2,148	$184	$174	$460	$2,967	$3,916	$1,686	$2,518	$4,652	$6,420
Medium Car– Performance												
Par HEV (SHEVP2)	29.2	0	$538	$184	$0	$168	$890	$1,201	$1,655	$2,473	$2,545	$3,654
Par PHEV20 (PHEV20T)	41.5	0	$764	$184	$174	$460	$1,583	$2,089	$1,655	$2,473	$3,238	$4,519
Par PHEV50 (PHEV50T)	100.23	0	$1,846	$184	$174	$460	$2,664	$3,517	$1,655	$2,473	$4,319	$5,939
Split HEV (SHEVPS)	112.45	58.4	$3,146	$184	$0	$168	$3,498	$4,670	$1,084	$1,619	$4,581	$6,305
Split PHEV20 (PHEV20)	122.77	60.41	$3,373	$184	$174	$460	$4,192	$5,533	$1,686	$2,518	$5,877	$8,035
Small SUV– Performance												
Par HEV (SHEVP2)	29.54	0	$544	$184	$0	$168	$896	$1, 209	$1,655	$2,473	$2,551	$3,663
Par PHEV20 (PHEV20T)	43.25	0	$796	$184	$174	$460	$1,615	$2,132	$1,655	$2,473	$3,270	$4,561
Par PHEV50 (PHEV50T)	108.23	0	$1,993	$184	$174	$460	$2,811	$3,711	$1,655	$2,473	$4,466	$6,133
Split HEV (SHEVPS)	108.91	54.25	$3,004	$184	$0	$168	$3,356	$4,481	$1,084	$1,619	$4,440	$6,116
Split PHEV20 (PHEV20)	118.09	56.21	$3,210	$184	$174	$460	$4,028	$5,317	$1,686	$2,518	$5,714	$7,820
Medium SUV– Performance												
Par HEV (SHEVP2)	33.22	0	$612	$184	$0	$168	$964	$1,301	$1,655	$2,473	$2,619	$3,755
Par PHEV20 (PHEV20T)	48.92	0	$901	$184	$174	$460	$1,719	$2,269	$1,655	$2,473	$3,374	$4,699
Par PHEV50 (PHEV50T)	121.62	0	$2,240	$184	$174	$460	$3,058	$4,036	$1,655	$2,473	$4,713	$6,458

[445] Numbers in this table are rounded.

Electric Powertrain	Traction Motor calculated using Peak Power (kW)	Motor-Generator calculated using Continuous Power (kW)	Total Cost of ETDS (Motor and Inverter)	DC to DC Converter	On-board Charger	Power Distribution Cables	Total DMC of Electrical Components	Total Electrification RPE	DMC of CVT or AT8L2	RPE Cost of CVT or AT8L2	Total Electrification Cost (DMC)	Total Electrification Cost (RPE) - from Tech file
Split HEV (SHEVPS)	124.62	61.59	$3,429	$184	$0	$168	$3,781	$5,047	$1,084	$1,619	$4,864	$6,684
Split PHEV20 (PHEV20)	134.67	63.71	$3,653	$184	$174	$460	$4,471	$5,902	$1,686	$2,518	$6,157	$8,404
Pickup – Performance												
Par HEV (SHEVP2)	36.96	0	$681	$184	$0	$168	$1,032	$1,394	$1,655	$2,473	$2,687	$3,848
Par PHEV20 (PHEV20T)	58.26	0	$1,073	$184	$174	$460	$1,891	$2,496	$1,655	$2,473	$3,546	$4,925
Par PHEV50 (PHEV50T)	140.04	0	$2,579	$184	$174	$460	$3,397	$4,484	$1,655	$2,473	$5,052	$6,904

As part of the NPRM analysis, in response to comments from the National Academies of Sciences, Engineering, and Medicine (NASEM) that the strong hybrid costs in our 2020 final rule were significantly higher than what NAS estimated in their 2021 report, we compared the estimated costs between the 2021 NAS report and our costs for converting a conventional vehicle powertrain to a strong hybrid powertrain

To compare the strong hybrid costs in this analysis to the 2021 NAS report, we compare the costs of a Ford Fusion with a conventional powertrain to a Ford Fusion PS powertrain in the CAFE Model in MY 2025 to the 2021 NAS study that converts a naturally aspirated medium car to PS hybrid technology.[446] As expected, the components considered, component sizes, and component costs are not identical between the NAS analysis and this analysis. Table 3-96 shows the components we consider and those in the 2021 NAS analysis.

Table 3-96 – Components Considered in Upgrading from Conventional Powertrain to SHEVPS in MY 2025 in the CAFE Model and NAS 2021 Analysis

Part Removed	Parts added	CAFE Analysis	NAS
IC Engine		(Naturally Aspirated DOHC+VVT+SGDI)	not changed[447]
Transmission		AT6	AT8
	IC engine for SHEV	SHEVPS	not changed
	Motor+ inverter	73 kW	Size not mentioned (approx. 74 kW[448])
	Generator+ Regen brake	37 kW	Size not mentioned (approx. 28 kW[449])
	Transmission	eCVT	eCVT
	Battery + battery management unit (BMU)[450]	1.7 kWh[451]	1 kWh
	High voltage cable	Yes	Yes
	DC/DC converter	1.1 kW	2 kW
	Power electronics or ECU[452]	Considered	Considered

[446] 2021 NAS report, Table 4.6 Projected Costs and Effectiveness of Representative PS Hybrid Technology Packages, 2025-2035.
[447] NAS's vehicle of choice (a Toyota Camry 2021) has no engine upgrade when advancing from a conventional powertrain to PS hybrid powertrain.
[448] Based on NAS assumption of 10 percent decrease on cost of motor + inverter from 2010 cost of $15/kW, the cost for 2025 will be $10.935/kW. The overall cost of motor+inverter reported $810 ($320+$490) which results in 74 kW.
[449] With the same analysis of motor+inverter.
[450] Includes battery + battery management unit + battery thermal management.
[451] The selected vehicle to present the transformation from ICE to PS Hybrid is with no mass upgrade (MR0) thus heavier. In the battery sizing algorithm, the heavier the vehicle gets, the higher battery energy is required.
[452] Assumed NAS referred to power electronics as ECU.

Part Removed	Parts added	CAFE Analysis	NAS
	AC modification	Assumed as part of the thermal management system	Considered
	Water pump	Assumed as part of the thermal management system	Considered
	Thermal management system	Considered	AC modification and water pump upgrades

As mentioned in Chapter 3.3.5.2, we use the UBS study to estimate the cost of the ETDS, which includes the motor, inverter, power electronics and thermal management system. For the sake of this comparison, we separate the motor and inverter cost to be more consistent with how NAS presents costs. Based on the UBS report, about 72 percent of the ETDS' cost comes from the e-motor and inverter, which means for year 2025 and based on 2018$, the cost of the e-motor and inverter is $10.08/kW. This leaves $3.92/kW for the power electronics and thermal management system, summing up the whole ETDS to $14/kW.

One of the biggest differences in components between the two studies is the internal combustion engine; the 2021 NAS study does not consider the IC engine upgrade costs whereas the CAFE analysis does. Other differences between the studies include the component sizes, even though we endeavor to compare an equivalent vehicle class, a midsize passenger car. Other small differences include the minor components considered in each study.

Based on comments and further analysis of component costs, we updated some hybrid system costs from the NPRM. Our updated costs are shown in the last column of Table 3-97.

Table 3-97 – Comparison of Components Included in this CAFE Model Analysis and 2021 NAS Study

Component	CAFE Analysis	CAFE Net Cost (NPRM)	NAS Analysis	NAS Net Cost	CAFE Net Cost (Final Rule)
IC engine	Naturally Aspirated DOHC+VVT+SGDI to SHEVPS	$178		0	$178
Transmission	AT6 to eCVT	$292	AT8 to eCVT	($435)	($362)[453]
Motor+ inverter	73 kW	$732	Size not mentioned (approx. 74 kW)	$810	$732
Generator+ Regen brake	37 kW	$379	Size not mentioned (approx. 28 kW)	$310	$379

[453] To be consistent with NAS analysis this price reflects AT8 to eCVT, although the specific example used for this comparison had an AT6 transmission.

Component	CAFE Analysis	CAFE Net Cost (NPRM)	NAS Analysis	NAS Net Cost	CAFE Net Cost (Final Rule)
Battery + BMU	1.7 kWh[454]	$1,013	1 kWh	$880	$1,013
High voltage cable	Yes	$350	Yes	$130	$168
DC/DC converter	2 kW	$140	1.1 kW	$90	$140
ECU				$45	
AC modification				$170	
Water pump				$55	
Power electronics and thermal management system		$432			$432
Total		$3,516		$2,055	$2,680

There are a few important observations in this cost comparison. First, in the NPRM analysis we had considered the cost of a CVTL2 as a proxy for the eCVT. Considering comments on the NPRM and the NAS study, we updated the cost of the transmission for PS hybrids to reflect the lower eCVT cost. The eCVT cost comes from data in the 2021 NAS Report and the 2011 EPA-sponsored 2011 Ford Fusion strong hybrid teardown study.[455, 456] Both the 2021 NAS study and the Ford Fusion teardown study use incremental costs, which we cannot use as a direct input into the CAFE Model, so we calculate an absolute value for use in the CAFE Model. Second, as discussed in Chapter 3.3.5.2, the strong hybrid high voltage cable costs now reflect high voltage cable costs presented in the Ford Fusion teardown study, in 2018$. Third, there are costs associated with some component assumptions as well as component sizing, which play an additional role in the cost difference between CAFE analysis and NAS study. While the costs presented in this analysis still differ from those in the 2021 NAS report, we believe that the estimated costs in this rulemaking analysis appropriately consider all of the component costs that must be subtracted and added to implement a strong hybrid powertrain system.

3.3.5.3.4 BEV Cost

For this analysis, the total costs of BEVs includes the optimized battery pack and electric machine costs. Like the other electrified powertrains, Autonomie optimizes both the size of the battery pack and electric machine to fulfill the performance neutrality requirements for each vehicle. Further discussion of electrification technology component sizing and optimization is provided in Chapter 3.3.4. Electrification component costing is discussed in Chapter 3.3.5.1 and 3.3.5.2.

The model calculates the total cost of a BEV by first removing the cost of the IC engine and transmission associated with the conventional or hybridized powertrain and replacing that cost

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454 The specific example picked for this comparison has a MR0 weight thus battery selection algorithm associated a bigger battery energy capacity to that.

455 2021 NAS report, at 4-68-4-69.

456 EPA. “Light Duty Technology Cost Analysis, Power-Split and P2 HEV Case Studies.’ November 2011. EPA-420-R-11-015. https://nepis.epa.gov/Exe/ZyPDF.cgi/P100EG1R.PDF?Dockey=P100EG1R.PDF. (Accessed: February 15, 2022).

with the cost of an ETDS (*i.e.*, the motor and inverter). It is important to accurately estimate the motor size (rating) because the cost of the ETDS accounts for a significant portion of the total cost of electrifying a vehicle. We use the MY 2017 Market Data file (originally used for the 2020 final rule) to compute the average engine power for each technology class. Table 3-98 shows the steps taken to calculate the equivalent electric motor power required to replace each engine technology, derived from the MY 2017 Market Data file. These power ratings can be found under appropriate engine tabs in the Technologies file. The cost of the rest of the non-battery electrification components can be found under vehicle tabs of the Technologies file. Summing these two cost leads to the total BEV electrified powertrain cost shown in the final column of Table 3-98. The values in this table are for DMC year 2017 in 2018$.

Table 3-98 – Cost of ETDS for BEVs in 2020 (in 2018$)

Technology Class	HP Estimate	Power in kW	ETDS DMC	ETDS with RPE	Cost of Other Electric Components[457]	Cost of Other Electrical Components with RPE	Total BEV Electrification Cost with RPE
2C1B_SOHC	38.00	28.33	$521.72	$782.58	$1,244.99	$1,867.49	$2,650.07
2C1B	38.00	28.33	$521.72	$782.58	$1,244.99	$1,867.49	$2,650.07
3C1B_SOHC	122.06	91.01	$1,675.77	$2,513.65	$1,244.99	$1,867.49	$4,381.14
3C1B	122.06	91.01	$1,675.77	$2,513.65	$1,244.99	$1,867.49	$4,381.14
4C1B_SOHC	175.05	130.51	$2,403.30	$3,604.95	$1,244.99	$1,867.49	$5,472.44
4C1B	197.81	147.49	$2,715.87	$4,073.81	$1,244.99	$1,867.49	$5,941.30
4C2B_SOHC	180.51	134.59	$2,478.34	$3,717.51	$1,244.99	$1,867.49	$5,585.00
4C2B	180.51	134.59	$2,478.34	$3,717.51	$1,244.99	$1,867.49	$5,585.00
5C1B_SOHC	226.86	169.14	$3,114.61	$4,671.92	$1,244.99	$1,867.49	$6,539.41
5C1B	226.86	169.14	$3,114.61	$4,671.92	$1,244.99	$1,867.49	$6,539.41
6C1B_SOHC	255.00	190.13	$3,501.02	$5,251.52	$1,244.99	$1,867.49	$7,119.01
6C1B	255.00	190.13	$3,501.02	$5,251.52	$1,244.99	$1,867.49	$7,119.01
6C1B_OHV	255.00	190.13	$3,501.02	$5,251.52	$1,244.99	$1,867.49	$7,119.01
6C2B_SOHC	285.48	212.86	$3,919.52	$5,879.28	$1,244.99	$1,867.49	$7,746.77
6C2B	285.48	212.86	$3,919.52	$5,879.28	$1,244.99	$1,867.49	$7,746.77
6C2B_OHV	285.48	212.86	$3,919.52	$5,879.28	$1,244.99	$1,867.49	$7,746.77
8C2B_SOHC	328.70	245.08	$4,512.85	$6,769.28	$1,244.99	$1,867.49	$8,636.77
8C2B	369.40	275.43	$5,071.70	$7,607.55	$1,244.99	$1,867.49	$9,475.04
8C2B_OHV	401.34	299.24	$5,510.15	$8,265.23	$1,244.99	$1,867.49	$10,132.72
10C2B	497.94	371.26	$6,836.41	$10,254.62	$1,244.99	$1,867.49	$12,122.11
10C2B_OHV	665.67	496.32	$9,139.25	$13,708.88	$1,244.99	$1,867.49	$15,576.37
12C2B_SOHC	558.86	416.68	$7,672.82	$11,509.22	$1,244.99	$1,867.49	$13,376.71
12C2B	558.86	416.68	$7,672.82	$11,509.22	$1,244.99	$1,867.49	$13,376.71
12C4B_SOHC	558.86	416.68	$7,672.82	$11,509.22	$1,244.99	$1,867.49	$13,376.71
12C4B	558.86	416.68	$7,672.82	$11,509.22	$1,244.99	$1,867.49	$13,376.71
16C4B_SOHC	621.00	463.02	$8,526.00	$12,789.01	$1,244.99	$1,867.49	$14,656.50
16C4B	601.31	448.33	$8,255.64	$12,383.46	$1,244.99	$1,867.49	$14,250.95

[457] Other electric components in BEVs are charger, DC/DC converter, and electrical cables.

3.3.5.3.5 FCEV Cost

For this analysis, we consider technology advancements in fuel cell systems, hydrogen storage tanks and hydrogen delivery systems, sensors and control systems, and market penetration. The cost of hydrogen storage tanks and fuel cells come from a Department of Energy (DOE), Office of Energy Efficiency and Renewable Energy (EERE), Fuel Cell Technologies Office cost analysis. In these studies, DOE estimates the cost for 10,000 units per year production of a compressed gas storage system at around $26/kWh (2016$, equivalent to $27.11 in 2018), and the cost of the fuel cell system at about $85/kW (2017$, equivalent to $86.96 in 2018).[458,459] The DMC for FCEVs in this analysis is $12,082.67 in 2020 in 2018$. After RPE, the cost is $13,804.13 in 2020 in 2018$.

The total cost of a FCEV includes the fuel cell, control systems, motors, inverters, hydrogen storage tanks, wiring harness, hydrogen fuel delivery lines, sensors, and hardware. The cost of the battery pack and battery management system is not included in the cost of the fuel cell vehicle. See the Vehicle tabs in the Technologies file for the total cost of the FCEV in this analysis across model years.

3.3.5.3.6 Example Electrification Cost Technology Walk

This section shows how the costs are computed for a vehicle that progresses from a lower level to a higher level of electrified powertrain. We use a GMC Acadia AWD (vehicle code 1101008) as an example to walk through costs incurred during the progress from a vehicle with a mild hybrid SS12V system to a full BEV300 powertrain. The same methodology could be used for any other technology advancement in the electric technology tree path.

We use platform data from the reference run CAFE Model standard setting vehicle_report.csv results file. As seen in the vehicle_report.csv file, the MY 2024 GMC Acadia AWD SLT with a SS12V system adopts a BEV300 powertrain in MY 2025. The change in technology and associated incremental technology cost from MY 2024 to MY 2025 are shown in Table 3-99.

Table 3-99 – Cost and Technology Difference Between MY 2024 and MY 2025 for GMC Acadia AWD Simulated Platform

MY	Tech Key	Tech Cost (2018$)
2024	DOHC; VVT; SGDI; DEAC; AT9L2; EPS; SS12V; LDB; SAX; ROLL20; AERO0; MR3	$321.04
2025	IACC; BEV300; LDB; SAX; ROLL20; AERO20; MR3	$13,696.96
Cost Difference		$13,375.92

458 James et al., Final Report: Hydrogen Storage System Cost Analysis (September 2016), available at https://www.osti.gov/servlets/purl/1343975. (Accessed: February 15, 2022). Page 20 -Table 6.

459 James et al., Direct hydrogen fuel cell electric vehicle cost analysis: System and high-volume manufacturing description, validation, and outlook, https://www.osti.gov/pages/biblio/1489250. (Accessed: February 15, 2022). Page 8 – Fig. 6.

As seen in Table 3-99, the MY 2024 GMC Acadia AWD begins with the following technology key: DOHC; VVT; SGDI; DEAC; AT9L2; EPS; SS12V; LDB; SAX; ROLL20; AERO0; MR3. To progress to the BEV300 configuration, the following technologies need to be removed: DOHC, VVT, SGDI, DEAC, AT9L2, EPS, SS12V, and AERO0; and the following technologies need to be added: IACC, BEV300, and LDB, and AERO20.

Table 3-100 shows the costs associated with the drivetrain and other components that the model removes from MY 2024 GMC Acadia AWD, and where to find them. To properly cost the engine, it is important to note the engine is designated as a 6C2B engine (6 cylinders, 2 banks). For more information about engine geometry designation in the Technologies file please see Chapter 2.2 and Chapter 3.1.2.

Table 3-100 – Costs Removed during Electrification Cost Integration for GMC Acadia Example

Technology	Location of Data in Technologies Input File and Battery Input File	MY 2025 Value (2018$)
DOHC Engine	'6C2B' Tab and 'DOHC' row	$5,830.76
AT9L2 Transmission	'MedSUVPerf' Tab and 'AT9L2' row	$2,498.29
VVT	'6C2B' Tab and 'VVT' row	$221.54
SGDI	'6C2B' Tab and 'SGDI' row	$501.67
DEAC	'6C2B' Tab and 'DEAC' row	$203.35
EPS	'MedSUVPerf' Tab, and 'EPS' row	$117.28
SS12V	'MedSUVPerf' Tab, 'SS12V' Row	$247.43
SS12V Battery	CAFE Model Battery Cost Input File and 'MedSUVPerf' Tab, 'SS12V' Row	$146.9
AERO0	'MedSUVPerf' Tab, 'AERO0' Row	0

We determine the SS12V battery pack cost by multiplying the baseline battery pack cost (now $113, as discussed above) by the RPE and learning curve factor. The learning factor is taken from the Technologies file. Table 3-103 shows the calculation of the battery pack cost.

Table 3-101 – Battery Pack Cost for GMC Acadia Example

Base Cost (2018) Battery_Costs.csv File	Learning for MY 2025 Technologies Input File 'MedSUVPerf' Tab, 'SS12V' Row	MY 2025 Battery Cost (2018$)
$113	1.3	$146.9

After removing the conventional powertrain component costs, we must add the costs for the new electrification technology. In this example the simulated vehicle platform is converted to a BEV300 powertrain. For all electrification path technologies, we must add two major component groups: the battery pack and the non-battery electrification components. Hybrid electric technologies will also include the cost for an engine and in some cases a change in cost for the transmission. Table 3-102 shows the added cost for the non-battery pack electrification technology components for the MY 2025 GMC Acadia AWD, and where those data can be found.

Table 3-102 – Costs Added for the Non-Battery Pack Electrification Technology Components for GMC Acadia Example

Technology	Location of Data in Technologies Input File and Battery Input File	MY 2025 Value (2018$)
BEV300 Engine	'6C2B Tab', 'BEV300' row	$3,581.65
IACC	'MedSUVPerf' Tab, 'IACC' row	$146.68
BEV300 non-battery components	'MedSUVPerf' Tab, 'BEV300' row	$1,137.67
BEV300 battery cost	CAFE Model Battery Cost Input File[460]	$17,955.29
AERO20	'MedSUVPerf' Tab, 'AERO20' row	$248.9

The battery pack is cost is determined by multiplying the baseline battery pack cost by the learning curve factor. The baseline battery costs are determined per discussions in Chapter 3.3.5.1, and are found in the battery_cost.csv file. The learning factor is found in the Technologies file. Table 3-103 shows the calculation of battery pack costs.

Table 3-103 – Battery Pack Cost for GMC Acadia Example

Base Cost (2020 DMC in 2018$) Battery_Costs.csv file	Learning for MY 2025 Technologies Input File 'MedSUVPerf' Tab, 'BEV300' Row	MY 2025 Battery Cost (2018$)
$15,069	1.1915	$17,955.29

Summing these costs will result in a net added cost for the progression of a MY 2024 GMC Acadia mild hybrid to a MY 2025 Acadia BEV300. Table 3-104 shows a summary of the total cost application for this technology transition.

Table 3-104 – Summary of Technology Cost Change for GMC Acadia Example

	Technology Removed	Technology Added	MY 2025 Cost of Technology (2018$)	MY 2025 Overall Technology Cost (2018$)
MY 2024				888.7
Removed Technologies	Engine (DOHC)		(5830.76)	(5482.2)
	VVT		(221.54)	(5703.74)
	SGDI		(501.67)	(6205.41)
	DEAC		(203.35)	(6408.76)
	Transmission (AT9L2)		(2498.29)	(8907.05)

[460] Note that this is only DMC. RPE and a learning rate needs to apply to align with MY 2025 values in 2018$. So, in this case the battery DMC is $15,069 multiplied by 1.5 RPE multiplied by the 0.79 learning rate.

	Technology Removed	Technology Added	MY 2025 Cost of Technology (2018$)	MY 2025 Overall Technology Cost (2018$)
	EPS		(117.28)	(9024.33)
	SS12V		(247.43)	(9271.76)
	SS12V battery		(146.90)	(9418.66)
	AERO0		(0)	9418.66)
Added Technologies		BEV300 - ETDS	3581.65	(5837.01)
		IACC	146.68	(5690.33)
		Non-battery components	1137.67	(4552.66)
		Battery Pack Cost	17955.29	13402.63
		AERO20	248.9	13651.53
		Total AC/OC Adjustments	45.43	13696.96
MY 2025				13696.96

Please note that in this calculation the CAFE Model accounts for the AC and off-cycle technologies (grams per mile or g/mi) applied to each vehicle model. The cost for the AC/OC adjustments are in the CAFE Model Scenarios File. The AC and off-cycle cost values are discussed further in Chapter 3.8.

The methodology shown above can be used to walk through other electrification advancements in any other vehicle models.

3.4 Mass Reduction

Mass reduction is a relatively cost-effective means of improving fuel economy, and vehicle manufacturers are expected to apply various mass reduction technologies to meet fuel economy standards. Vehicle manufacturers can reduce vehicle mass through several different techniques, such as modifying and optimizing vehicle component and system designs, part consolidation, and adopting lighter weight materials (advanced high strength steel (AHSS), aluminum, magnesium, and plastics including carbon fiber reinforced plastics).

The cost for mass reduction depends on the type and amount of materials used, the manufacturing and assembly processes required, and the degree to which manufacturers need to make changes to plants and new manufacturing and assembly equipment. In addition, manufacturers may develop expertise and invest in certain mass reduction strategies that may affect the approaches for mass reduction they consider and the associated costs. Manufacturers may also consider vehicle attributes like noise-vibration-harshness (NVH), ride quality, handling, crash safety and various acceleration metrics when considering how to implement any mass reduction strategy. These are considered to be aspects of performance, and for this analysis any identified pathways to compliance are intended to maintain performance neutrality. Therefore, we do not consider mass reduction via elimination of, for example, luxury items such as climate control, or interior vanity mirrors, leather padding, etc., in the mass reduction pathways for this analysis.

The automotive industry uses different metrics to measure vehicle weight. Some commonly used measurements are vehicle curb weight,[461] gross vehicle weight (GVW),[462] gross vehicle weight rating (GVWR),[463] gross combined weight (GCVW),[464] and equivalent test weight (ETW),[465] among others. The vehicle curb weight is the most commonly used measurement when comparing vehicles. A vehicle's curb weight is the weight of the vehicle including fluids, but without a driver, passengers, and cargo. A vehicle's glider weight, which is vehicle curb weight minus the powertrain weight, is used to track the potential opportunities for weight reduction not including the powertrain. A glider's subsystems may consist of the vehicle body, chassis, interior, steering, electrical accessory, brake, and wheels systems. The percentage of weight assigned to the glider will remain constant for any given final rule, but that percentage will most likely change in subsequent final rules. For example, as electric powertrains including motors, batteries, inverters, etc. become a greater percent of the fleet, glider weight percentage will change compared to earlier fleets which had higher dominance of ICE powertrains. Therefore, in going from fleets dominated by ICEs to subsequent fleets dominated by battery electric powertrains, the glider percent share will decrease because BEV powertrains weigh more than ICE powertrains.

For this analysis, we consider six levels of mass reduction technology that include increasing amounts of advanced materials and mass reduction techniques applied to the glider. We account for mass changes associated with powertrain changes separately. Glider mass reduction can sometimes enable a smaller engine while maintaining performance neutrality. Smaller engines typically weight less than bigger ones. We capture any changes in the resultant fuel savings associated with powertrain mass reduction and downsizing via the Autonomie simulation. Autonomie calculates a hypothetical vehicle's theoretical fuel mileage using a mass reduction to the vehicle curb weight equal to the sum of mass savings to the glider plus the mass savings associated with the downsized powertrain.

Costs for the first four levels of mass reduction are the same as those used in the 2020 final rule. The costs for each of the top two of the six levels of mass reduction technology are based on vehicle mass reduction design concept studies, teardown studies, and the NAS 2021 report. The incremental increase in price is not linear going from MR1 to MR6. Rather, the costs increase in a quasi-exponential fashion. This is because as more mass is removed, there is a necessity to employ more and more expensive materials and processes. These costs consider both primary and secondary mass reduction opportunities and mass reduction of primary versus secondary structure, all of which are discussed further later in this Chapter. In addition, the following

[461] This is the weight of the vehicle with all fluids and components but without the drivers, passengers, and cargo.
[462] This weight includes all cargo, extra added equipment, and passengers aboard.
[463] This is the maximum total weight of the vehicle, passengers, and cargo to avoid damaging the vehicle or compromising safety.
[464] This weight includes the vehicle and a trailer attached to the vehicle, if used.
[465] For the EPA two-cycle regulatory test on a dynamometer, an additional weight of 300 lbs. is added to the vehicle curb weight. This additional 300 lbs. represents the weight of the driver, passenger, and luggage. Depending on the final test weight of the vehicle (vehicle curb weight plus 300 lbs.), a test weight category is identified using the table published by EPA according to 40 CFR 1066.805. This test weight category is called "Equivalent Test Weight" (ETW).

sections discuss the assumptions for the six mass reduction technology levels, the process used to assign initial analysis fleet mass reduction assignments, the effectiveness for applying mass reduction technology, and mass reduction costs.

3.4.1 Mass Reduction in the CAFE Model

The CAFE Model considers six levels of mass reduction technologies that manufacturers could use to comply with CAFE standards. The magnitude of mass reduction in percent for each of these levels is shown in Table 3-105 as a percentage of vehicle glider weight, and curb weight for both passenger cars and light trucks.

Table 3-105 – Mass Reduction Technology Level and Associated Glider and Curb Mass Reduction

MR Level	Percent Glider Weight	Percent Vehicle Curb Weight (Passenger Cars)	Percent Vehicle Curb Weight (Light Trucks)
MR0	0%	0.00%	0.00%
MR1	5%	3.55%	3.55%
MR2	7.5%	5.33%	5.33%
MR3	10%	7.10%	7.10%
MR4	15%	10.65%	10.65%
MR5	20%	14.20%	14.20%
MR6	28%	20.00%	20.00%

For this analysis, we consider mass reduction opportunities from the glider subsystems of a vehicle first, and then consider associated opportunities to downsize the powertrain, which we account for separately.[466] As explained below, in the Autonomie simulations, the glider includes the body, chassis, interior, electrical accessories, steering, brakes and wheels, which encompass both primary and secondary systems that the model can light-weight. In this analysis, we assume the glider share is 71 percent of vehicle curb weight. Autonomie sizes the powertrain based on the glider weight and the mass of some of the powertrain components in an iterative process. The mass of the powertrain depends on the powertrain size. Therefore, the weight of the glider impacts the weight of the powertrain.[467]

We use glider weight to apply non-powertrain mass reduction technology in the CAFE Model and use Autonomie simulations to determine the size of the powertrain and corresponding powertrain weight for the respective glider weight. The combination of glider weight (after mass reduction) and re-sized powertrain weight equal the vehicle curb weight. See Chapter 3.4.4 for more detail on glider mass and glider mass reduction. The cost and fuel savings effectiveness calculation for curb weight mass reduction (described in a subsequent section) occurs within

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[466] When the mass of the vehicle is reduced by an appropriate amount, the engine may be downsized to maintain performance. *See* Chapter 2.4.5 for more details.

[467] Since powertrains are sized based on the glider weight for the analysis, glider weight reduction beyond a threshold amount during a redesign will lead to re-sizing of the powertrain. For the analysis, the glider was used as a base for the application of any type of powertrain. A conventional powertrain consists of an engine, transmission, exhaust system, fuel tank, radiator, and associated components. A hybrid powertrain also includes a battery pack, electric motor(s), generator, high voltage wiring harness, high voltage connectors, inverter, battery management system(s), battery pack thermal system, and electric motor thermal system.

Autonomie. The Autonomie simulation takes into account both glider mass reduction and powertrain mass reduction in its calculations of a vehicle's fuel mileage.

3.4.1.1 Assumptions Behind the Mass Reduction Levels

While there are a range of mass reduction technologies that manufacturers can apply to vehicles to achieve each of the six mass reduction levels, there are some general trends that are helpful to illustrate the more widely used approaches. Typically, MR0 reflects vehicles with widespread use of mild steel structures and body panels, and very little or no use of high strength steel or aluminum. MR0 reflects materials in use for average vehicles in the MY 2008 timeframe. MR1-MR3 can be achieved with a steel body structure. In going from MR1 to MR3, expect that mild steel to be replaced by high strength and then AHSS. In going from MR3 to MR4 light metals like aluminum and magnesium are required. This will start at using aluminum closure panels and then to get to MR4 the vehicle's primary structure will need to be mostly made from aluminum. In the majority of cases, carbon fiber technology is necessary to reach MR5, perhaps with a mix of some aluminum and/or magnesium. MR6 can only be attained in anything resembling a passenger car by making nearly every structural component from carbon fiber. This means the body structure and closure panels like hoods and door skins are wholly made from carbon fiber. There may be some use of aluminum in the suspension.

As discussed further in Chapter 3.4.5, the cost studies that we use to generate cost curves assume mass can be reduced in levels that require different materials and different components to be utilized, in a specific order. Our mass reduction levels are loosely based on those studies' conclusions about what materials and components are required for each percent of mass reduction.

3.4.1.1.1 Traditional Mass Reduction Materials Used to Achieve MR1 through MR4

AHSS and aluminum (AL) have played a major role in recent years as materials used to reduce vehicle mass. The penetration rate of AHSS or AL depends on a number of factors such as vehicle redesign cycle timing, material availability, accompanying changes in manufacturing equipment, and changes in joining methods, among other things. A study conducted for the American Iron and Steel Institute shows the application of AHSS in vehicles increased from 81 lbs. on average in 2006 to 254 lbs. in 2015.[468]

[468] Abey Abraham, Metallic Material Trends in the North American Light Vehicle (May 2015), available online at - http://www.steelsustainability.org/~/media/Files/Autosteel/Great%20Designs%20in%20Steel/GDIS%202015/Track%202%20-%20Abraham.pdf. (Accessed: February 15, 2022).

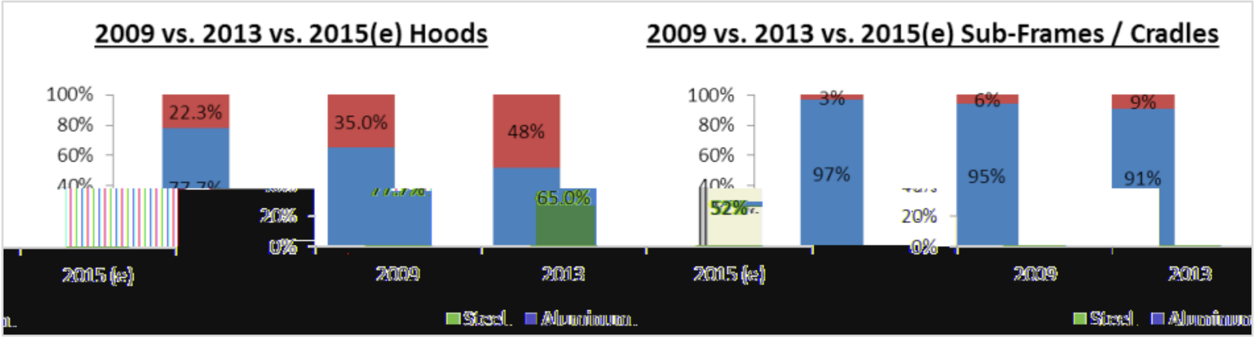

Figure 3-25 – Penetration of AL in Hoods and Sub-Frames/Cradles from 2009 to 2015

According to a study conducted for the Aluminum Association, aluminum content in vehicles increased from nearly 300 lbs. in 2005, to 394 lbs. in 2015, up from roughly 80 lbs. in 1975, and a little more than 150 lbs. in 1990.[469] Since the 1980s, many castings have migrated from steel to aluminum.[470] Figure 3-25 shows AL replacing steel in greater percentages in vehicle hoods, and AL beginning to penetrate sub-frames/engine cradles in small percentages.[471]

A 2017 report published by American Chemistry Council shows that while the overall share of plastics and polymer composites in vehicles have decreased by 0.1 percent in the last 10 years,[472] the share of AL has increased by 2.3 percent.[473] The report also published data on material content in vehicles as shown in Table 3-106 and Table 3-107.

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[469] Available online at - http://www.autonews.com/assets/PDF/CA95065611.PDF. (Accessed: February 15, 2022).
[470] For instance, engine blocks and transmission cases are nearly universally aluminum in the MY 2016 fleet, but aluminum was rarely used in these applications prior to the 1990's.
[471] Id.
[472] After rapidly increasing in the 1960's through the 1990's.
[473] American Chemistry Council Economics & Statistics Department, "Plastics and Polymer Composites in Light Vehicles" p. 5 (November 2017). This article is available in the rulemaking docket at NHTSA-2021-0053-0011.

Table 3-106 – Average Materials Content of U.S./Canada Light Vehicles (lbs./vehicle)

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Average Weight	4,081	4,103	4,046	3,953	3,960	4,007	3,896	3,900	3,928	3,991	4,026
Regular Steel	1,622	1,644	1,627	1,501	1,458	1,439	1,368	1,354	1,342	1,330	1,335
High- & Medium-Strength[474]	502	518	523	524	555	608	619	627	649	701	742
Stainless Steel	73	75	75	69	72	73	68	74	73	75	74
Other Steels	34	34	33	31	32	32	30	32	32	32	32
Iron Castings	331	322	253	206	242	261	270	271	278	268	249
Aluminum	323	319	316	324	338	344	349	355	368	395	410
Magnesium	10	10	11	11	11	12	10	10	10	10	11
Copper and Brass	67	66	71	71	74	73	71	70	68	67	66
Lead	39	41	44	42	41	39	35	35	36	35	35
Zinc Castings	10	9	9	9	9	9	8	8	8	8	8
Powder Metal	42	43	43	41	41	42	44	45	46	45	44
Other Metals[475]	5	5	5	5	5	5	5	5	4	5	5
Plastics/Polymer Composites	342	339	348	384	359	353	332	328	329	334	332
Rubber	198	192	204	245	228	223	205	198	196	198	199
Coatings	30	30	31	36	36	33	28	28	28	28	28
Textiles	47	46	48	58	56	50	49	50	49	45	44
Fluids and Lubricants	211	215	214	217	219	221	219	222	224	225	226
Glass	105	103	99	88	92	98	95	96	96	95	93
Other	89	92	91	90	92	93	91	92	93	95	92

[474] Despite long lead times for material qualification of new metal alloys, medium and high strength steels have been and continue to be widely adopted in the automotive industry at a rapid pace. Advanced steel materials typically replace regular steel, and often compete with aluminum and composites in body systems.
[475] "Other Metals" are typically used sparingly in specialty applications in the auto industry, and these metals make up a small portion of total vehicle weight.

Table 3-107 – Average Materials Content of U.S./Canada Light Vehicles (Percentage of Total Weight per Vehicle)

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Regular Steel	39.7%	40.1%	40.2%	38.0%	36.8%	35.9%	35.1%	34.7%	34.2%	33.3%	33.2%
High- & Medium-Strength	12.3%	12.6%	12.9%	13.3%	14.0%	15.2%	15.9%	16.1%	16.5%	17.6%	18.4%
Stainless Steel	1.8%	1.8%	1.9%	1.7%	1.8%	1.8%	1.7%	1.9%	1.9%	1.9%	1.8%
Other Steels	0.8%	0.8%	0.8%	0.8%	0.8%	0.8%	0.8%	0.8%	0.8%	0.8%	0.8%
Iron Castings	8.1%	7.8%	6.3%	5.2%	6.1%	6.5%	6.9%	6.9%	7.1%	6.7%	6.2%
Aluminum	7.9%	7.8%	7.8%	8.2%	8.5%	8.6%	9.0%	9.1%	9.4%	9.9%	10.2%
Magnesium	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%	0.2%	0.2%	0.3%
Copper and Brass	1.6%	1.6%	1.7%	1.8%	1.9%	1.8%	1.8%	1.8%	1.7%	1.7%	1.6%
Lead	1.0%	1.0%	1.1%	1.1%	1.0%	1.0%	0.9%	0.9%	0.9%	0.9%	0.9%
Zinc Castings	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%
Powder Metal	1.0%	1.0%	1.1%	1.0%	1.0%	1.0%	1.1%	1.2%	1.2%	1.1%	1.1%
Other Metals	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%
Plastics/Polymer Composites	8.4%	8.3%	8.6%	9.7%	9.1%	8.8%	8.5%	8.4%	8.4%	8.4%	8.3%
Rubber	4.8%	4.7%	5.1%	6.2%	5.8%	5.6%	5.3%	5.1%	5.0%	5.0%	4.9%
Coatings	0.7%	0.7%	0.8%	0.9%	0.9%	0.8%	0.7%	0.7%	0.7%	0.7%	0.7%
Textiles	1.2%	1.1%	1.2%	1.5%	1.4%	1.3%	1.3%	1.3%	1.2%	1.1%	1.1%
Fluids and Lubricants	5.2%	5.2%	5.3%	5.5%	5.5%	5.5%	5.6%	5.7%	5.7%	5.6%	5.6%
Glass	2.6%	2.5%	2.4%	2.2%	2.3%	2.4%	2.4%	2.5%	2.4%	2.4%	2.3%
Other	2.2%	2.2%	2.2%	2.3%	2.3%	2.3%	2.3%	2.4%	2.4%	2.4%	2.3%

Adding aluminum to a vehicle's primary and/or secondary structure is useful in reaching higher levels of mass reduction. To reach MR5 or MR6, extensive application of carbon fiber technology is typically needed.

3.4.1.1.2 Requirements for Achieving MR5 and MR6

Manufacturers have begun to experiment with advanced composites, such as carbon fiber, to achieve mass reduction. Carbon fiber reinforced plastic (CFRP) composite materials offer many opportunities for meaningful mass reduction in automotive applications. Components made from CFRP can typically be engineered to be 30 to 50 percent lighter than components made from conventional materials. An individual carbon fiber can have up to nearly three times the stiffness of steel. Some aerospace grade individual carbon fibers can be up to seven times stronger than even advanced high-strength steels used in passenger cars.[476]

When automotive grade carbon fibers are incorporated with a plastic resin, such as epoxy, the density normalized strength (*i.e.*, specific strength) of the composite can be well over seven times that of automotive AHSS. The density normalized stiffness (*i.e.*, specific stiffness) of the composite can be nearly two and half times that of steel. These properties, for a highly-idealized carbon fiber composite structural member, can translate to anywhere between a 50 to 70 percent mass savings depending on the mode of loading (tensile, compression, bending torsion, etc.) to which the structural member is subject.[477] Manufacturers have used carbon fiber technology not only to reduce mass, but also to change the vehicle's center of gravity and improve the vehicle's weight distribution.

However, mass production and vehicle packaging related design limitations preclude achieving these levels of mass reduction on real automotive structures. Challenges to using CFRP include high cost of materials, failure mode unpredictability in crashes, cycle time to manufacture, and special tools required to assemble, join components with other metallic components, and stranded capital for manufacturing equipment.

When estimating the mass savings potential of carbon fiber technology applied to passenger automobiles, it is important to note that carbon fibers come in a broad spectrum of grades. The highest grades, with the highest strength and stiffness, can be hundreds of dollars per pound. They are consequently not realistic for use in high volume road vehicles. The only grades that may be practicably affordable for mainstream automotive applications are the lowest ones. They also offer the least potential for meaningful mass savings. Therefore, it should not be assumed that mass savings achieved in aerospace applications should translate to road vehicle applications. It should also not be assumed that carbon fiber technology affords the same mass saving potential to automotive structures that it does to upper echelon sporting goods. For example, professional racing bicycles are often made from aerospace grade fiber, as are Wimbledon-level tennis rackets.

Regardless, the auto industry has used carbon fiber successfully for light-weighting automotive primary and secondary structure for nearly five decades. Formula One Grand Prix teams used the material for small components like wing supports starting in the mid-1970s. In 1981, British Grand Prix team McLaren built the MP4/1 which was the first racing car, and also the first automobile, with a primary structure made wholly from carbon fiber. Today, carbon fiber primary structure is the standard construction method from which F1 Grand Prix, Indy Car and Le Mans series racing cars are built. There are few other lower racing series that can justify the extreme cost of a full carbon fiber composite primary structure.

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[476] Toray Torayca Technical Manual, 2020.

[477] D.M. Baskin, S. Dinda, and T.S. Moore, "A Simple Approach to Selecting Automotive Body-in-White Primary Structural Materials," SAE Paper # 2002-01-2050, 2002.

Note that primary and secondary structure is different than primary and secondary mass reduction. A car's or truck's primary structure reacts the main loads fed into the vehicle from its suspension. It also reacts impact loads and protects passengers from injury. Examples include unit bodies, suspension sub-frames, bumper beams, side intrusion beams, etc. However, for most passenger cars, the term primary structure refers to the unit body. This is different to secondary structure, which only reacts lower magnitude inputs such as aero loads or loads from ancillary equipment like interior trim, radio antennae, lighting components, etc. Examples of secondary structure includes items like bolt-on fenders, side mirrors, deck lids, front and rear fascia, etc. The loads reacted by primary structure are nearly always higher in magnitude than that of those reacted by secondary structure. As a further clarification, a vehicle with all secondary structure removed would be functional and safe, but may look unfinished or be uncomfortable to driver and passengers.

Application of carbon fiber technology to road vehicles has been sparse and intermittent. Most applications have been to secondary structure that offer limited mass reduction. Today, General Motors offers pick-up trucks with pick-up boxes made from carbon fiber composite material. But the material used in that application does not have sufficient mechanical properties to carry a safe and stiff primary structure. BMW offers a few high-end vehicles with carbon fiber roof panels, side view mirrors, rear wings, and other hang-on components. Nissan offers a select few aero-surface components on their GTR Model. None of these vehicles are considered below average in mass.

Far fewer road cars possess primary structure wholly made from carbon fiber. Some examples in recent U.S. fleets include the Alfa Romeo 4C, Bugatti Chiron, and the Lamborghini Aventador. In every one of these vehicles, the primary structure looks much like that of at least a Le Mans racing car with a central carbon fiber passenger cell and fore and aft structures supporting the powertrain and suspension. In most every way, these vehicles are more racecars for the road than affordable car for the everyman. They are far too expensive for high volume cars sales. Although the Alfa 4C may approach affordability at $75,000, the other vehicles mentioned are all above $300,000 and go into the millions of dollars for the Bugatti.

The exception is the BMW i3. It is the first and only mass-volume vehicle to have the majority of its primary structure made from carbon fiber composites. Its primary structure is split into two main modules. The base of the vehicle, which contains the battery pack, motor and all the suspension mounting points is made from aluminum castings, extrusions, and sheet materials. This structure is sometimes referred to as a "skateboard" architecture.[478] The upper section of the i3's primary structure, including body-side assemblies, roof assembly, floor pan assemblies and front and rear clip are made from carbon fiber reinforced polymer materials. The manufacturing methods used to make these carbon fiber reinforced plastic structures took decades to develop and represent intellectual property, closely held trade secrets, and tacit secrets held tightly by assembly line-workers. A teardown study by Munro & Associates showed the BMW i3 cab structure plus the aluminum skateboard is 68 kg lighter than a comparable steel

[478] W.J. Mitchell, C.E. Borroni-Bird and L.D. Burns, "Reinventing the Automobile; Personal Urban Mobility for the 21st Century," MIT Press, Cambridge, MA, 2010.

structure.[479] This study also estimated the upfront investment and resulting part cost to manufacture CFRP components.

In addition to solving the many technical challenges associated with mass-volume carbon fiber component manufacture, BMW also addressed the many challenging supply chain issues with carbon fiber component production. BMW went as far as setting up purpose-built carbon fiber processing plants using hydro-electric energy in Washington state. BMW also set up their own facility in Wackersdorf, Germany to weave the dry fiber into useable matte materials. At this same facility, the matte material is pressed into a fiber pre-form using a light press and then made into useable panels using a liquid resin infiltration process (i.e., RIM).

Any automaker or automotive supplier considering carbon fiber technologies would most likely require a decade or two of time and extensive financial resources to develop a carbon-fiber program for high volume vehicle application.

The high cost of carbon fiber composite light-weighting technology is a result of many factors. First, most carbon fiber is made from a polymer fiber known as polyacrylonitrile (PAN). Because this fiber is made from petroleum products, it is an expensive pre-cursor. The conversion of the PAN to carbon fiber is also quite expensive. This is because it involves stretching strands of PAN fibers under intense heat to burn-off any non-carbon elements in their composition and to straighten carbon chain structures in the fiber. This requires a lot of energy which is typically supplied from burning fossil fuels. In addition, the process takes hours because the fiber material must traverse literally miles of serpentine distance within a pyrolization furnace. It therefore takes a formidable amount of time and energy to convert the PAN fiber to carbon fiber yarn, or "tows."

Second, incorporating these tows into a polymer matrix material (such as epoxy) with sufficient fiber content and lack of voids is no trivial matter. A reasonable description of the various methods of manufacturing carbon fiber reinforced plastic composites is out of the scope of this document. None of them approach the ultra-low costs of the stamped sheet metal paradigm in which the mainstream automotive industry lives today. For example, the composite industry has struggled to reduce the cycle time to produce a carbon body panel down to one minute. A similar steel body panel can go from raw sheet to a finished panel in seconds. From a manufacturing perspective, the source of the added cost belongs to the extra time required to incorporate the carbon fibers into finished components.

Another impediment to deployment of carbon fiber technology into the mainstream automotive industry is limited global supply of the raw carbon fibers. It is reported by composite materials industry publications[480] that in 2019, the sum total of worldwide carbon pyrolization facilities produced 161,200 metric tons of dry carbon fiber (just the fiber). Most of this dry fiber material is made by Toray of Japan. The next largest producer is Hexcel in the United States. Of the material that is produced, little is currently allocated to the automotive industry. About half of

[479] Singh, Harry, FSV Body Structure Comparison with 2014 BMW i3, Munro and Associates for World Auto Steel (June 3, 2015).

[480] J. Sloan, "Carbon Fiber Suppliers Gear up for Next Generation Growth," compositesworld.com, February 11, 2020.

this carbon fiber dry tow material goes to industrial applications. About 15 percent goes to aerospace applications and about 10 percent goes to sporting goods manufacturers. Finally, another 10 percent goes to the automotive industry.

Light-weighting studies completed by the engineering consultancy EDAG[481] estimate that effective weight reduction results when approximately 400 kg of carbon fiber composite material is used per vehicle on average. Assuming a fiber volume fraction of 60 percent and accounting for the density differences between dry carbon fiber and epoxy, about 232 kg of the 400 kg is dry fiber material. This means that in 2019, there would have been enough carbon fiber available to make almost 70,000 vehicles. Although global dry carbon fiber output is projected to increase by 10.2 percent compound annual growth rate out until 2029,[482] this still will not be enough to supply the full number of vehicles sold in the United States each year, which is approximately 17 million vehicles.

As a final point for this section, a recent National Academies study assessing technologies for improving the fuel economy of light-duty vehicles included a section on the potential to reduce vehicle mass using carbon fiber technology. The NAS study mentioned that the current state of the art methods for producing structural carbon fiber automotive components including resin transfer molding (RTM), are prone to generating a lot of scrap fiber material. This of course adds to the cost of the vehicle and deducts from the limited amount of fiber material available to the auto industry. The study also notes that alternate methods of constructing carbon fiber structural members, such as pultrusion methods, are much more efficient from a materials scrappage perspective. Indeed, pultrusions made from carbon fibers are under continuing development for application in primary automotive structures. They have potential to improve the affordability of applying carbon fiber technology to high volume automotive manufacture.

Carbon fiber is particularly relevant to this analysis as higher levels of stringency require higher levels of mass reduction technology be applied to vehicles. As discussed above, the highest levels of mass reduction technology considered in this analysis (MR5 and MR6) include an assumption that a significant amount of carbon fiber will be required for the vehicle's body structure. If made mostly from carbon fiber, vehicles sold in high volumes (hundreds of thousands of cars) might demand so much material that it would outstrip global carbon fiber supply. Accordingly, as discussed in Chapter 3.4.3, we have limited the amount of MR5 and MR6 that can be applied to vehicles in the analysis. We will continue to monitor this technology. Any additional feedback on developing carbon fiber manufacturing technologies that have potential to increase the affordability of this technology for mass application is encouraged.

3.4.1.1.3 Primary and Secondary Mass Reduction

Each of the subsystems in a vehicle presents an opportunity for weight reduction; however, some weight reduction is dependent on the weight reduction of other subsystems. Mass reduction is often characterized as either primary mass reduction or secondary mass reduction. Primary mass reduction involves reducing mass of components that can occur independent from the mass of

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[481] DOT HS 812 487, "Mass Reduction for Light-Duty Vehicles for Model Years 2017-2025".

[482] J. Sloan, "For Carbon Fiber, the Future Certainly Looks Bright," compositesworld.com, Dec 12, 2015.

other components. For example, reducing the mass of a hood (*e.g.*, replacing a steel hood with an aluminum hood) or reducing the mass of a seat, are examples of primary mass reduction because each can be implemented independently. Other components and systems that may contribute to primary mass reduction include the vehicle body, chassis, and interior components.

When significant primary mass reduction occurs, other components designed based on the mass of primary components may be redesigned as well. An example of a subsystem where secondary mass reduction can be applied is the brake system. If the mass of primary components is reduced sufficiently, the resulting lighter weight vehicle could safely maintain braking performance and attributes with a lighter weight brake system. Other examples of components where secondary mass reduction can be applied are wheels and tires.

Our mass reduction levels implicitly assume primary and secondary mass reduction happens in a specific order, to apply technologies in the order of cost effectiveness while ensuring that secondary mass reduction is applied after sufficient primary mass reduction has been applied to enable the secondary mass reduction.

Some mass reduction is more valuable to fuel savings than other mass reduction. All mass on a vehicle contributes to the translating (vehicle reference frames move relative to its surroundings) mass of the vehicle. However, some mass on a vehicle is simultaneously translating and rotating (rotates relative to the reference frame of the vehicle.) For example, wheels, brake rotors, and hub flanges fall into this category. This is in contrast to components like fuel tanks, windshields, rear seats, etc. that only translate with the vehicle. Weight reduction of components that are rotating and translating offer greater fuel savings. This is because when a vehicle accelerates not only the translational inertia must be overcome, but additionally the rotational moment of inertia must be overcome for these components as well. This requires more energy than if they were just translating. Therefore, reducing the mass of these components provides an increased benefit.

As discussed further in Chapter 3.4.5, we developed the cost curves used in this analysis by sequencing the light-weighted components from the MY 2011 Honda Accord and MY 2014 Chevrolet Silverado studies based on cost effectiveness. They assumed the vehicle body, chassis, interior, and other primary components were light-weighted first, followed then by light-weighting powertrain components and other secondary systems after there is sufficient primary mass reduction. Following the publication of these light-weighting studies, peer reviewers and manufacturers commented that many common components that are shared across all of the powertrains and vehicle models, such as drive axles, engine cradles, and radiator engine support that are considered to be non-powertrain secondary mass reduction opportunities cannot be downsized. This is because the same components are used across many vehicles with different powertrain options. Even though some of these components may provide opportunities for additional mass reduction, we agree with peer reviewers and manufacturers that retaining a common design for all powertrain options avoids the proliferation of complexity to maintain economies of scale.

The cost curves based on our light-weighting studies reflect that, returning to this example, secondary mass reduction for the brake system is only applied after there has been sufficient primary mass reduction to allow the smaller brake system to provide safe braking performance and to maintain mechanical functionality. This allows us to estimate the cost of mass reduction independently of the cost associated with downsized advanced engines and advanced transmissions, as the cost of downsized advanced engines and transmissions are accounted for separately in the CAFE Model. Therefore, the six mass reduction levels included in this analysis appropriately reflect both primary and secondary mass reduction opportunities.

3.4.2 Mass Reduction Analysis Fleet Assignments

To assign baseline mass reduction levels (MR0 through MR6) for vehicles in the analysis fleet, we use previously-developed regression models that were used for the 2015 rulemaking analysis to estimate curb weight for each vehicle based on observable vehicle attributes. We originally developed the mass reduction regression models using MY 2015 fleet data; for this analysis, we used MY 2016 and 2017 analysis fleet data to update the models.

To develop the original curb weight regressions, we grouped vehicles into three separate body design categories: 3-box, 2-box, and pickup, as seen in Table 3-108. A 3-box can be explained as having a box in the middle for the passenger compartment, a box in the front for the engine and a box in the rear for the luggage compartment. A 2-box has a box in front for the engine and then the passenger and luggage box are combined into a single box.

Table 3-108 – Mass Reduction Body Style Sets

3-Box	2-Box	Pick-up
Coupe Sedan Convertible	Hatchback Wagon Sport Utility Minivan Van	Pick-up

For 2020 rulemaking and this analysis, we retain the MY 2015 regressions for 3-Box and 2-Box vehicles. While many of the vehicles share the same powertrain for passenger cars and SUVs or for cars and pickup trucks, the utility and functionality of the vehicle in SUVs and pickup trucks (2-box) is different than passenger cars (3-box). The presence of additional structure for towing or higher capacity towing, rear cross member, higher capacity suspension, and other differences, enable SUVs and pickup trucks to have towing and heavier payload capability. For example, Ford uses the nearly similar displacement and horsepower engines in Mustang Ecoboost Coupe and in F150 2WD XL, Regular Cab, Long Box. However, the curb weight for the pickup truck is higher than the Mustang. Directionally, this suggests that the 2-box weight per horsepower coefficient should be greater than the 3-box coefficient, just as it is in the regression. The coefficient for passenger cars and SUVs has not changed since the MY 2015 vehicle fleet analysis.

For 2020 rulemaking and this analysis, we upgraded the pickup category regression in response to comments on the 2016 Draft TAR. We estimated a new regression with EPA MY 2014 CAFE compliance data and add pick-up bed length as an independent variable. As a result of stepping back to MY 2014 data for the pick-up regression, the dataset did not include the all-aluminum body Ford F-150 in the calculation of the baseline. The advanced F-150 in the MY 2015 pick-up regression meaningfully affected Draft TAR regression statistics because the F-150 accounted for a large portion of observations in the analysis fleet, and the F-150 included advanced weight savings technology.

We leverage many documented variables in the analysis fleet as independent variables in the regressions. Continuous independent variables include footprint (wheelbase x track width) and powertrain peak power. Binary independent variables include strong HEV (yes or no), PHEV (yes or no), BEV or FCV (yes or no), AWD (yes or no), rear-wheel drive (yes or no), pick-up bed length (for the pick-up truck regression only) and convertible (yes or no). In addition, for PHEV and BEV/FCV vehicles, the capacity of the battery pack is included in the regression as a continuous independent variable. In some body design categories, the analysis fleet does not cover the full spectrum of independent variables. For instance, in the pickup body style regression, there is no front-wheel drive vehicles in the analysis fleet, so the regression defaulted to AWD and left an independent variable for rear-wheel drive.

Previously, we evaluated alternative regression variables, including overall dimensions of vehicles, such as height, width, and length, instead of and in addition to just wheelbase and track width. The experimental regression variables only marginally changed predicted curb weight residuals as a percentage of predicted curb weight, at an industry level and for most manufacturers. The results were not significantly different, and therefore we opted not to add these variables to regressions or replace independent variables presented in this analysis.

The regression results for 3-Box, 2-Box and Pickup trucks are shown in Table 3-109, Table 3-110, and Table 3-111.

Table 3-109 – Regression Statistics for Curb Weight (lbs.) for 3-Box Vehicles

Observations	**822**					
Adjusted R Square	**0.87**					
Standard Error	**228.70**					
Regression Statistics	**Coefficients**	**Standard Error**	**t Stat**	**P-value**	**Lower 95%**	**Upper 95%**
Intercept	-1581.63	98.50	-16.06	0.00	-1775.00	-1388.30
Footprint (s.f.)	100.5	2.2	44.79	0	69.1	104.9
Power (hp)	1.22	0.1	14.85	0	1.1	1.4
Bed length (inches)	-	-	-	-	-	-
Strong HEV (1,0)	200.36	46.3	4.33	0	109.5	291.2
PHEV (1,0)	259.28	96.8	2.68	0.0075	69.3	449.2
BEV or FCV (1,0)	602.33	215	2.8	0.0052	180.3	1024.3
Battery pack size (kWh)	-2.48	4.1	-0.6	0.5461	-10.6	5.6
AWD (1,0)	294.51	24.5	12.03	0	246.4	342.6
RWD (1,0)	117.2	23.7	4.94	0	70.6	163.8
Convertible (1,0)	273.65	25.3	10.84	0	224.1	323.2

Table 3-110 – Regression Statistics for Curb Weight (lbs.) for Pick-up Vehicles

Observations	**312**					
Adjusted R Square	**0.84**					
Standard Error	**206.80**					
Regression Statistics	**Coefficients**	**Standard Error**	**t Stat**	**P-value**	**Lower 95%**	**Upper 95%**
Intercept	1062.21	130.23	8.16	0.00	805.95	1318.48
Footprint (s.f.)	58.31	2.37	24.96	0	53.72	62.91
Power (hp)	2.5	0.21	11.79	0	2.08	2.92
Bed length (inches)	-9.57	1.14	-8.4	0	-11.81	-7.32
Strong HEV (1,0)	-	-	-	-	-	-
PHEV (1,0)	-	-	-	-	-	-
BEV or FCV (1,0)	-	-	-	-	-	-
Battery pack size (kWh)	-	-	-	-	-	-
AWD (1,0)	260.91	23.62	11.05	0	214.43	307.38
RWD (1,0)	-	-	-	-	-	-
Convertible (1,0)	-	-	-	-	-	-

Table 3-111 – Regression Statistics for Curb Weight (lbs.) for 2-Box Vehicles

Observations	**584**					
Adjusted R Square	**0.88**					
Standard Error	**332.80**					
Regression Statistics	**Coefficients**	**Standard Error**	**t Stat**	**P-value**	**Lower 95%**	**Upper 95%**
Intercept	-1930.09	142.50	-13.54	0.00	-2210.00	-1650.20
Footprint (s.f.)	104.72	3.6	28.69	0	97.5	111.9
Power (hp)	3.09	0.2	13.42	0	2.6	3.5
Bed length (inches)	-	-	-	-	-	-
Strong HEV (1,0)	358.97	80.3	4.47	0	201.3	516.6
PHEV (1,0)	462.9	169.7	2.73	0.01	129.5	796.3
BEV or FCV (1,0)	374.24	152.1	2.46	0.01	75.5	673
Battery pack size (kWh)	-1.32	3.7	-0.36	0.72	-8.5	5.9
AWD (1,0)	353.91	33.4	10.59	0	288.3	419.5
RWD (1,0)	208.02	54.1	3.84	0	101.7	314.3
Convertible (1,0)	-	-	-	-	-	-

Each of the three regressions produces outputs effective for identifying vehicles with a significant amount of mass reduction technology in the analysis fleet. Many coefficients for independent variables provide clear insight into the average weight penalty for the utility feature. In some cases, like battery size, the relatively small sub-sample size and high collinearity with other variables confound coefficient estimates.

By design, no independent variable directly accounts for the degree of weight savings technology applied to the vehicle. Residuals of the regression capture weight reduction efforts and noise from other sources.

As a practical matter, we cannot conduct a tear down study and detailed cost assessment for every vehicle in every model year. However, upon review of many vehicles and their subsystems, review of fleet assignments in the 2020 final rule identifies a few vehicles with MR0 or MR1 assignments where the vehicles contain some advanced weight savings technologies, yet they and their platforms still produce small residuals. Engineers from industry confirm that important factors other than glider weight savings and the independent variables considered in the regressions might factor into the use of light-weight technologies. Such factors include the desire to lower the center of gravity of a vehicle, improve the vehicle weight distribution for handling, optimize noise-vibration-and-harshness, increase torsional rigidity of the platform, offset increased vehicle content, and many other factors. In addition, engineers highlight the importance of sizing shared components for the most demanding applications on the vehicle platform; optimum weight savings for one platform application may not be suitable for all platform applications. For future analysis, we will continue to look for practical ways to improve the assessment of mass reduction content and the forecast of incremental mass reduction costs for each vehicle.

Figure 3-26 shows results from the pickup truck regression on predicted curb weight versus actual curb weight. Points above the solid regression line represent vehicles heavier than predicted (with lower mass reduction technology levels); points below the solid regression line represent vehicles lighter than predicted (with higher mass reduction technology levels). The dashed lines in Figure 3-26 show the thresholds (5, 7.5, 10, 15, 20 and 28 percent of glider weight). Again, this analysis assumes the glider weight is 71 percent of vehicle curb weight.

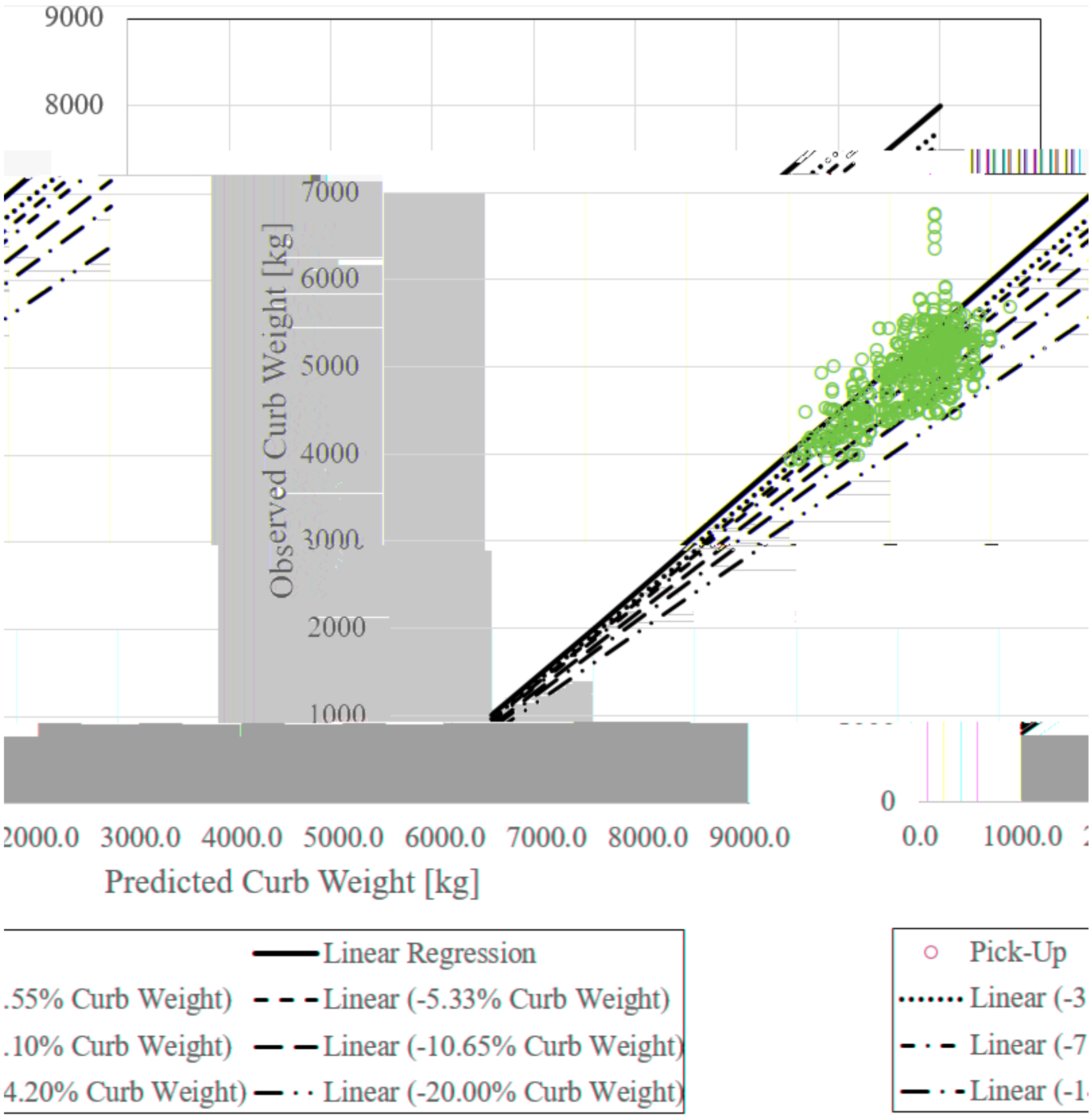

Figure 3-26 – Predicted Curb Weight vs. Actual Curb Weight for the MY 2020 Analysis Fleet for 71 Percent Glider Share

For points with actual curb weight below the predicted curb weight, we use the residual as a percent of predicted weight to get a sense for the level of current mass reduction technology used in the vehicle. Notably, vehicles approaching -20 percent curb weight widely use advanced composites throughout major vehicle systems, and few examples exist in the MY 2020 fleet.[483]

Generally, residuals of regressions as a percent of predicted weight appropriately stratify vehicles by mass reduction level. Most vehicles show near zero residuals or had actual curb weights close to the predicted curb weight. Few vehicles in the analysis fleet achieve the highest

[483] This evidence suggests that achieving a 20 percent curb weight reduction for a production vehicle with a baseline defined with this methodology is extremely challenging and requires advanced materials and disciplined design.

levels of mass reduction. Most vehicles with the largest negative residuals demonstrably adopt advanced weight savings technologies at the most expensive end of the cost curve.

To validate the residuals, we estimate the mass reduction technology level for several vehicle models in the analysis fleet and compare those estimates to the numerical results from the regression analysis. To estimate the mass reduction technology level for the selected vehicles, we conduct an in-depth review of available information on the materials, design, and last redesign year for those vehicle models. We then compare that information with the designs and materials used in the mass reduction feasibility and cost studies summarized in Chapter 3.4.5. That comparison showed consistent agreement with the technology levels derived from the regression analysis. We therefore believe the regression methodology is a technically sound approach for estimating mass reduction levels in the analysis fleet.

Manufacturers generally apply mass reduction technology at a vehicle platform level (*i.e.*, using the same components across multiple vehicle models that share a common platform) to leverage economies of scale and to manage component and manufacturing complexity, so conducting the regression analysis at the platform level leads to more accurate estimates for the real-world vehicle platform mass reduction levels. The platform approach also addresses the impact of potential weight variations that might exist for specific vehicle models, as all the individual vehicle models are aggregated into the platform group, and are effectively averaged using sales weighting, which minimizes the impact of any outlier vehicle configurations.

Table 3-112 shows the results of the regression for a few select vehicles.

Table 3-112 – Mass Reduction Technology Levels for the MY 2020 Analysis Fleet for 71% Glider Share of Curb Weight

CAFE Model Platform Code	Example Code	Mass Reduction Residual (%)	Mass Reduction Level for 71% Glider Weight
Lamborghini-A	Aventador	-28.2%	MR6
Alfa	Alfa Romeo 4C	-23.0%	MR6
Li8	BMW i8	-21.7%	MR6
Lamborghini-H	Huracan	-17.5%	MR5
MB.SmallVan	Mercedes Metris	-15.1%	MR5
Li8	BMW i3 94 R19	-14.9%	MR5
44.D7a	Jaguar XF	-14.1%	MR4
MB.Gtsegment	Mercedes AMG GT Roadster	-13.8%	MR4
12M2	Chrysler Pacifica	-13.5%	MR4
MAZDA.ND	Mazda Miata MX5	-12.9%	MR4
T3	Ford F-150	-12.0%	MR4
RamVan	Ram ProMaster	-11.6%	MR4
Y-CAR/Y1XX	Chevrolet Corvette	-11.5%	MR4
HK.DE.Ecocar	Kia Niro	-10.7%	MR4
NBC(2)	Toyota Prius C	-10.2%	MR3

CAFE Model Platform Code	Example Code	Mass Reduction Residual (%)	Mass Reduction Level for 71% Glider Weight
Global Epsilon/E2XX	Chevrolet Malibu	-9.6	MR3
II	Honda Civic	-8.8	MR3
MODEL 3	Tesla Model 3	-7.3%	MR3
MAZDA.BPDM	Mazda 3	-7.3%	MR3
V	Nissan Versa	-7.2%	MR3
Excellence	Lotus Evora	-7.0%	MR2
MODEL S	Tesla Model S	-6.4%	MR2
44-D6a	Jaguar F-Type	-5.7%	MR2

3.4.3 Mass Reduction Adoption Features

Given the degree of commonality among the vehicle models built on a single platform, manufacturers do not have complete freedom to apply unique technologies to each vehicle that shares the platform. While some technologies (*e.g.*, low rolling resistance tires) are very nearly "bolt-on" technologies, others involve substantial changes to the structure and design of the vehicle, and therefore often necessarily affect all vehicle models that share that platform. In most cases, mass reduction technologies are applied to platform level components and therefore the same design and components are used on all vehicle models that share the platform.

Each vehicle in the analysis fleet is associated with a specific platform. Similar to the application of engine and transmission technologies, the CAFE Model defines a platform "leader" as the vehicle variant of a given platform that has the highest level of observed mass reduction present in the analysis fleet. If there is a tie, the CAFE Model begins mass reduction technology on the vehicle with the highest sales in model year 2020. If there remains a tie, the model begins by choosing the vehicle with the highest manufacturer suggested retail price (MSRP) in MY 2020. As the model applies technologies, it effectively levels up all variants on a platform to the highest level of mass reduction technology on the platform. So, if the platform leader is already at MR3 in MY 2020, and a "follower" starts at MR0 in MY 2020, the follower will get MR3 at its next redesign (unless the leader is redesigned again before that time, and further increases the mass reduction level associated with that platform, then the follower would receive the new mass reduction level).

Important for analysis fleet mass reduction assignments, and for understanding adoption features as well, is our handling of vehicles that traditionally operated on the same platform but had a mix of old and new platforms in production at the time we created the analysis fleet. For example, the Honda Civic and Honda CR-V traditionally share the same platform. In MY 2016, Honda redesigned the Civic and updated the platform to include many mass reduction technologies. Also in MY 2016, Honda continued to build the CR-V on the previous generation platform that did not include many of the mass reduction technologies on the all new MY 2016 Civic. In MY 2017, Honda launched the new CR-V that incorporated changes to the Civic platform, and the

Civic and CR-V again shared the same platform with common mass reduction technologies. This analysis treats the old and new platforms separately to assign technology levels in the baseline, and the CAFE Model brings vehicles on the old platform up to the level of mass reduction technology on the new shared platform at the first available redesign year.

In addition to the platform-sharing logic employed in the model, we apply phase-in caps for MR5 and MR6 (15 percent and 20 percent reduction of a vehicle's curb weight, respectively), based on the current state of mass reduction technology. As discussed above, for nearly every type of vehicle, with the exception of the smallest sports cars, an auto manufacturer's strategy to achieve mass reduction consistent with MR5 and MR6 will require extensive use of carbon fiber technologies in the vehicles' primary structures. For example, one way of using carbon fiber technology to achieve MR6 is to develop a carbon fiber monocoque structure. A monocoque structure is one where the outer most skins support the primary loads of the vehicle. For example, they do not have separate non-load bearing aero surfaces. All of the vehicle's primary loads are supported by the monocoque. In the most structurally efficient automotive versions, the monocoque is made from multiple well-consolidated plies of carbon fiber infused with resin. Such structures can require low hundreds of pounds of carbon fiber for most passenger vehicles. Add to this another roughly equivalent mass of petroleum-derived resins and even at aspirational prices for dry carbon fiber of $10-20 per pound it is easy to see how direct materials alone can easily climb into the five-figure dollar range per vehicle.

High CAFE stringency levels will push the CAFE Model to select compliance pathways that include these higher levels of mass reduction for vehicles produced in the mid and high hundreds of thousands of vehicles per year. We assume, based on material costs and availability, that achieving MR6 levels of mass reduction will cost more than ten thousand dollars per car. Therefore, application of such technology to high volume vehicles is unrealistic today and will, with certainty, remain so for the next several years.

The CAFE Model applies technologies to vehicles that provide a cost-effective pathway to compliance. In some cases, the direct manufacturing cost, indirect costs, and applied learning factor do not capture all the considerations that make a technology more or less costly for manufacturers to apply in the real world. For example, there are direct labor, R&D overhead, manufacturing overhead, and amortized tooling costs that will likely be higher for carbon fiber production than current automotive steel production, due to fiber handling complexities. In addition, R&D overhead will also increase because of the knowledge base for composite materials in automotive applications is simply not as deep as it is for steel and aluminum. Indeed, the intrinsic anisotropic mechanical properties of composite materials compared to the isotropic properties of metals complicates the design process. Added testing of these novel anisotropic structures and their associated costs will be necessary for decades.

In addition, the CAFE Model does not currently enable direct accounting for the stranded capital associated with a transition away from stamped sheet metal construction to molded composite materials construction. For decades, or in some cases half-centuries, car manufacturers have invested billions of dollars in capital for equipment that supports the industry's sheet metal forming paradigm. A paradigm change to tooling and equipment developed to support molding carbon fiber panels and monocoque chassis structures would leave that capital stranded in equipment that would be rendered obsolete. Doing this is possible, but the financial ramifications are not currently reflected in the CAFE Model for MR5 and MR6 compliance pathways.

Financial matters aside, carbon fiber technology and how it is best used to produce light-weight primary automotive structures is far from mature. In fact, no car company knows for sure the best way to use carbon fiber to make a passenger car's primary structure. Using this technology in passenger cars is far more complex than using it in racing cars where passenger egress, longevity, corrosion protection, crash protection, etc., are lower on the list of priorities for the design team. BMW may be the manufacturer most able to accurately opine on the viability of carbon fiber technology for primary structure on high-volume passenger cars, and even it decided to use a mixed materials solution for their next generation of EVs (the iX and i4) after the i3, thus eschewing a wholly carbon fiber monocoque structure.

Another factor limiting the application of carbon fiber technology to mass volume passenger vehicles is indeed the availability of dry carbon fibers. There is high global demand from a variety of industries for a limited supply of carbon fibers. Aerospace, military/defense, and industrial applications demand most of the carbon fiber currently produced. Today, only roughly 10 percent of the global dry fiber supply goes to the automotive industry, which translates to the global supply base only being able to support approximately 70,000 cars.[484]

To account for these cost and production considerations, including the limited global supply of dry carbon fiber, we apply phase-in caps that limit the number of vehicles that can achieve MR5 and M6 levels of mass reduction in the CAFE Model. We apply a phase-in cap for MR5 level technology so that 75 percent of the vehicle fleet starting in 2020 could employ the technology, and the technology could be applied to 100 percent of the fleet by MY 2025. We also apply a phase-in cap for MR6 technology so that five percent of the vehicle fleet starting in MY 2020 could employ the technology, and the technology could be applied to 10 percent of the fleet by MY 2025.

To develop these phase-in caps, we select a 40,000 unit thresholds for both MR5 and MR6 technology (80,000 units total), because it roughly reflects the number of BMW i3 cars produced per year worldwide.[485] As discussed above, the BMW i3 is the only high-volume vehicle currently produced with a primary structure mostly made from carbon fiber (except the skateboard, which is aluminum). Because mass reduction is applied at the platform level (meaning that every car of a given platform would receive the technology, not just special low volume versions of that platform), only platforms representing 40,000 vehicles or less are eligible to apply MR5 and MR6 toward CAFE compliance. Platforms representing high volume sales, like a Chevrolet Traverse, for example, where hundreds of thousands are sold per year, are

[484] J. Sloan, "Carbon Fiber Suppliers Gear up for Next Generation Growth," compositesworld.com, February 11, 2020.

[485] However, even this number is optimistic because only a small fraction of i3 cars is sold in the U.S. market, and combining MR5 and MR6 allocations equates to 80k vehicles, not 40k. Regardless, if the auto industry ever seriously committed to using carbon fiber in mainstream high-volume vehicles, competition with the other industries would rapidly result in a dramatic increase in price for dry fiber. This would further stymie the deployment of this technology in the automotive industry.

therefore blocked from access to MR5 and MR6 technology. There are no phase-in caps for mass reduction levels MR1, MR2, MR3 or MR4.

In addition to determining that the caps were reasonable based on current global carbon fiber production, we determine that the MR5 phase-in cap is consistent with the NHTSA light-weighting study that found that a 15 percent curb weight reduction for the fleet is possible within the rulemaking timeframe.[486]

These phase-in caps appropriately function as a proxy for the cost and complexity currently required (and that likely will continue to be required until manufacturing processes evolve) to produce carbon fiber components. Again, MR6 technology in this analysis reflects the use of a significant share of carbon fiber content, as seen through the BMW i3 and Alfa Romeo 4c as discussed above.

3.4.4 Mass Reduction Effectiveness

As discussed in Chapter 2.4, Argonne develops databases of vehicle attributes and characteristics for each vehicle technology class that includes over 100 different attributes. Some examples from these 100 attributes include frontal area, drag coefficient, fuel tank weight, transmission housing weight, transmission clutch weight, hybrid vehicle components, and weights for components that comprise engines and electric machines, tire rolling resistance, transmission gear ratios, and final drive ratio. Argonne uses these attributes to "build" each vehicle that it uses for the effectiveness modeling and simulation. Important for precisely estimating the effectiveness of different levels of mass reduction is an accurate list of initial component weights that make up each vehicle subsystem, from which Autonomie considers potential mass reduction opportunities.

As stated above, glider weight, or the vehicle curb weight minus the powertrain weight, is used to determine the potential opportunities for weight reduction irrespective of the type of powertrain.[487] This is because weight reduction can vary depending on the type of powertrain. For example, an 8-speed transmission may weigh more than a 6-speed transmission, and a basic engine without VVT may weigh more than an advanced engine with VVT. Autonomie simulations account for the weight of the powertrain system inherently as part of the analysis, and the powertrain mass accounting is separate from the application and accounting for mass reduction technology levels (MR0-MR6) that are applied to the glider in the simulations. Similarly, Autonomie also accounts for battery and motor mass used in hybrid and electric vehicles separately. This secondary mass reduction is discussed further below.

Accordingly, in the Autonomie simulations, mass reduction technology is simulated as a percentage of mass removed from the specific subsystems that make up the glider, as defined for that set of simulations (including the non-powertrain secondary mass systems such as the brake system).

[486] DOT HS 811 666: Mass Reduction for Light Duty Vehicles for Model Years 2017-2025: Figure 397 at page 356.
[487] Depending on the powertrain combination, the total curb weight of the vehicle includes glider, engine, transmission and/or battery pack and motor(s).

3.4.4.1 Glider Mass and Mass Reduction

Autonomie accounts for the mass of each subsystem that comprises the glider. For the purposes of determining a reasonable percentage for the glider, We consulted with Argonne to examine glider weight data available in the A2Mac1 database.[488] The A2Mac1 database tool is widely used by industry and academia to determine the bill of materials and mass of each component in the vehicle system.[489] We analyzed a total of 147 MY 2014 to 2016 vehicles, covering 35 vehicle brands with different powertrain options representing a wide array of vehicle classes to determine the percentage of the vehicle comprised by the glider.[490]

We also consider that the NHTSA passenger car and light truck light-weighting studies examine mass reduction in the body, chassis, interior, brakes, steering, electrical accessory, and wheels subsystems and has developed costs for light-weighted components in those subsystems. As a result, we believe that it is appropriate to include all of those subsystems as available for mass reduction as part of the glider. Therefore, all of these systems are included for the analysis of glider weight using the A2Mac1 database. Table 3-113 shows the average mass for each subsystem and the glider share for each of the vehicle classes for all powertrain combinations.

Table 3-113 – Glider Mass Share Assessment using A2Mac1 Data

	1	2	3	4	5	6	7	8	9	10
Vehicle Class	**Avg. Body Mass [kg]**	**Avg. Chassis Mass [kg]**	**Avg. Interior Mass [kg]**	**Avg. Brakes Mass [kg]**	**Avg. Steering Mass [kg]**	**Avg. Electrical Accessory Mass [kg]**	**Avg. Wheels Mass [kg]**	**Avg. Glider Mass (Sum of 1 to 7) [kg]**	**Avg. Curb Weight [kg]**	**% Glider Share**
Compact Non-Performance	525.00	160.00	150.00	50.13	20.00	30.26	42.00	977.40	1338.71	73.01%
Compact Performance	525.00	160.00	200.00	55.12	22.00	35.25	45.00	1042.37	1455.85	71.60%
Midsize Non-Performance	650.00	200.00	175.00	60.13	25.00	30.26	54.00	1194.40	1611.24	74.13%
Midsize Performance	650.00	200.00	200.00	65.12	28.00	40.25	57.00	1240.37	1734.89	71.50%
Small SUV Non-Performance	650.00	200.00	180.00	60.13	25.00	30.26	60.00	1205.40	1651.09	73.01%
Small SUV Performance	650.00	200.00	220.00	75.12	28.00	40.25	66.00	1279.37	1792.46	71.38%

488 A2Mac1: Automotive Benchmarking. (n.d.). Retrieved from https://portal.a2mac1.com/. (Accessed: February 15, 2022).

489 Bill of material (BOM) is a list of the raw materials, sub-assemblies, parts, and quantities needed to manufacture an end-product.

490 Docket No. NHTSA-2018-0067-1490.

	1	2	3	4	5	6	7	8	9	10
Vehicle Class	**Avg. Body Mass [kg]**	**Avg. Chassis Mass [kg]**	**Avg. Interior Mass [kg]**	**Avg. Brakes Mass [kg]**	**Avg. Steering Mass [kg]**	**Avg. Electrical Accessory Mass [kg]**	**Avg. Wheels Mass [kg]**	**Avg. Glider Mass (Sum of 1 to 7) [kg]**	**Avg. Curb Weight [kg]**	**% Glider Share**
Midsize SUV Non-Performance	650.00	200.00	200.00	70.13	30.00	30.26	66.00	1246.40	1754.57	71.04%
Midsize SUV Performance	750.00	225.00	240.00	75.12	30.00	50.25	78.00	1448.37	2045.42	70.81%
Pickup Non-Performance	650.00	300.00	160.00	90.12	30.00	80.47	78.00	1388.58	2020.13	68.74%
Pickup Performance	800.00	350.00	200.00	95.11	30.00	100.44	90.00	1665.55	2345.18	71.02%
Average										71.62%

These data are also compared with the glider weight measured in the NHTSA MY 2014 Chevrolet Silverado light-weighting study[491] (discussed further below), and the glider weight data range is similar to the analysis results. Accordingly, we assumed that the glider weight comprised 71 percent of the vehicle curb weight.

3.4.4.2 Powertrain Mass Reduction

We account for all mass reduction due to powertrain improvements separately from glider mass reduction. Autonomie considers several components for powertrain mass reduction, including engine downsizing, and transmission, fuel tank, exhaust systems, and cooling system light-weighting.

The 2015 NAS report suggested an engine downsizing opportunity exists when the glider mass is light-weighted by at least 10 percent. The 2015 NAS report also suggested that 10 percent light-weighting of the glider mass alone would boost fuel economy by 3 percent and any engine downsizing following the 10 percent glider mass reduction would provide an additional 3 percent increase in fuel economy.[492] The NHTSA light-weighting studies applied engine downsizing (for some vehicle types but not all) when the glider weight was reduced by 10 percent. Accordingly, the analysis limits engine resizing to several specific incremental technology steps; important for this discussion, engines in the analysis are only resized when mass reduction of 10 percent or greater is applied to the glider mass, or when one powertrain architecture replaces another architecture.

[491] DOT HS 812 487: Mass Reduction for Light-Duty Vehicles for Model Years 2017-2025.
[492] National Research Council. 2015. Cost, Effectiveness, and Deployment of Fuel Economy Technologies for Light-Duty Vehicles. Washington, D.C. - The National Academies Press. https://doi.org/10.17226/21744. (Accessed: February 15, 2022).

Argonne performed a regression analysis of engine peak power versus weight for a previous analysis based on attribute data taken from the A2Mac1 benchmarking database, to account for the difference in weight for different engine types. For example, to account for weight of different engine sizes like 4-cylinder versus 8-cylinder, Argonne developed a relationship curve between peak power and engine weight based on the A2Mac1 benchmarking data. For this analysis, we use this relationship to estimate mass for all engine types regardless of technology type (e.g., VVL and direct injection). We apply weight associated with changes in engine technology by using this linear relationship between engine power and engine weight from the A2Mac1 benchmarking database. When a vehicle in the analysis fleet with an 8-cylinder engine adopts a more fuel-efficient 6-cylinder engine, the total vehicle weight reflects the updated engine weight with two less cylinders based on the peak power versus engine weight relationship.

When Autonomie selects a powertrain combination for a light-weighted glider, the engine and transmission are selected such that there is no degradation in the performance of the vehicle relative to the baseline vehicle. The resulting curb weight is a combination of the light-weighted glider with the resized and potentially new engine and transmission. This methodology also helps in accurately accounting for the cost of the glider and cost of the engine and transmission in the CAFE Model.

Secondary mass reduction is possible from some of the components in the glider after mass reduction has been incorporated in primary subsystems (body, chassis, and interior). Similarly, engine downsizing and powertrain secondary mass reduction is possible after certain level of mass reduction is incorporated in the glider. For the analysis, we include both primary mass reduction, and when there is sufficient primary mass reduction, additional secondary mass reduction. The Autonomie simulations account for the aggregate of both primary and secondary glider mass reduction, and separately for powertrain mass.

Note that secondary mass reduction is integrated into the mass reduction cost curves. Specifically, the NHTSA studies, upon which the cost curves depend, first generated costs for light-weighting the vehicle body, chassis, interior, and other primary components, and then calculated costs for light-weighting secondary components. Accordingly, the cost curves reflect that, for example, secondary mass reduction for the brake system is only applied after there has been sufficient primary mass reduction to allow the smaller brake system to provide safe braking performance and to maintain mechanical functionality.

We enhanced the accuracy of estimated engine weights by creating two curves to represent separately naturally aspirated engine designs and turbocharged engine designs.[493] This achieves two benefits. First, small naturally aspirated 4-cylinder engines that adopt turbocharging technology reflect the increased weight of associated components like ducting, clamps, the turbocharger itself, a charged air cooler, wiring, fasteners, and a modified exhaust manifold. Second, larger cylinder count engines like naturally aspirated 8-cylinder and 6-cylinder engines that adopt turbocharging and downsized technologies would have lower weight due to having fewer engine cylinders. For this analysis, a naturally aspirated 8-cylinder engine that adopts turbocharging technology and is downsized to a 6-cylinder turbocharged engine appropriately

[493] Autonomie model documentation, Chapter 5.2.9.

reflects the added weight of the turbocharging components, and the lower weight of fewer cylinders.

We believe it is reasonable to allow engine resizing upon adoption of 7.1, 10.7, 14.2, and 20 percent curb weight reduction, but not at 3.6 and 5.3 percent.[494] Resizing is also allowed upon changes in powertrain type or the inheritance of a powertrain from another vehicle in the same platform. The increments of these higher levels of mass reduction, or complete powertrain changes, more appropriately match the typical engine displacement increments that are available in a manufacturer's engine portfolio.

3.4.4.3 The Summary of Mass Reduction Technology Effectiveness

The range of effectiveness values for the mass reduction technologies, for all ten vehicle technology classes are shown in Figure 3-27. In the graph, the box shows the inner quartile range (IQR) of the effectiveness values and whiskers extend out 1.5 x IQR.[495] The blue dots show a few values outside these ranges. As discussed earlier, Autonomie simulates all possible combinations of technologies for fuel consumption improvements. For a few technology combinations mass reduction has minimal impact on effectiveness on the regulatory 2-cycle test. For example, if an engine is operating in an efficient region of the fuel map on the 2-cycle test further reduction of mass may have smaller improvement on the regulatory cycles. And so, the Figure 3-27 shows the range improvements based on the full range of other technology combinations.

[494] These curb weight reductions equate to the following levels of mass reduction as defined in the analysis: MR3, MR4, MR5 and MR6, but not MR1 and MR2; additional discussion of engine resizing for mass reduction can be found in Chapter 2.4.

[495] The IQR is the interquartile range – the difference between the upper quartile and the lower quartile. Each whisker shows the data points between that range.

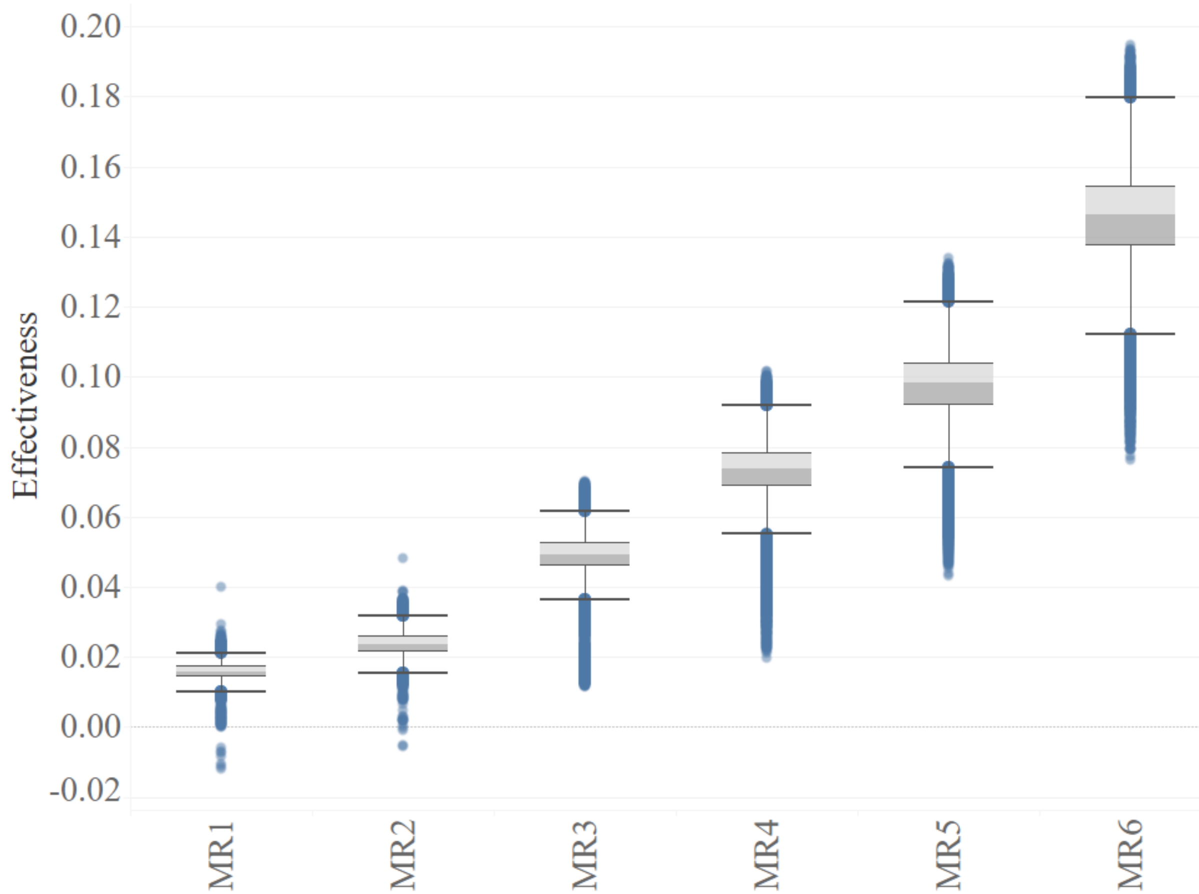

Figure 3-27 – Mass Reduction Technologies Effectiveness Values for all the Vehicle Technology Classes

3.4.5 Mass Reduction Costs

The CAFE Model uses cost information collected from various studies and industry data to determine which pathways to compliance are most financially efficient. This cost information does not come in the form of a single cost point for a given piece of technology. Rather, it comes in the form of a cost curve that shows how the cost of a technology is estimated to change with time. This approach better reflects reality because technology tends to become less expensive with time as people and companies learn how to produce it more efficiently. Including the estimated cost over time of a technology also allows the CAFE Model to determine cost effective pathways to compliance that may shift based on the changes in cost effectiveness over time.

Several mass reduction studies have used either a mid-size passenger car or a full-size pickup truck as an exemplar vehicle to demonstrate the technical and cost feasibility of mass reduction. While the findings of these studies may not apply directly to different vehicle classes, the cost estimates derived for the mass reduction technologies identified in these studies can be useful for formulating general estimates of costs. As discussed further below, the mass reduction cost curves developed for this analysis are based on two previous NHTSA light-weighting studies, and were updated based on more recent studies to better account for the cost of carbon fiber needed for the highest levels of mass reduction technology. The two NHTSA-sponsored studies used for MR1 through MR4 costs include the teardown of a MY 2011 Honda Accord and a MY 2014 Chevrolet Silverado pickup truck, and the carbon fiber costs for MR5 and MR6 were updated based on the 2021 NAS report.[496]

Both NHTSA-sponsored teardown studies are structured to derive the estimated cost for each of the mass reduction technology levels. We rely on the results of those studies because they consider an extensive range of material types, material gauge, and component redesign while taking into account real world constraints such as manufacturing and assembly methods and complexity, platform-sharing, and maintaining vehicle utility, functionality and attributes, including safety, performance, payload capacity, towing capacity, handling, NVH, and other characteristics. In addition, we believe that the baseline vehicles and mass reduction technologies assessed in the NHTSA-sponsored studies are still reasonably representative of the technologies that may be applied to vehicles in the MY 2020 analysis fleet to achieve up to MR4 level mass reduction in the rulemaking timeframe. We adjust the cost estimates derived from the two NHTSA light-weighting studies to reflect the assumption that a vehicle's glider weight consists of 71 percent of the vehicle's curb weight, and mass reduction as it pertains to achieving MR0-MR6 levels would only come from the glider.

After reviewing other agency, CARB, ICCT and industry studies,[497] we believe that the NHTSA-sponsored studies account for significant factors that are important to include on our analysis. The other studies often do not prioritize factors in an order that we agree with, make assumptions about key vehicle systems that we believe to be inaccurate, and/or apply secondary mass reduction before adequate primary mass reduction is applied to enable the secondary mass reduction, resulting in unrealistically low costs. In regard to safety, we use studies that consider small overlap impact tests conducted by the Insurance Institute for Highway Safety (IIHS) and not all studies take that test into account. In addition to considering platform-sharing constraints, the NHTSA pickup truck study accounts for vehicle functional performance for attributes including towing, noise and vibration, and gradeability. This is consistent with the objective to maintain vehicle functionality throughout technology application in the analysis.

Note that the mass reduction studies provide mass reduction costs for the glider, and this enables more direct use of cost curve data from the studies in the CAFE Model. This change also allows Autonomie to account for powertrain mass, which enables the CAFE Model to account more accurately for the unique mass of each of the powertrains that are available in each vehicle model. The cost of the engine, transmission, and electrification are accounted for separately from the glider in the CAFE Model.

We calculate the costs of mass reduction as an average cost per pound over the baseline (MR0) for the vehicle's glider weight. While the definitions of glider may vary from study to study, we reference the same dollar per pound of curb weight to develop costs for different glider

[496] This analysis applied the cost estimates per pound derived from passenger cars to all passenger car segments, and the cost estimates per pound derived from full-size pickup trucks to all light-duty truck and SUV segments. The cost estimates per pound for carbon fiber (MR5 and MR6) were the same for all segments.
[497] As for past rulemaking analyses, studies by EPA, CARB, Transport Canada, the American Iron and Steel Institute (AISI), the Aluminum Association, and the American Chemistry Council were all reviewed for potential incorporation into the analysis.

definitions. In translating these values, we take care to track units ($/kg vs. $/lb.) and the reference for percentage improvements (glider vs. curb weight).

We calculate the cost of mass reduction on a glider weight basis so that the weight of each powertrain configuration can be directly and separately accounted for. This approach provides the true cost of mass reduction without conflating the mass change and costs associated with downsizing a powertrain or adding additional advanced powertrain technologies. Hence, the mass reduction costs in this rule reflect the cost of mass reduction in the glider and do not include the mass reduction associated with engine downsizing. We account for mass reduction and costs associated with engine downsizing separately.

A second reason for using glider share instead of curb weight is that it affects the absolute amount of curb weight reduction applied, and therefore cost per pound for the mass reduction changes with the change in the glider share. The cost for removing 20 percent of the glider weight when the glider represents 75 percent of a vehicle's curb weight is not the same as the cost for removing 20 percent of the glider weight when the glider represents 50 percent of the vehicle's curb weight. For example, the glider share of 79 percent of a 3,000-pound curb weight vehicle is 2,370 lbs., while the glider share of 50 percent of a 3,000-pound curb weight vehicle is 1,500 lbs., and the glider share of 71 percent of a 3,000-pound curb weight vehicle is 2,130 lbs. The mass change associated with 20 percent mass reduction is 474 lbs. for 79 percent glider share (= [3,000 lbs. x 79% x 20%]), 300 lbs. for 50 percent glider share (= [3,000 lbs. x 50% x 20%]), and 426 lbs. for 71 percent glider share (= [3,000 lbs. x 71% x 20%]). The mass reduction cost studies that we rely on to develop mass reduction costs for this analysis show that the cost for mass reduction varies with the amount of mass reduction. Therefore, for a fixed glider mass reduction percentage, different glider share assumptions will have different costs.

The following sections discuss the light-weighting studies we use to create the passenger car and light truck cost curves, including new studies referenced to update the cost curves to better reflect the cost of carbon fiber required for the highest levels of mass reduction technology.

3.4.5.1 MY 2011 Honda Accord Teardown Study

We used on a MY 2011 Honda Accord light-weighting study to develop the passenger cost curve used for MR1-MR4 in this analysis. The NHTSA-funded study, performed by Electricore, Inc., George Washington University, and EDAG, Inc, was completed in 2012 and the final report peer reviewed by industry experts and Honda Motor Company. EDAG and Electricore conducted further work to consider and make changes to the light-weighted model based on the feedback from Honda and continued to make additional changes to the design concept to address the IIHS small overlap impact test. The investigators listed previously completed the study in February 2016.[498]

The curb weight of MY 2011 Honda Accord used in the light-weighting study is approximately 1480kg. The glider weight of the MY 2011 Honda Accord is approximately 1165 kg. In this

[498] Singh, H., Kan, C-D., Marzougui, D., & Quong, S. (2016, February). *Update to future midsize lightweight vehicle findings in response to manufacturer review and IIHS small-overlap testing* (Report No. DOT HS 812 237). Washington, DC: National Highway Traffic Safety Administration.

case, the glider represents 79 percent of curb weight.[499,500] As shown in Table 3-114, approximately 4.67 percent of the glider mass is light-weighted by substituting mild steel with AHSS in body-in-white structure. 3.39 percent of the glider mass is light-weighted by substituting mild steel with AL in closures (closures include hood, front door, rear door, and deck lid). Between body-in-white and closures, approximately 8.06 percent of glider mass is light-weighted by substituting mild steel with AL. The additional light-weighting was achieved by using advanced plastics for door trims, switching copper wiring harness to aluminum wiring harness, using AHSS for seat frames, using AHSS and optimizing design for parking brakes, among other substitutions. As shown in Table 3-114, a total of 13.65 percent of glider mass was light-weighted. This translates to 10.74 percent mass reduction at the curb weight level. The report noted that follow-on mass reduction can be achieved by downsizing the engine and optimizing the powertrain components, while maintaining the same level of performance. The report shows powertrain downsizing translates to some cost savings as well (the cost savings comes from manufacturers selecting downsized engines from the inventory of engines used in other product lines through economies of scale and common parts).

Table 3-114 shows the list of components identified in the MY 2011 Honda Accord light-weighting study and the corresponding direct manufacturing cost (DMC) estimated to light-weight those components. Cost estimates include consideration of advanced materials, redesign, tooling changes, and manufacturing setup changes. Figure 3-28 shows the cost curve derived from the list of components in Table 3-114. Figure 3-29 shows the direct manufacturing cost (DMC) at different levels of mass reduction for the passenger car. The DMC shown in Figure 3-29 is the average DMC and not the marginal cost for each additional mass reduction level. As the average cost per pound over baseline increases, the marginal cost per pound may increase dramatically.

[499] Glider weight is typically all components of the vehicle except the powertrain components such as engines, transmissions, radiator, fuel tank and exhaust systems.
[500] Not all subsystems considered in the light-weighting study were considered in the Autonomie simulations and CAFE Model.

Table 3-114 – List of Components Light-weighted in the Light-weighted Concept Study based on the MY 2011 Honda Accord ($/kg)

#	Vehicle Component/System	Baseline Mass	Substitution Material	Light-weighted Mass	Mass Saving	Δ Cost	Δ Cost	Cumulative Mass Saving	Cumulative MR	Cumulative Cost	Cumulative Cost
		(kg)		(kg)	(kg)	($)	($/kg)	(kg)	(%)	($)	($/kg)
1	Front Bumper	7.96	AHSS	4.37	3.59	-0.88	-0.25	3.59	0.31%	-0.88	-0.25
2	Front Door Trim	5.38	MuCell	4.04	1.34	0.00	0	4.93	0.42%	-0.88	-0.18
3	Front Door Wiring Harness	0.87	Al	0.57	0.3	0.00	0	5.23	0.45%	-0.88	-0.17
4	Head Lamps	6.86	MuCell	5.15	1.71	0.00	0	6.94	0.60%	-0.88	-0.13
5	HVAC	10.3	MuCell	7.7	2.6	0.00	0	9.54	0.82%	-0.88	-0.09
6	Insulation	9.35	Thinsulate & Quietblend	6.15	3.2	0.00	0	12.74	1.09%	-0.88	-0.07
7	Interior Trim	26.26	MuCell	23.23	3.03	0.00	0	15.77	1.35%	-0.88	-0.06
8	Parking Brake	3.31	Electronic	2.32	0.99	0.00	0	16.76	1.44%	-0.88	-0.05
9	Rear Door Trim	4.53	MuCell	3.4	1.13	0.00	0	17.89	1.54%	-0.88	-0.05
10	Rear Door Wiring Harness	0.33	Al	0.22	0.11	0.00	0	18	1.55%	-0.88	-0.05
11	Tail Lamps	2.54	MuCell	1.91	0.63	0.00	0	18.63	1.60%	-0.88	-0.05
12	Tires	37.1	Goodyear	32.65	4.45	0.00	0	23.08	1.98%	-0.88	-0.04
13	Wiring and Harness	21.7	Al	17.4	4.3	0.00	0	27.38	2.35%	-0.88	-0.03
14	Wheels	40.1	AHSS	38.66	1.44	0.00	0	28.82	2.47%	-0.88	-0.03
15	Rear Bumper	7.84	AHSS	4.33	3.51	2.10	0.6	32.33	2.78%	1.22	0.04
16	Instrument Panel	31.9	Mg	22.45	9.45	15.43	1.63	41.78	3.59%	16.65	0.40
17	Body Structure	328	AHSS	273.6	54.4	160.47	2.95	96.18	8.26%	177.12	1.84
18	Decklid	9.95	Al	4.74	5.21	17.04	3.27	101.39	8.70%	194.16	1.91
19	Hood	15.2	Al	7.73	7.47	24.61	3.29	108.86	9.34%	218.77	2.01
20	Front Door Frames	32.78	Al	17.38	15.4	56.30	3.66	124.26	10.67%	275.07	2.21
21	Fenders	7.35	Al	4.08	3.27	12.60	3.85	127.53	10.95%	287.67	2.26
22	Seats	66.77	Composite + Al + GFRP	46.74	20.03	96.84	4.83	147.56	12.67%	384.51	2.61
23	Rear Door Frames	26.8	Al	15.34	11.46	59.90	5.23	159.02	13.65%	444.41	2.79

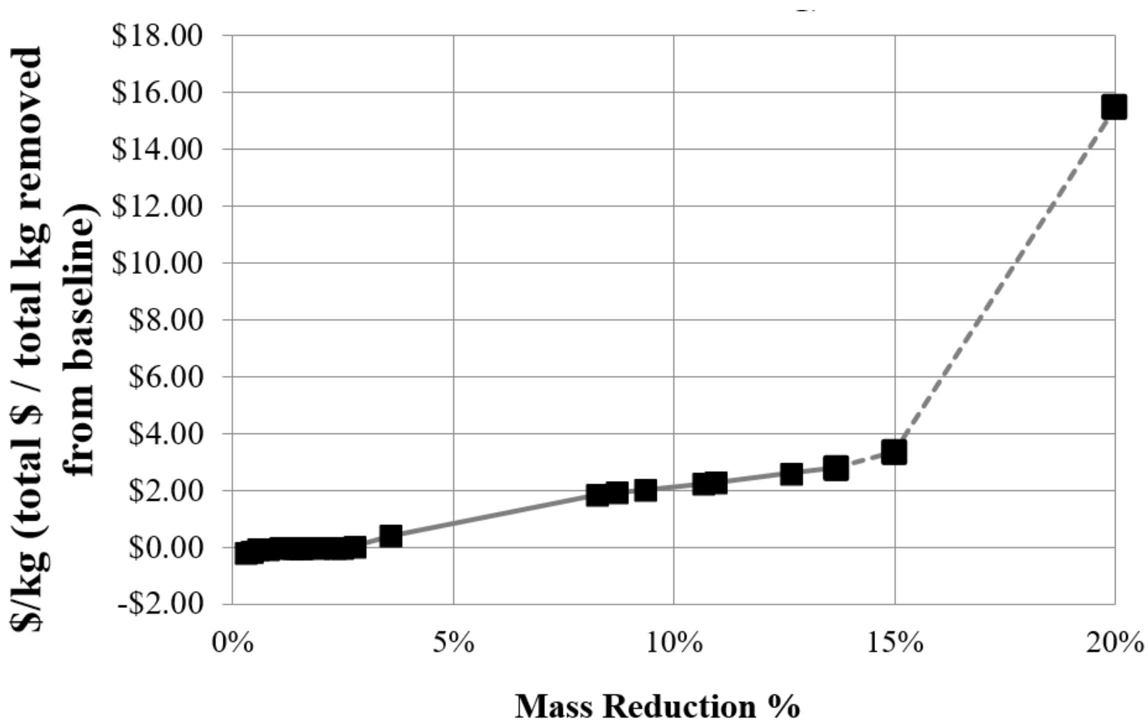

Figure 3-28 – Passenger Car Glider Cost Curve based on MY 2011 Honda Accord Light-Weight Vehicle (79 Percent of the Curb Weight)

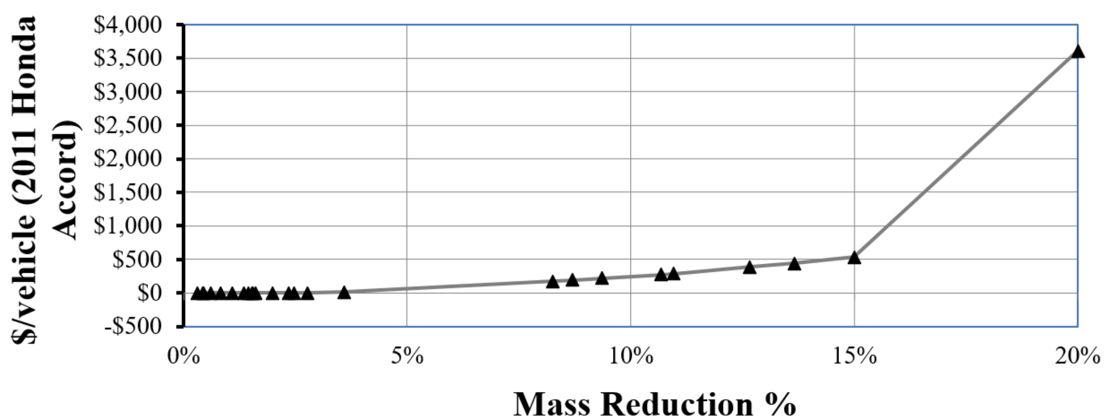

Figure 3-29 – Cumulative Direct Manufacturing Cost for Passenger Car Glider Mass Reduction (Glider - 79 Percent of Curb Weight)

Table 3-115 shows the cost per kilogram ($/kg) and estimated costs at discrete levels of mass reduction for a passenger car derived from light-weighting the MY 2011 Honda Accord. We used these costs to develop the mass reduction costs for mass reduction levels 1-4 in this analysis.

Table 3-115 – Cost Numbers Derived from Passenger Car Light-weighting Study

CURB WEIGHT	1480 KG				
PC Glider (79% of Curb Weight)	1165 kg				
MR% (of glider in PC light-weighting study)	MR (kg)	$/kg	Estimated DMC on MY 2011 Honda Accord	New Curb Weight after Glider Mass Reduction (kg)	Percentage Mass Reduction at Curb Weight Level
5.0%	58.25	$0.84	$48.93	1,421	4.0%
7.5%	87.38	$1.61	$140.67	1,392	5.9%
10.0%	116.50	$2.12	$246.98	1,363	7.9%
15.0%	174.75	$3.37	$535.90	1,320	10.8%
20.0%	233.00	$5.50	$3,611.50	1,247	15.7%

3.4.5.2 MY 2014 Chevrolet Silverado Teardown Study

Our original cost curve for light trucks was developed through a NHTSA-funded light-weighting study on a MY 2014 Chevrolet Silverado 1500 full-size pickup truck. This study considered lessons learned during the MY 2011 Honda Accord light-weighting study and included requirements that the vehicle meet the IIHS small overlap performance test. EDAG completed this project in 2016 and the final report is available on NHTSA's website.[501]

Table 3-116 shows the list of components light-weighted in the MY 2014 Chevrolet Silverado 1500 full-size pickup truck. Figure 3-30 shows the cost curve generated from the list of the light-weighted components, and Figure 3-31 shows the DMC at different levels of mass reduction.

[501] Singh, H., Davies, J., Kramer, D., Fisher, A., Paramasuwom, M., Mogal, V., ... and Ganesan, V. (2018, January). *Mass reduction for light-duty vehicles for model years 2017-2025* (Report No. DOT HS 812 487). Washington, DC: National Highway Traffic Safety Administration.

Table 3-116– List of Components Light-weighted in the MY 2014 Chevrolet Silverado 1500

#	Vehicle Component/ System	Baseline Mass (kg)	Substitution Material	Light-weighted Mass (kg)	Mass Saving (kg)	Δ Cost ($)	Δ Cost ($/kg)	Cumulative Mass Saving (kg)	Cumulative MR (%)	Cumulative Cost ($)	Cumulative Cost ($/kg)
1	Interior Electrical Wiring	6.9	Copper Clad Aluminum (CCA)	5.52	1.38	-28.07	-20.34	1.38	0.08%	-28.07	-20.34
2	Headliner	3.63	Cellmould	3.45	0.18	-0.93	-5.17	1.56	0.09%	-29	-18.59
3	Trim - Plastic	20.68	Cellmould	19.65	1.03	-5.3	-5.15	2.59	0.14%	-34.3	-13.24
4	Trim - misc.	34.67	Cellmould	32.94	1.73	-8.89	-5.14	4.32	0.24%	-43.19	-10.00
5	Floor Covering	9.75	Cellmould	9.26	0.49	-2.5	-5.10	4.81	0.27%	-45.69	-9.50
6	Headlamps	7.68	Mucell Housings	6.14	1.54	0	0.00	6.35	0.35%	-45.69	-7.20
7	HVAC System	25.88	MuCell & Cellmould	24.17	1.71	0	0.00	8.06	0.45%	-45.69	-5.67
8	Tail Lamps	2	Mucell Housings	1.6	0.4	0	0.00	8.46	0.47%	-45.69	-5.40
9	Chassis Frame	243.97	AHSS	197.61	46.36	48.26	1.04	54.82	3.06%	2.57	0.05
10	Front Bumper	25.55	AHSS	20.44	5.11	5.32	1.04	59.93	3.35%	7.89	0.13
11	Rear Bumper	15.14	AHSS	12.11	3.03	3.15	1.04	62.96	3.52%	11.04	0.18
12	Towing Hitch	16.56	AHSS	13.59	2.97	3.09	1.04	65.93	3.68%	14.13	0.21
13	Rear Doors	38.1	AHSS + Al	27.03	11.07	13.96	1.26	77	4.30%	28.09	0.36
14	Wheels	158.96	eVOLVE	133.71	25.25	40.8	1.62	102.25	5.71%	68.89	0.67
15	Front Doors	45.46	AHSS + Al	31.05	14.41	23.64	1.64	116.66	6.52%	92.53	0.79
16	Fenders	25.91	Al	14.25	11.66	42.34	3.63	128.32	7.17%	134.87	1.05
17	Front/Rear Seat & Console	97.45	Composite + Al + GFRP	68.21	29.24	137.7	4.71	157.56	8.80%	272.57	1.73
18	Steering Column Assy	9.21	Mg	5.99	3.22	15.33	4.76	160.78	8.98%	287.9	1.79
19	Pickup Box	109.9	Al	65.94	43.96	210.45	4.79	204.74	11.44%	498.35	2.43
20	Tailgate	20.99	Al	12.59	8.4	40.2	4.79	213.14	11.91%	538.55	2.53
21	Instrument Panel	12.27	Mg	6.75	5.52	26.51	4.80	218.66	12.22%	565.06	2.58
22	Instrument Panel Skin, Cover, Plastic	17.36	Low Density Foam + MuCell + Cellmould	14.45	2.91	15.43	5.30	221.57	12.38%	580.49	2.62

#	Vehicle Component/ System	Baseline Mass (kg)	Substitution Material	Light-weighted Mass (kg)	Mass Saving (kg)	Δ Cost ($)	Δ Cost ($/kg)	Cumulative Mass Saving (kg)	Cumulative MR (%)	Cumulative Cost ($)	Cumulative Cost ($/kg)
23	Cab (+Insulation)	259.92	Al	176.52	83.4	466.86	5.60	304.97	17.04%	1047.35	3.43
24	Radiator Support	20	Al + Mg	14.1	5.9	47.99	8.13	310.87	17.37%	1095.34	3.52

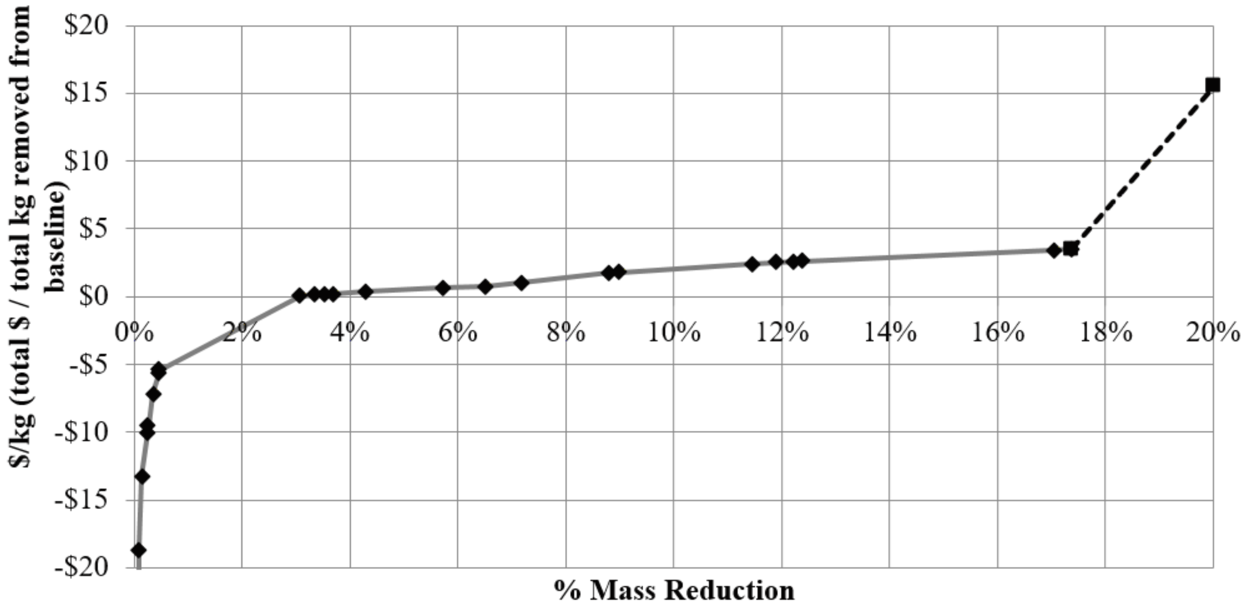

Figure 3-30 – Cost Curve for Glider Mass Reduction on Light-weighted Truck Based on MY 2014 Chevrolet Silverado 1500 Full Size Pickup (Glider Representing 73.6 Percent of Curb Weight)

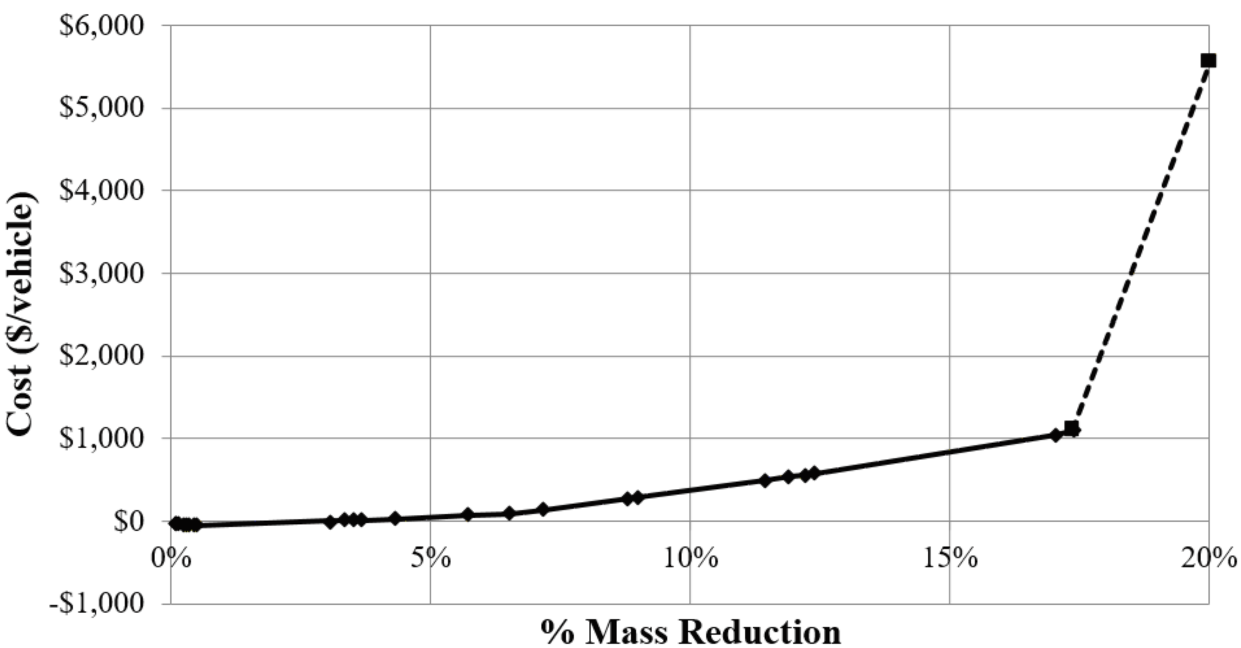

Figure 3-31 – DMC for Light Truck Glider Mass Reduction on MY 2014 Chevrolet Silverado Light-weighted Pickup (Glider - 73.6 Pecent of Curb Weight)

Table 3-117 shows the $/kg and cost associated at discrete mass reduction levels applicable to a light-weighted truck, per the MY 2014 Chevrolet Silverado study. These cost values were partially carried through to the cost values used in this analysis, *i.e.*, for mass reduction levels 1-4.

Table 3-117 – Cost Numbers Derived from Light Truck Light-weighting Study

CURB WEIGHT			2432 KG		
Glider (73.60% of Curb Weight)			1790 kg		
MR% (of glider in LT light-weighting study)	MR (kg)	$/kg	Estimated DMC on MY 2014 Chevrolet Silverado	New Curb Weight after Glider Mass Reduction (kg)	Percentage Mass Reduction at Curb Weight Level
5.0%	89.50	$0.50	$44.93	2,343	3.7%
7.5%	134.25	$1.20	$161.10	2,298	5.5%
10.0%	179.00	$2.09	$374.11	2,253	7.4%
15.0%	268.50	$3.09	$829.67	2,164	11.0%

3.4.5.3 Updates to MR5 and MR6 Costs based on Updated Carbon Fiber Studies

As discussed above, achieving the highest levels of mass reduction often necessitates extensive use of advanced materials like higher grades of aluminum, magnesium, or carbon fiber. Both NHTSA-funded light-weighting studies, summarized above, estimated a cost for carbon fiber. In the MY 2011 Honda Accord light-weighting study, the estimated cost of carbon fiber was $5.37/kg and the cost of carbon fiber used in the MY 2014 Chevy Silverado light-weighting study was $15.50/kg. The $15.50 estimate closely matched the cost estimates from a BMW i3 teardown analysis,[502] the cost figures provided by Oak Ridge National Laboratory for a study from the Institute for Advanced Composites Manufacturing Innovation (IACMI),[503] and from a Ducker Worldwide presentation at the Center for Automotive Research Management Briefing Seminar.[504]

For this analysis, we rely on the cost estimates for carbon fiber construction that the National Academies detailed in the 2021 Assessment of Technologies for Improving Fuel Economy of Light-Duty Vehicles – Phase 3.[505] The study indicates that the sum of direct materials costs plus manufacturing costs for carbon fiber composite automotive components is $25.97 per pound in high volume production. In order to use this cost in the CAFE Model it must be put in terms of dollars per pound saved. Using an average vehicle curb weight of 4000 lbs., a 71 percent glider share, and the percent mass savings associated with MR5 and MR6, it is possible to calculate the number of pounds to be removed to attain MR5 and MR6. Also taken from the NAS study is the assertion that carbon fiber substitution for steel in an automotive component results in a 50 percent mass reduction. Combining all this together, carbon fiber technology offers weight

[502] Singh, Harry, FSV Body Structure Comparison with 2014 BMW i3, Munro and Associates for World Auto Steel (June 3, 2015).
[503] IACMI Baseline Cost and Energy Metrics (March 2017), available at https://iacmi.org/wp-content/uploads/2017/12/IACMI-Baseline-Cost-and-Energy-Metrics-March-2017.pdf. (Accessed: February 15, 2022).
[504] Ducker Worldwide, The Road Ahead – Automotive Materials (2016), https://societyofautomotiveanalysts.wildapricot.org/resources/Pictures/SAA%20Sumit%20slides%20for%20Abey%20Abraham%20of%20Ducker.pdf. (Accessed: February 15, 2022).
[505] 2021 NAS report, at 7-242-3.

savings at $24.60 per pound saved. This dollar per pound savings figure must also be converted to a RPE to account for various commercial costs associated with all automotive components. This is accomplished by multiplying $24.60 by the factor 1.5. This brings the cost per pound saved for using carbon fiber to $36.90 per pound saved.[506] The analysis uses this cost for achieving MR5 and MR6.

Table 3-118 and Table 3-119 show the cost values used in the CAFE Model with MR1-4 costs based on the cost curves developed from the MY 2011 Honda Accord and MY 2014 Chevrolet Silverado studies, and the updated MR5 and MR6 values that account for the updated carbon fiber costs from the 2021 NAS report. Both tables assume a 71 percent glider share.

Table 3-118 – Mass Reduction Costs for MY 2020 in CAFE Model for Small Car, Small Car Performance, Medium Car, Medium Car Performance, Small SUV, Small SUV Performance

	Percentage Reduction in Glider Weight	Percentage Reduction in Curb Weight	Cost of Mass Reduction ($/lbs.)
MR0	0.00%	0.00%	0.00
MR1	5.00%	3.55%	0.46
MR2	7.50%	5.33%	0.86
MR3	10.00%	7.10%	1.22
MR4	15.00%	10.65%	1.59
MR5	20.00%	14.20%	36.90
MR6	28.00%	20%	36.90

Table 3-119 – Mass Reduction Costs for MY 2020 in CAFE Model for Medium SUV, Medium SUV Performance, Pickup, Pickup HT

	Percentage Reduction in Glider Weight	Percentage Reduction in Curb Weight	Cost of Mass Reduction ($/lbs.)
MR0	0	0.00%	0.00
MR1	5.00%	3.55%	0.30
MR2	7.50%	5.33%	0.70
MR3	10.00%	7.10%	1.25
MR4	15.00%	10.65%	1.70
MR5	20.00%	14.20%	36.90
MR6	27.25%	19.35%	36.90

There is a dramatic increase in cost going from MR4 to MR5 and MR6 for all classes of vehicles. However, while the increase in cost going from MR4 to MR5 and MR6 is dramatic, the MY 2011 Honda Accord study, the MY 2014 Chevrolet Silverado study, and the 2021 NAS report all included a steep increase to achieve the highest levels of mass reduction technology, as seen in Figure 3-31. Figure 3-32 shows the cost per pound for various materials used for light-weighting from 2021 NAS, the NHTSA Accord study, and the NHTSA Silverado study. Again, based on studies such as the NHTSA Accord and Silverado studies, enough mass reduction to

[506] *See* MR5 and MR6 CFRP Cost Increase Calculator.xlsx in the docket for this action.

reach MR5 will require a majority of secondary structure and some primary structure be made from carbon fiber. Reaching MR6 will require a primary structure made almost entirely from carbon fiber. This is true for nearly every vehicle except for the smallest sports cars with minimal interior luxury, like the Lotus Elise. The increase in cost in going from MR5 to MR6 can be justified by considering the dollar amount to purchase a pound of fully laminated and manufactured carbon fiber reinforced plastic compared to the dollar amount to purchase a pound of aluminum, magnesium, or steel as shown in Figure 3-32.

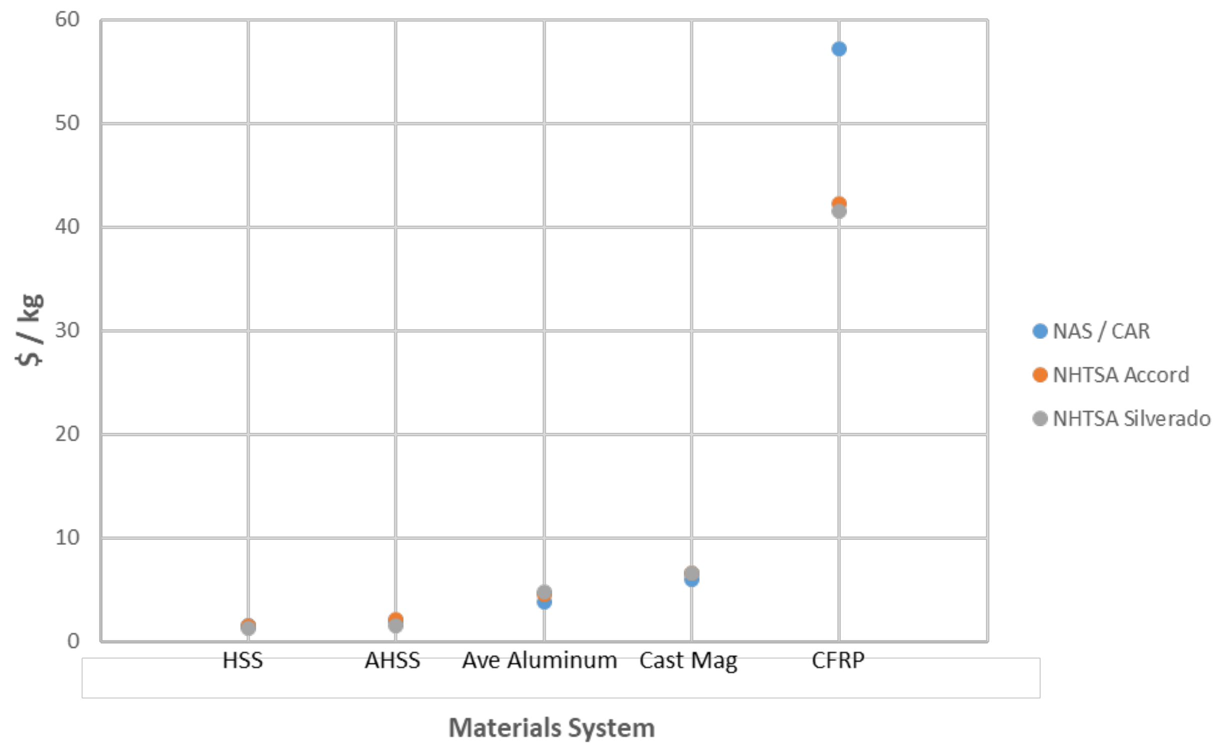

Figure 3-32 – Cost per Kilogram Including Manufacturing for Various Materials Used for Light-weighting from NAS, [507] the NHTSA Accord Study, [508] and the NHTSA Silverado Study[509]

3.5 Aerodynamics

The energy required to overcome aerodynamic drag accounts for a significant portion of a vehicle's energy consumption and can become the dominant factor for a vehicle's energy consumption at high speeds. The power needed to propel a vehicle increases as the cube of the velocity. For example, doubling of velocity with a given amount of power to overcome aerodynamic drag would require eight times that power to overcome drag at the higher velocity. Reducing aerodynamic drag can, therefore, be an effective way to reduce fuel consumption and emissions.

[507] 2021 NAS report, at 7-242-3.
[508] DOT HS 811 666, at p. 145, Figure 138.
[509] DOT HS 812 487, at p. 102, Figure 113.

Aerodynamic drag is proportional to the frontal area (A) of the vehicle and coefficient of drag (C_d), such that aerodynamic performance is often expressed as the product of the two values, C_dA, which is also known as the drag area of a vehicle. The coefficient of drag (C_d) is a dimensionless value that essentially represents the aerodynamic efficiency of the vehicle shape. The frontal area (A) is the cross-sectional area of the vehicle as viewed from the front. It acts with the coefficient of drag as a sort of scaling factor, representing the relative size of the vehicle shape that the coefficient of drag describes. The force imposed by aerodynamic drag increases with the square of vehicle velocity, accounting for the largest contribution to road loads at higher speeds.

Manufacturers can reduce aerodynamic drag via two approaches, either by reducing the drag coefficient or reducing vehicle frontal area, with two different categories of technologies, passive and active aerodynamic technologies. Passive aerodynamics refers to aerodynamic attributes that are inherent to the shape and size of the vehicle, including any components of a fixed nature. Active aerodynamics refers to technologies that variably deploy in response to driving conditions. These include technologies such as active grille shutters, active air dams, and active ride height adjustment. It is important to note that manufacturers may employ both passive and active aerodynamic technologies to improve aerodynamic drag values.

The greatest opportunity for improving aerodynamic performance is during a vehicle redesign cycle when the manufacturer can make significant changes to the shape and size of the vehicle. Manufacturers may also make incremental improvements during a mid-cycle vehicle refresh using restyled exterior components and add-on devices, including, for example, restyled front and rear fascia, modified front air dams and rear valances, addition of rear deck lips and underbody panels, and low-drag exterior mirrors. While manufacturers may nudge the frontal area of the vehicle during redesigns, large changes in frontal area are typically not possible without impacting the utility and interior space of the vehicle. Similarly, manufacturers may improve C_d by changing the frontal shape of the vehicle or lowering the height of the vehicle, among other approaches, but the form drag of certain body styles and airflow needs for engine cooling often limit C_d improvements.

The following sections discuss the CAFE Model's four levels of aerodynamic improvements, how we assign baseline aerodynamic technology levels to vehicles in the fleet (i.e., on a relative basis based on C_d reduction), the Autonomie simulations' estimates of effectiveness improvements from aerodynamic technologies, and the costs for adding that aerodynamic technology.

3.5.1 Aerodynamics in the CAFE Model

We bin aerodynamic improvements into four levels – 5, 10, 15, and 20 percent aerodynamic drag improvement values over a baseline computed for each vehicle body style – which correspond to aero drag reduction, level 1 (AERO5), aero drag reduction, level 2 (AERO10), AERO15, and AERO20, respectively.

Technology pathway logic for levels of aerodynamic improvement consists of a linear progression, with each level superseding all previous levels. Technology paths for AERO are illustrated in Figure 3-33.

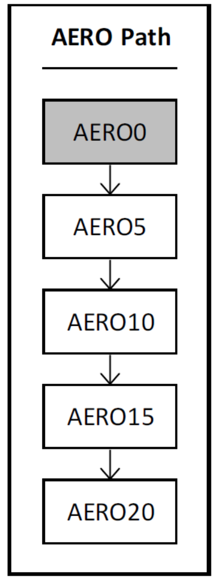

Figure 3-33 – Technology Pathway for Levels of Aerodynamic Drag Reduction

While the four levels of aerodynamic improvements are technology-agnostic, we provide a pathway to compliance for each level based on aerodynamic data from a National Research Council (NRC) of Canada-sponsored wind tunnel testing program. The program included an extensive review of production vehicles utilizing these technologies, and industry comments.[510,511] Again, we intend to show a *potential* way that manufacturers could achieve each aerodynamic improvement level; however, in the real world, manufacturers may implement different combinations of aerodynamic technologies to achieve a percentage improvement over their baseline vehicles. Table 3-120 and Table 3-121 show the aerodynamic technologies that a manufacturer could use to achieve 5, 10, 15, and 20 percent improvements in passenger cars and SUVs, and 5, 10, and 15 percent improvements in pickup trucks.

As discussed further in Chapter 3.5.3, we do not allow the model to apply AERO20 to pickup trucks, which is why there is no pathway to AERO20 shown in Table 3-121. While a manufacturer could apply some aerodynamic improvement technologies across vehicle classes, like active grille shutters (used in the 2015 Chevrolet Colorado),[512] we believe that there are limitations that make it infeasible for vehicles with some body styles to achieve a 20 percent reduction in the coefficient of drag from their baseline. This technology path is an example of

[510] Larose, G., Belluz, L., Whittal, I., Belzile, M. et al., "Evaluation of the Aerodynamics of Drag Reduction Technologies for Light-duty Vehicles - a Comprehensive Wind Tunnel Study," SAE Int. J. Passeng. Cars - Mech. Syst. 9(2):772-784, 2016, https://doi.org/10.4271/2016-01-1613. (Accessed: February 15, 2022).
[511] Larose, Guy & Belluz, Leanna & Whittal, Ian & Belzile, Marc & Klomp, Ryan & Schmitt, Andreas. (2016). Evaluation of the Aerodynamics of Drag Reduction Technologies for Light-duty Vehicles - a Comprehensive Wind Tunnel Study. SAE International Journal of Passenger Cars - Mechanical Systems. 9. 10.4271/2016-01-1613.
[512] Chevrolet Product Information, available at https://media.chevrolet.com/content/media/us/en/chevrolet/vehicles/colorado/2015/_jcr_content/iconrow/textfile/file.res/15-PG-Chevrolet-Colorado-082218.pdf. (Accessed: February 15, 2022).

how a manufacturer *could* reach each AERO level, but they would not necessarily be *required* to use the technologies.

Table 3-120 – Combinations of Technologies That Could Achieve Aerodynamic Improvements Used in the Current Analyses for Passenger Cars and SUVs

Aero Improvement Level	Components	Effectiveness (%)
AERO5	Front Styling	2.0%
	Roof Line raised at forward of B-pillar	0.5%
	Faster A pillar rake angle	0.5%
	Shorter C pillar	1.0%
	Low drag wheels	1.0%
AERO10	Rear Spoiler	1.0%
	Wheel Deflector / Air outlet inside wheel housing	1.0%
	Bumper Lip	1.0%
	Rear Diffuser	2.0%
AERO15	Underbody Cover Incl. Rear axle cladding)	3.0%
	Lowering ride height by 10mm	2.0%
AERO20	Active Grill Shutters	3.0%
	Extend Air dam	2.0%

Table 3-121 – Combinations of Technologies That Could Achieve Aerodynamic Improvements Used in the Current Analyses for Pickup Trucks

Aero Improvements	Components	Effectiveness (%)
AERO5	Whole Body Styling (Shape Optimization)	1.5%
	Faster A pillar rake angle	0.5%
	Rear Spoiler	1.0%
	Wheel Deflector / Air outlet inside wheel housing	1.0%
	Bumper Lip	1.0%
AERO10	Rear Diffuser	2.0%
	Underbody Cover Incl. Rear axle cladding)	3.0%
AERO15	Active Grill Shutters	3.0%
	Extend Air dam	2.0%

As discussed further in Chapter 3.8, we assume manufacturers apply off-cycle technology at defined rates in the Market Data file. While the AERO levels in the analysis are technology-agnostic, achieving AERO20 improvements does assume the use of active grille shutters, which are an off-cycle technology.

3.5.2 Aerodynamics Analysis Fleet Assignments

We use a relative performance approach to assign an initial level of aerodynamic drag reduction (AERO) technology to each vehicle. Each AERO level represents a percent reduction in a vehicle's aerodynamic drag coefficient (C_d) from a baseline value for its body style. AERO technologies and their definitions, as well as their prevalence in the 2020 fleet, are given in Table 3-122. For a vehicle to achieve AERO5, the C_d must be at least 5 percent below the baseline for the body style; for AERO10, 10 percent below the baseline, and so on.

Table 3-122 – Penetration Rates of Aerodynamic Drag Reduction Levels in the 2020 Fleet

Technology	Technology Description	Sales Volume	Penetration Rate
AERO0	Baseline aero	3,199,634	24%
AERO5	Aero drag reduction, level 1 (5% reduction)	4,839,840	36%
AERO10	Aero drag reduction, level 2 (10% reduction)	3,866,017	28%
AERO15	Aero drag reduction, level 3 (15% reduction)	1,233,140	9%
AERO20	Aero drag reduction, level 4 (20% reduction)	453,920	3%

We assign every vehicle in the fleet a body style; available body styles include convertible, coupe, sedan, hatchback, wagon, SUV, pickup, minivan, and van. These assignments do not necessarily match the body styles that manufacturers use for marketing purposes. Instead, we make these assignments based on engineering judgement, taking into account how we might affect a vehicle's AERO and vehicle technology class assignments. Different body styles offer different utility and have varying levels of baseline form drag. In addition, frontal area is a major factor in aerodynamic forces, and the frontal area varies by vehicle. This analysis considers both frontal area and body style as utility factors affecting aerodynamic forces; therefore, the analysis assumes all reduction in aerodynamic drag forces come from improvement in the drag coefficient.

We compute average drag coefficients for each body style using manufacturers' published MY 2015 drag coefficients, which we use as the baseline values in the analysis. Table 3-123 lists the baseline drag coefficients by body style for all levels of AERO that we use in the analysis for fleet assignments. We harmonize the Autonomie simulation baselines with the analysis fleet assignment baselines to the fullest extent possible.[513]

We source drag coefficients for each vehicle in the analysis fleet from manufacturer specification sheets, when possible. However, manufacturers did not consistently publicly report drag coefficients for MY 2020 vehicles. We use engineering judgment to assign an AERO level where we could not find a publicly available drag coefficient. If we cannot manually assign an AERO level, we use the drag coefficient obtained from manufacturers to build the MY 2016

[513] *See* Table 2-19 in Chapter 2.4.2 for the table of vehicle attributes used to build the Autonomie baseline vehicle models. That table includes a drag coefficient for each vehicle class.

fleet,[514] if available. The MY 2016 drag coefficient values may not accurately reflect the current technology content of newer vehicles but are, in many cases, the most recent data available. The AERO technology penetration values for the analysis fleet are detailed in Table 3-124 and likely include higher levels of AERO0 that we are unable to account for due to lack of drag coefficients, resulting in some understatement of the actual aerodynamic technology applied in the MY 2020 fleet.

Table 3-123 – Baseline AERO Technologies and Technology Steps by Body Style

Body Style	**Aero Level & MY 2020 Volume Distribution**					
	Labels	AERO0	AERO5	AERO10	AERO15	AERO20
Convertible	Volume Share	75.4%	14.9%	9.6%	0.0%	0.0%
	C_d	0.334	0.317	0.301	0.284	0.267
Coupe	Volume Share	50.9%	44.8%	3.4%	1.0%	0.0%
	C_d	0.319	0.303	0.287	0.271	0.255
Hatchback	Volume Share	49.1%	17.9%	15.6%	4.5%	13.0%
	C_d	0.333	0.316	0.3	0.283	0.266
Minivan	Volume Share	14.4%	60.1%	25.5%	0.0%	0.0%
	C_d	0.326	0.31	0.293	0.277	0.261
Pickup	Volume Share	10.3%	46.5%	5.6%	37.5%	0.0%
	C_d	0.42	0.399	0.378	0.357	0.336
Sedan	Volume Share	25.2%	35.9%	28.4%	5.7%	4.8%
	C_d	0.302	0.287	0.272	0.257	0.242
Sport Utility	Volume Share	24.0%	33.7%	36.7%	3.4%	2.2%
	C_d	0.363	0.345	0.327	0.309	0.29
Van	Volume Share	9.5%	0.0%	16.3%	52.0%	22.2%
	C_d	0.389	0.37	0.35	0.331	0.311
Wagon	Volume Share	7.2%	1.8%	0.4%	10.8%	79.8%
	C_d	0.342	0.325	0.308	0.291	0.274

Baseline drag coefficients are also utilized in the final assignment of aerodynamic improvement levels. The drag coefficient of each vehicle is compared to the baseline average drag coefficient value for the vehicle's body style to perform the assignment. Note that the highest AERO levels, AERO15 and AERO20, are not considered for certain body styles; see Chapter 3.5.3 for more detail.

Table 3-124 – Aerodynamic Application by Manufacturer as a Percent of MY 2020 Sales

Manufacturer	**AERO0**	**AERO5**	**AERO10**	**AERO15**	**AERO20**
BMW	50%	15%	35%	0%	0%
Daimler	38%	4%	29%	0%	29%

[514] *See* 83 Fed. Reg. 42986 (Aug. 24, 2018). The MY 2016 fleet was built to support the 2018 NPRM.

Fiat-Chrysler	61%	20%	1%	18%	0%
Ford	8%	7%	34%	52%	0%
General Motors	16%	46%	38%	0%	0%
Honda	8%	52%	35%	2%	2%
Hyundai	2%	52%	42%	0%	3%
Kia	25%	50%	24%	1%	0%
Jaguar Land Rover	53%	44%	2%	0%	1%
Mazda	16%	63%	7%	13%	0%
Mitsubishi	35%	0%	65%	0%	0%
Nissan	13%	38%	46%	1%	2%
Subaru	31%	43%	26%	0%	0%
Tesla	0%	0%	0%	0%	100%
Toyota	27%	50%	20%	0%	3%
Volvo	2%	20%	40%	7%	32%
Volkswagen	50%	20%	28%	1%	1%

3.5.3 Aerodynamics Adoption Features

We use a relative performance approach to assign current aerodynamic technology (AERO) level to a vehicle. For some body styles with different utility, such as pickup trucks, SUVs and minivans, frontal area can vary, and this can affect the overall aerodynamic drag forces. To maintain vehicle utility and functionality related to passenger space and cargo space, we assume all technologies that improve aerodynamic drag forces do so by reducing C_d while maintaining frontal area.

Technology pathway logic for levels of aerodynamic improvement consists of a linear progression, with each level superseding all previous ones. Technology paths for AERO are illustrated in Figure 3-33.

The highest levels of AERO are not considered for certain body styles. In these cases, this means that we do not apply AERO20 and AERO15 in the baseline fleet, and the model cannot adopt AERO20, and sometimes AERO15. For these body styles, there are no commercial examples of drag coefficients that demonstrate the required AERO15 or AERO20 improvement over baseline levels. We also deem the most advanced levels of aerodynamic drag simulated as not technically practicable given the form drag of the body style and costed technology, especially given the need to maintain vehicle functionality and utility, such as interior volume, cargo area, and ground clearance. As seen in Table 3-120, example technologies that may be used to achieve high AERO levels include lowered ride height, active grill shutters, and extended air dams. Therefore, the analysis does not consider the highest levels of drag improvement for convertibles, minivans, pickups, and wagons as a potential pathway to compliance in response to regulatory alternatives. The SKIP logic used to implement these restrictions is given in Table 3-125.

Table 3-125 – SKIP Logic Based on Body Style

Body Style	AERO15	AERO20
Convertible		SKIP
Coupe		
Hatchback		
Minivan	SKIP	SKIP
Pickup		SKIP
Sedan		
Sport Utility		
Van		
Wagon		SKIP

We also do not allow application of AERO15 and AERO20 technology to vehicles with more than 780 horsepower. There are two main types of vehicles that inform this threshold: performance internal combustion engine (ICE) vehicles and high-power battery electric vehicles (BEVs). In the case of the former, we recognize that manufacturers tune aerodynamic features on these vehicles to provide desirable downforce at high speeds and to provide sufficient cooling for the powertrain, rather than reducing drag, resulting in middling drag coefficients despite advanced aerodynamic features. Therefore, manufacturers may have limited ability to improve aerodynamic drag coefficients for high performance vehicles with internal combustion engines without reducing horsepower. 1,655 units of sales volume in the baseline fleet include limited application of aerodynamic technologies because of ICE vehicle performance.[515]

In the case of high-power battery electric vehicles, the 780-horsepower threshold is set above the highest peak system horsepower present on a BEV in the 2020 fleet. BEVs have different aerodynamic behavior and considerations than ICE vehicles, allowing for features such as flat underbodies that significantly reduce drag.[516] BEVs are therefore more likely to achieve higher AERO levels, so the horsepower threshold is set high enough that it does not restrict AERO15 and AERO20 application. Note that the CAFE Model does not force high levels of AERO adoption; rather, higher AERO levels are usually adopted organically by BEVs because

[515] *See* the Market Data file.
[516] 2020 EPA Automotive Trends Report, at p. 227.

significant drag reduction allows for smaller batteries and, by extension, cost savings. BEVs represent 252,023 units of sales volume in the baseline fleet.[517]

Note that while many aerodynamic features that contribute to drag reduction (*e.g.*, active grill shutters) are considered off-cycle technologies, AERO levels and the off-cycle program are modeled separately for the analysis. For further discussion of off-cycle technologies, see Chapter 3.8.

3.5.4 Aerodynamics Effectiveness

To determine aerodynamic effectiveness, the CAFE Model and Autonomie use individually assigned road load technologies for each vehicle to appropriately assign initial road load levels and appropriately capture benefits of subsequent individual road load improving technologies.

The analysis includes four levels of aerodynamic improvements, AERO5, AERO10, AERO15, and AERO20, representing 5, 10, 15, and 20 percent reduction in drag coefficient (C_d), respectively. See Chapter 3.5.1 for a list of aerodynamic improving features and components that manufacturers could apply to achieve these levels. The analysis assumes that aerodynamic drag reduction can only come from reduction in C_d and not from reduction of frontal area, to maintain vehicle functionality and utility, such as passenger space, ingress/egress ergonomics, and cargo space.

The effectiveness values for the aerodynamic improvement levels relative to AERO0, for all ten vehicle technology classes, are shown in Figure 3-34. Each of the effectiveness values shown is representative of the improvements seen for upgrading only the listed aerodynamic technology level for a given combination of other technologies. In other words, the range of effectiveness values seen for each specific technology (*e.g.*, AERO 15) represents the addition of AERO15 technology (relative to AERO0 level) for every technology combination that could select the addition of AERO15. Here, we use the change in fuel consumption values between entire technology keys,[518] and not the individual technology effectiveness values. Using the change between whole technology keys captures the complementary or non-complementary interactions among technologies.

[517] *See* the Market Data file.
[518] Technology key is the unique collection of technologies that constitutes a specific vehicle (see Chapter 2.4).

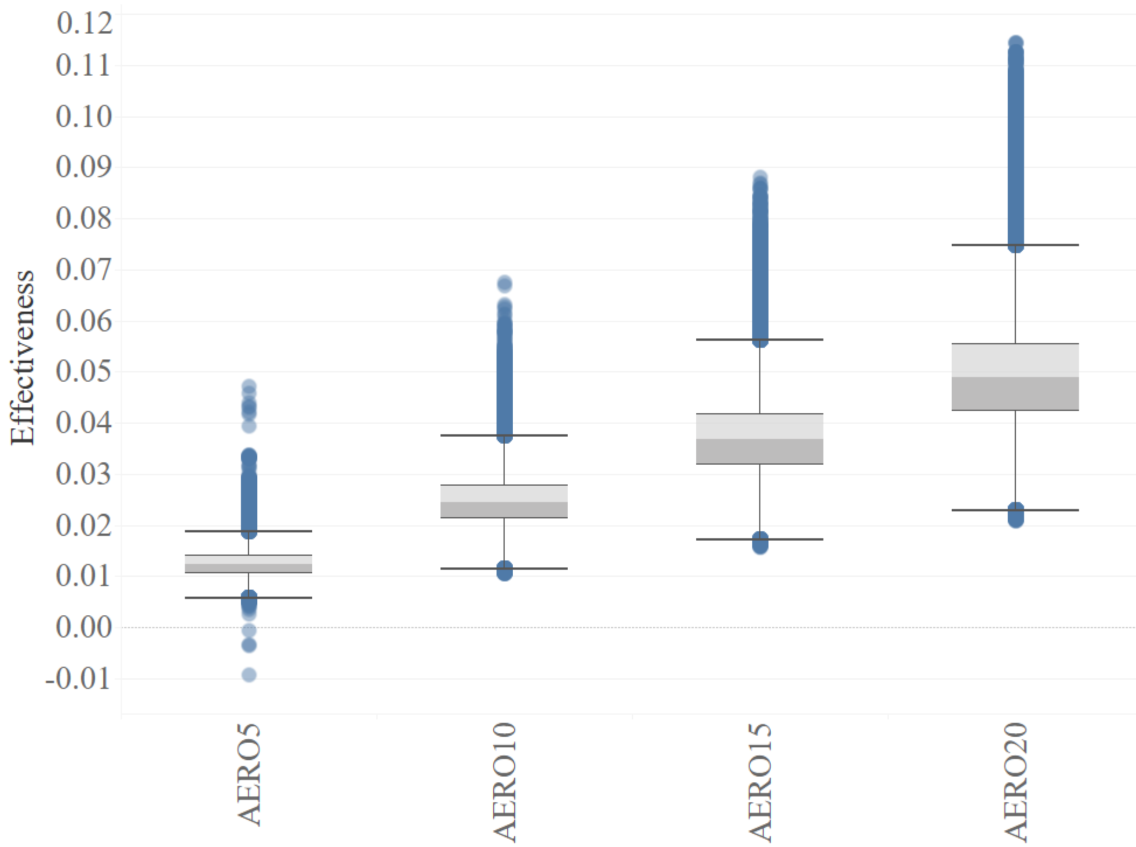

Figure 3-34 – AERO Technology Effectiveness[519]

3.5.5 Aerodynamics Costs

This analysis uses the AERO technology costs established in the 2020 CAFE final rule.[520] The cost estimates are based on confidential business information submitted by the automotive industry in advance of the 2018 CAFE NPRM, and on our assessment of manufacturing costs for specific aerodynamic technologies. See the 2018 PRIA for discussion of the cost estimates.[521] We received no additional comments from stakeholders regarding the costs established in the 2018 PRIA and continue to use the established costs for this analysis, as shown in Table 3-126 and Table 3-127.

The cost to achieve AERO5 is relatively low, as manufacturers can make most of the improvements through body styling changes. The cost to achieve AERO10 is higher than AERO5, due to the addition of several passive aerodynamic technologies, and the cost to achieve AERO15 and AERO20 is higher than AERO10 due to use of both passive and active aerodynamic technologies.

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[519] The box shows the inner quartile range (IQR) of the effectiveness values and whiskers extend out 1.5 x IQR. The blue dots show effectiveness values outside those thresholds. The data used to create this figure can be found in the FE_1 Improvements file.
[520] *See* the FRIA accompanying the 2020 final rule, Chapter VI.C.5.e.
[521] *See* the PRIA accompanying the 2018 NPRM, Chapter 6.3.10.1.2.1.2 for a discussion of these cost estimates.

Table 3-126 and Table 3-127 show the initial DMC values for aerodynamic improvement technologies in MY 2017 and reported in 2018$. The tables also show the total costs for the technologies across multiple model years, also in 2018$. The total cost includes the application of RPE and learning factors. See the Technologies file for all costs across all model years.

Table 3-126 – DMC and Total Costs of Aerodynamic Improvement Technology for Passenger Cars and SUVs (in 2018$) - Includes RPE and Learning Effects

Aero Improvements for Passenger Cars and SUV	DMC (2018$)	Total Cost: Including RPE and Learning Factors (2018$)			
	MY 2017	MY 2020	MY 2022	MY 2024	MY 2030
0%	$0.00	$0.00	$0.00	$0.00	$0.00
5%	$39.38	$53.96	$51.41	$49.50	$45.73
10%	$80.51	$110.32	$105.11	$101.19	$93.49
15%	$113.76	$155.88	$148.53	$142.99	$132.10
20%	$201.27	$275.80	$262.78	$245.24	$233.72

Table 3-127 – DMC and Total Costs of Aerodynamic Improvement Technology for Pickup Trucks (in 2018$) - Includes RPE and Learning Effects

Aero Improvements for Pickups	DMC (2018$)	Total Cost: Including RPE and Learning Factors (2018$)			
	MY 2017	MY 2020	MY 2022	MY 2024	MY 2030
0%	$0.00	$0.00	$0.00	$0.00	$0.00
5%	$39.38	$53.96	$51.41	$49.50	$45.73
10%	$80.51	$110.32	$105.11	$101.19	$93.49
15%	$201.27	$275.80	$262.78	$252.98	$233.72

3.6 Tire Rolling Resistance

Tire rolling resistance is a road load force that arises primarily from the energy dissipated by elastic deformation of the tires as they roll. Tire design characteristics (for example, materials, construction, and tread design) have a strong influence on the amount and type of deformation and the energy it dissipates. Designers can select these characteristics to minimize rolling resistance. However, these characteristics may also influence other performance attributes, such as durability, wet and dry traction, handling, and ride comfort.

Lower-rolling-resistance tires have characteristics that reduce frictional losses associated with the energy dissipated mainly in the deformation of the tires under load, thereby improving fuel economy. OEMs increasingly specify low rolling resistance tires for new vehicles and low rolling resistance tires are also increasingly available from aftermarket tire vendors. They commonly include attributes such as higher inflation pressure, material changes, tire construction optimized for lower hysteresis, geometry changes (*e.g.*, reduced aspect ratios), and reduced sidewall and tread deflection. Manufacturers also apply additional changes to vehicle suspension tuning and/or suspension design to mitigate any potential impact on other performance attributes of the vehicle.

We continue to assess the potential impact of tire rolling resistance changes on vehicle safety. We have been following the industry developments and trends in application of rolling resistance technologies to light duty vehicles. As stated in the NAS special report on Tires and Passenger Vehicle Fuel Economy,[522] national crash data does not provide data about tire structural failures specifically related to tire rolling resistance, because the rolling resistance of a tire at a crash scene cannot be determined. However, other metrics like brake performance compliance test data are helpful to show trends like that stopping distance has not changed in the last ten years,[523] during which time many manufacturers have installed low rolling resistance tires in their fleet—meaning that manufacturers were successful in improving rolling resistance while maintaining stopping distances through tire design, tire materials, and/or braking system improvements. In addition, NHTSA has addressed other tire-related issues through rulemaking,[524] and continues to research tire problems such as blowouts, flat tires, tire or wheel deficiency, tire or wheel failure, and tire degradation.[525] However, there are currently no data connecting low rolling resistance tires to accident or fatality rates.

Based on tire rolling resistance tests and wet grip index tests on original equipment tires installed on new vehicles,[526] we can observe that there is no degradation in wet grip index values (no degradation in traction) for tires with improved rolling resistance technology. With better tire design, tire compound formulations and improved tread design, tire manufacturers have tools to balance stopping distance and reduced rolling resistance. Tire manufacturers can use “higher performance materials in the tread compound, more silica as reinforcing fillers and advanced tread design features” to mitigate issues related to stopping distance.[527]

The following sections discuss levels of tire rolling resistance technology that we apply in the CAFE Model, how the technology is assigned in the analysis fleet, adoption features specified to maintain performance, effectiveness, and cost.

3.6.1 Tire Rolling Resistance in the CAFE Model

We continue to consider two levels of improvement for low rolling resistance tires in the analysis: the first level of low rolling resistance tires reduce rolling resistance 10 percent from an

[522] Tires and Passenger Vehicle Fuel Economy: Informing Consumers, Improving Performance - - Special Report 286 (2006), available at https://www.nap.edu/read/11620/chapter/6. (Accessed: February 15, 2022).
[523] *See*, *e.g.*, NHTSA Office of Vehicle Safety Compliance, Compliance Database, https://one.nhtsa.gov/cars/problems/comply/index.cfm. (Accessed: February 15, 2022).
[524] 49 CFR 571.138, Tire pressure monitoring systems.
[525] Tire-Related Factors in the Pre-Crash Phase, DOT HS 811 617 (April 2012), available at https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/811617. (Accessed: February 15, 2022).
[526] The results of these tests are presented in Docket No. NHTSA-2021-0053-0010, Memo to Docket - Rolling Resistance Phase One and Two.
[527] Jesse Snyder, A big fuel saver: Easy-rolling tires (but watch braking) (July 21, 2008), https://www.autonews.com/article/20080721/OEM01/307219960/a-big-fuel-saver-easy-rolling-tires-but-watch-braking. (Accessed: February 15, 2022).

industry-average baseline rolling resistance coefficient (RRC) value, while the second level reduce rolling resistance 20 percent from the baseline.[528]

We use an industry average RRC baseline of 0.009 based on a CONTROLTEC study prepared for the California Air Resources Board,[529] in addition to confidential business information submitted by manufacturers prior to the 2018 NPRM analysis. The average RRC from the CONTROLTEC study, which surveyed 1,358 vehicle models,[530] is 0.009. CONTROLTEC also compared the findings of their survey with values provided by Rubber Manufacturers Association (renamed as USTMA-U.S. Tire Manufacturers Association) for original equipment tires. The average RRC from the data provided by RMA is 0.0092,[531] compared to average of 0.009 from CONTROLTEC.

In past agency actions, commenters have argued that based on available data on current vehicle models and the likely possibility that there would be additional tire improvements over the next decade, we should consider ROLL30 technology, or a 30 percent reduction of tire rolling resistance over the baseline.[532]

As stated in Joint TSD for the 2017-2025 final rule and 2020 final rule, tire technologies that enable rolling resistance improvements of 10 and 20 percent have been in existence for many years.[533] Achieving improvements of up to 20 percent involves optimizing and integrating multiple technologies, with a primary contributor being the adoption of a silica tread technology. Tire suppliers have indicated that additional innovations are necessary to achieve the next level of low rolling resistance technology on a commercial basis, such as improvements in material to retain tire pressure, tread design to manage both stopping distance and wet traction, and development of carbon black material for low rolling resistance without the use of silica to reduce cost and weight.[534]

We believe that the tire industry is in the process of moving automotive manufacturers towards higher levels of rolling resistance technology in the vehicle fleet. Importantly, as shown below, the MY 2020 fleet does include a higher percentage of vehicles with ROLL20 technology than the MY 2017 fleet. However, we believe that at this time, the emerging tire technologies that would achieve 30 percent improvement in rolling resistance, like changing tire profile, stiffening tire walls, or adopting improved tires along with active chassis control,[535] among other technologies, will not be available for widespread commercial adoption in the fleet during the

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528 To achieve ROLL10, the tire rolling resistance must be at least 10 percent better than baseline (.0081 or better). To achieve ROLL20, the tire rolling resistance must be at least 20 percent better than baseline (.0072 or better).

529 Technical Analysis of Vehicle Load Reduction by CONTROLTEC for California Air Resources Board (April 29, 2015).

530 The RRC values used in this study were a combination of manufacturer information, estimates from coast down tests for some vehicles, and application of tire RRC values across other vehicles on the same platform.

531 Technical Analysis of Vehicle Load Reduction by CONTROLTEC for California Air Resources Board (April 29, 2015), at 40.

532 NHTSA-2018-0067-11985.

533 EPA-420-R-12-901, at pp. 3–210.

534 2011 NAS report, at p. 103.

535 Mohammad Mehdi Davari, Rolling resistance and energy loss in tyres (May 20, 2015), available at https://www.sveafordon.com/media/42060/SVEA-Presentation_Davari_public.pdf. (December 30, 2019).

rulemaking timeframe. As a result, we continue to not to incorporate a 30 percent reduction in rolling resistance technology.

3.6.2 Tire Rolling Resistance Analysis Fleet Assignments

Tire rolling resistance is not a part of tire manufacturers' publicly released specifications and thus it is difficult to assign this technology to the analysis fleet. Manufacturers also often offer multiple wheel and tire packages for the same nameplates, further increasing the complexity of this assignment. We employ an approach consistent with previous rulemaking in assigning this technology. We rely on previously submitted rolling resistance values supplied by manufacturers in the process of building older fleets and bolstered it with an agency-sponsored tire rolling resistance study by Smithers.[536]

We carry over rolling resistance assignments for nameplates where manufacturers had submitted data on the vehicles' rolling resistance values, even if the vehicle was redesigned. If Smithers data were available, we use that data in place any older or missing values. We assign ROLL0 to vehicles for which no information is available from either previous manufacturer submissions or Smithers data. All vehicles under the same nameplate are assigned the same rolling resistance technology level even if manufacturers do outfit different trim levels with different wheels and tires.

Table 3-128 shows the distribution of ROLL technology for the 2017 and 2020 fleets. This table illustrates that the majority of the fleet has now adopted some form of improved rolling resistance technology. The majority of the change has been in implementing ROLL20 technology. There is likely more proliferation of rolling resistance technology, but we would need further information from manufacturers to account for it.

Table 3-128 – Distribution of Tire Rolling Resistance Technology for the MY 2017 and MY 2020 Fleets

Technology	MY 2017 Fleet	MY 2020 Fleet
ROLL0	59%	44%
ROLL10	21%	20%
ROLL20	20%	36%

3.6.3 Tire Rolling Resistance Adoption Features

The model can apply rolling resistance technology with either vehicle refresh or redesign. In some cases, low rolling resistance tires can affect traction, which may adversely impact acceleration, braking, and handling characteristics for some high-performance vehicles. Similar to past rulemakings, we recognize that to maintain performance, braking, and handling functionality, some high-performance vehicles would not adopt low rolling resistance tire technology. For cars and SUVs with more than 405 horsepower (hp), we restrict the application of ROLL20. For cars and SUVs with more than 500 hp, we restrict the application of any additional rolling resistance technology (ROLL10 or ROLL20). We apply these cutoffs based on

[536] "Evaluation of Rolling Resistance and Wet Grip Performance of OEM Stock Tires Obtained from NCAP Crash Tested Vehicles Phase One and Two" (NHTSA-2021-0053).

a review of confidential business information and the distribution of rolling resistance values in the fleet.

3.6.4 Tire Rolling Resistance Effectiveness

As discussed above, based on a thorough review of confidential business information submitted by industry, and a review of other literature, we use a baseline rolling resistance of 0.009. To achieve ROLL10, the tire rolling resistance must be at least 10 percent better than baseline (.0081 or better). To achieve ROLL20, the tire rolling resistance must be at least 20 percent better than baseline (.0072 or better).

We determine effectiveness values for rolling resistance technology adoption using Autonomie modeling. Figure 3-35 below shows the range of effectiveness values used for adding tire rolling resistance technology to a vehicle in this analysis. The graph shows the change in fuel consumption values between entire technology keys,[537] and not the individual technology effectiveness values. Using the change between whole technology keys captures the complementary or non-complementary interactions among technologies. In the graph, the box shows the inter quartile range (IQR) of the effectiveness values and whiskers extend out 1.5 x IQR. The blue dots show values for effectiveness that are outside these bounds.

The data points with the highest effectiveness values are almost all exclusively BEV and FCV technology combinations for medium sized non-performance cars. The effectiveness for these vehicles, when the low rolling resistance technology is applied, is amplified by a complementary effect where the lower rolling resistance reduces road load and the vehicle can use a smaller battery pack (and still meet range requirements). The smaller battery pack reduces the overall weight of the vehicle, further reducing road load, and improving fuel efficiency. All vehicle technology classes experience this complementary effect, but the strongest effect is on the midsized vehicle non-performance classes. By using full vehicle simulations, we can capture these effects that demonstrate the full interactions of the technologies.

[537] Technology key is the unique collection of technologies that constitutes a specific vehicle (see Chapter 2.4.7).

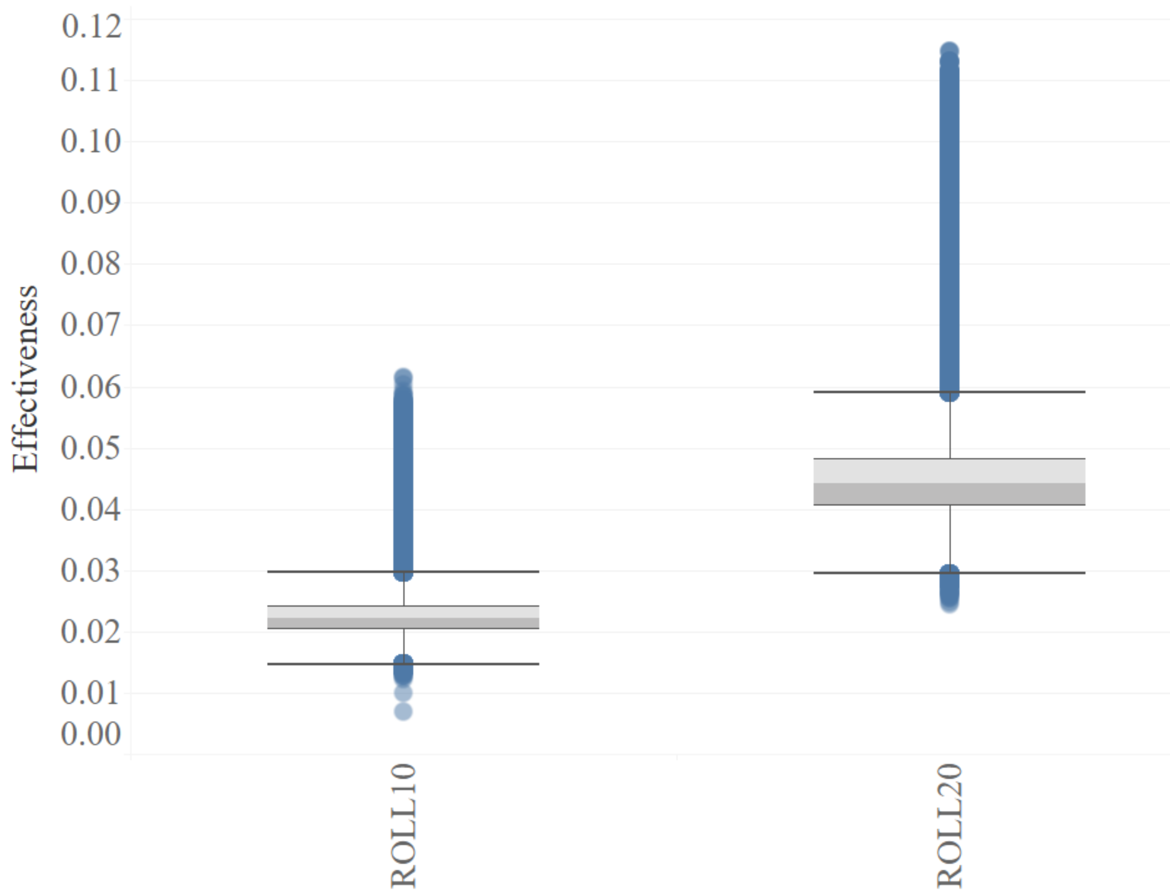

Figure 3-35 – Final Rule Analysis ROLL Technology Effectiveness

3.6.5 Tire Rolling Resistance Costs

We use the same DMC values for ROLL technology that were used for the 2020 CAFE final rule. The costs are in 2018$ dollars. Table 3-129 shows the different levels of tire rolling resistance technology cost.

Table 3-129 – Cost for Tire Rolling Resistance Technologies Relative to ROLL0

Technology	**Tire Rolling Resistance Technology Costs for MY 2020 (2018$)**	
	Direct Manufacturing Cost	Total Cost (includes RPE and Learning)
ROLL0	$0.00	$0.00
ROLL10	$5.186	$7.78
ROLL20	$40.54	$60.81

3.7 Other Vehicle Technologies

We include four other vehicle technologies in the analysis—electric power steering (EPS), improved accessories (IACC), low drag brakes (LDB), and SAX (which may only be applied to vehicles with all-wheel-drive or four-wheel-drive). The CAFE Model directly applies these technologies' effectiveness, with unique effectiveness values for each technology and for each technology class. We use this methodology in these four cases because the effectiveness of these technologies varies little with combinations of other technologies. Also, applying these technologies directly in the CAFE Model significantly reduces the required number of Autonomie simulations.

3.7.1 Electric Power Steering

Electric power steering reduces fuel consumption by reducing load on the engine. Specifically, it reduces or eliminates the parasitic losses associated with engine-driven power steering pumps, which pump hydraulic fluid continuously through the steering actuation system even when no steering input is present. By selectively powering the electric assist only when steering input is applied, the power consumption of the system is reduced in comparison to the traditional "always-on" hydraulic steering system. Power steering may be electrified on light duty vehicles with standard 12V electrical systems and is also an enabler for vehicle electrification because it provides power steering when the engine is off (or when no combustion engine is present).

Power steering systems can be electrified in two ways. Manufacturers may choose to eliminate the hydraulic portion of the steering system and provide electric-only power steering (EPS) driven by an independent electric motor, or they may choose to move the hydraulic pump from a belt-driven configuration to a stand-alone electrically driven hydraulic pump. The latter system is commonly referred to as electro-hydraulic power steering (EHPS). As discussed in the past rulemakings, manufacturers have informed us that full EPS systems are being developed for all types of light-duty vehicles, including large trucks.

3.7.1.1 Electric Power Steering Technology Fleet Assignments

Like low drag brakes, EPS can be difficult to observe and assign to the analysis fleet, however, it is found more frequently in publicly available information than low drag brakes. Based on comments received during the 2020 rulemaking, we increased EPS application rate to nearly 90 percent for the 2020 final rule. We are maintaining this level of EPS fleet penetration for this analysis, recognizing that some specialized, unique vehicle types or configurations still implement hydraulically actuated power steering systems.

3.7.1.2 Electric Power Steering Technology Adoption Features

When not already applied, we believe that manufacturers would primarily apply EPS during a redesign when implementing extensive architecture revisions. In addition, we believe there are much longer implementation lead times that involve extensive validation efforts based on the close relationship of steering to vehicle control and safety. However, the OEMs may still be able, and choose, to apply EPS at a vehicle refresh as its implementation may be tied to strategic powertrain-related upgrades that include the elimination of the engine driven power steering pump.

3.7.1.3 Electric Power Steering Technology Effectiveness Values

The effectiveness of both EPS and EHPS is derived from the decoupling of the pump from the crankshaft and is practically the same for both. Thus, we use a single effectiveness value for both EPS and EHPS. As indicated in the following table, the effectiveness of EPS and EHPS varies based vehicle technology class. This variance is a direct result of vehicle size and the amount of energy the vehicle requires to turn the two front wheels about their vertical axis. More simply put, vehicles that weigh more require more energy and typically have larger tire contact patches.

Table 3-130 – Fuel Consumption Improvement Values for Electric Power Steering

Tech Class	EPS
SmallCar	1.50%
SmallCarPerf	
MedCar	1.30%
MedCarPerf	
SmallSUV	1.20%
SmallSUVPerf	
MedSUV	1.00%
MedSUVPerf	
Pickup	0.80%
PickupHT	

3.7.1.4 Electric Power Steering Technology Costs

The cost estimates for EPS relies on previous work published as part of the rulemaking processes, for the 2012 rule and the Draft TAR. The cost values are the same values that were used for the Draft TAR and 2020 final rule, updated to 2018 dollars. Learning rates for these technologies are shown in Chapter 2.6.4.

Table 3-131 below shows the absolute costs for EPS for select model years. The Technologies file shows the costs for all model years.

Table 3-131 – Absolute Costs for Electric Power Steering, Including Learning Effects and Retail Price Equivalent (2018$)

Technology	2017	2021	2025	2029
EPS	$133.23	$124.42	$117.28	$111.97

3.7.2 Improved Accessories (IACC)

Engine accessories typically include the alternator, coolant pump, cooling fan, and oil pump, and are traditionally driven mechanically via belts, gears, or directly by other rotating engine components such as camshafts or the crankshaft. These can be replaced with improved accessories (IACC), which may include high efficiency alternators, electrically driven (*i.e.*, on-demand) coolant pumps, electric cooling fans, variable geometry oil pumps, and a mild regeneration strategy.[538] Replacing lower-efficiency and/or mechanically-driven components with these improved accessories results in a reduction in fuel consumption, as the improved accessories can conserve energy by being turned on/off "on demand" in some cases, driven at partial load as needed, or by operating more efficiently.

For example, electric coolant pumps and electric powertrain cooling fans provide better control of engine cooling. Flow from an electric coolant pump can be varied, and the cooling fan can be shut off during engine warm-up or cold ambient temperature conditions, reducing warm-up time, fuel enrichment requirements, and, ultimately, reducing parasitic losses.

3.7.2.1 Improved Accessories Technology Fleet Assignments

IACC technology is difficult to observe and therefore there is uncertainty in assigning it to the analysis fleet. As in the past, we rely on industry-provided information and comments to assess the level of IACC technology applied in the fleet. We believe there continues to be opportunity for further implementation of IACC. The MY 2020 analysis fleet has an IACC fleet penetration of approximately eight percent compared to the six percent value in the MY 2017 analysis fleet used for the 2020 final rule analysis.

3.7.2.2 Improved Accessories Technology Adoption Features

We believe that improved accessories may be incorporated in coordination with powertrain related changes occurring at either a vehicle refresh or vehicle redesign. This coordination with powertrain changes enables related design and tooling changes to be implemented and systems development, functionality, and durability testing to be conducted in a single product change program to efficiently manage resources and costs.

3.7.2.3 Improved Accessories Technology Effectiveness Values

This analysis carries forward work on the effectiveness of IACC systems conducted in the Draft TAR and EPA Proposed Determination. This work involved gathering information by monitoring press reports, holding meetings with suppliers and OEMs, and attending industry technical conferences. The resulting effectiveness estimates used in this analysis are shown below. As indicated in the table, the effectiveness of IACC is simulated with differing values based on the vehicle technology class it is being applied to. This variance, like EPS, is a direct result of vehicle size and the amount of energy required perform the work necessary for the vehicle to operate as expected. This variance is related to the amount energy generated by the

[538] IACC in this analysis excludes other electrical accessories such as electric oil pumps and electrically driven air conditioner compressors.

alternator, the size of the coolant pump to the cool the necessary systems, the size of the cooling fan required, among other characteristics and it directed related to a vehicle size and mass.

Table 3-132 – Fuel Consumption Improvement Values for Improved Accessories

Tech Class	IACC
SmallCar	1.85%
SmallCarPerf	
MedCar	2.36%
MedCarPerf	
SmallSUV	1.74%
SmallSUVPerf	
MedSUV	2.34%
MedSUVPerf	
Pickup	2.15%
PickupHT	

3.7.2.4 Improved Accessories Technology Costs

The cost estimates for IACC rely on previous work published as part of the rulemaking processes, for the 2012 rule and the 2016 Draft TAR. The cost estimates for IACC for this analysis are the same values that were used for the 2016 Draft TAR and 2020 final rule, updated to 2018 dollars. Learning rates for these technologies can be seen in Chapter 2.6.4.

Table 3-133 shows the absolute costs for IACC for select model years. The Technologies file shows costs for all model years.

Table 3-133 – Absolute Costs for Improved Accessories, Including Learning Effects and Retail Price Equivalent (2018$)

Technology	2017	2021	2025	2029
IACC	$196.39	$163.40	$146.67	$136.96

3.7.3 Low Drag Brakes (LDB)

Since 2009, for the MY 2011 CAFE rule, we have defined low drag brakes (LDB) as brakes that reduce the sliding friction of disc brake pads on rotors when the brakes are not engaged because the brake pads are pulled away from the rotating disc either by mechanical or electric methods.[539] We estimated the effectiveness of LDB technology to be a range from 0.5-1.0 percent, based on CBI data. We applied a learning curve to the estimated cost for LDB, but noted that the technology was considered high volume, mature, and stable. We explained that

[539] Final Regulatory Impact Analysis, Corporate Average Fuel Economy for MY 2011 Passenger Cars and Light Trucks (March 2009), at p. V-135.

confidential manufacturer comments in response to the NPRM for MY 2011 indicated that most passenger cars have already adopted LDB technology, but ladder frame trucks have not.

We and EPA continued to use the same definition for LDB in the MY 2012-2016 rule, with an estimated effectiveness of up to 1 percent based on CBI data.[540] We only allowed LDB technology to be applied to large car, minivan, medium and large truck, and SUV classes because the agency determined the technology was already largely utilized in most other subclasses. The 2011 NAS committee also utilized the agencies' definition for LDB and added that most new vehicles have low-drag brakes.[541] The committee confirmed that the impact over conventional brakes may be about a 1 percent reduction of fuel consumption.

For the MY 2017-2025 rule, however, the agencies updated the effectiveness estimate for LDB to 0.8 percent based on a 2011 Ricardo study and updated lumped-parameter model.[542] The agencies considered LDB technology to be off the learning curve (i.e., the DMC does not change year-over-year). The 2015 NAS report continued to use the agencies' definition for LDB and commented that the 0.8 percent effectiveness estimate is a reasonable estimate.[543] The 2015 NAS committee did not opine on the application of LDB technology in the fleet. The agencies used the same definition, cost, and effectiveness estimates for LDB in the Draft TAR, but also noted the existence of zero drag brake systems which use electrical actuators that allow brake pads to move farther away from the rotor.[544] However, the agencies did not include zero drag brake technology in either compliance simulation. EPA continued with this approach in its first 2017 Proposed Determination that the standards through 2025 were appropriate.[545]

In the 2020 final rule, the agencies applied LDB sparingly in the MY 2017 analysis fleet using the same cost and effectiveness estimates from the 2011 Ricardo study, with approximately less than 15 percent of vehicles being assigned the technology. In addition, we noted the existence of zero drag brakes in production for some BEVs, similar to the summary in the Draft TAR, but did not opine on the existence of zero drag brakes in the fleet. Some stakeholders commented to the 2020 rule that other vehicle technologies, including LDB, were actually overapplied in the analysis fleet.

For this action, we considered the conflicting statements that LDB were both universally applied in new vehicles and that the new vehicle fleet still had space to improve LDB technology. We determined that LDB technology as previously defined going back to the MY 2011 rule was universally applied in the MY 2020 fleet. However, we determined that zero drag brakes, the next level of brake technology, was sparingly applied in the MY 2020 analysis fleet. Currently, we do not believe that zero drag brake systems will be available for wide scale application in the rulemaking timeframe and did not include it as a technology for this analysis. We will consider

[540] Final Regulatory Impact Analysis, Corporate Average Fuel Economy for MY 2012 - MY 2016 Passenger Cars and Light Trucks (March 2010), at p. 249.
[541] 2011 NAS report, at p. 104.
[542] Joint Technical Support Document: Final Rulemaking for 2017-2025 Light-Duty Vehicle Greenhouse Gas Emission Standards and Corporate Average Fuel Economy Standards (August 2012), at 3-211.
[543] 2015 NAS report, at p. 231.
[544] Draft TAR at pp. 5-207.
[545] EPA Proposed Determination TSD, at pp. 2–422.

how to define a new level of low drag brake technology that either encompasses the definition of zero drag brakes or similar technology in future rulemakings.

3.7.4 Secondary Axle Disconnect (SAX)

All-wheel drive (AWD) and four-wheel drive (4WD) vehicles provide improved traction by delivering torque to the front and rear axles, rather than just one axle. When a second axle is rotating, it tends to consume more energy because of additional losses related to lubricant churning, seal friction, bearing friction, and gear train inefficiencies.[546] Some of these losses may be reduced by providing a SAX function that disconnects one of the axles when driving conditions do not call for torque to be delivered to both.

The terms AWD and 4WD are often used interchangeably, although they have also developed a colloquial distinction, and are two separate systems. The term AWD has come to be associated with light-duty passenger vehicles providing variable operation of one or both axles on ordinary roads. The term 4WD is often associated with larger truck-based vehicle platforms providing a locked driveline configuration and/or a low range gearing meant primarily for off-road use.

Many 4WD vehicles provide for a single-axle (or two-wheel) drive mode that may be manually selected by the user. In this mode, a primary axle (usually the rear axle) will be powered, while the other axle (known as the secondary axle) is not. However, even though the secondary axle and associated driveline components are not receiving engine power, they are still connected to the non-driven wheels and will rotate when the vehicle is in motion. This unnecessary rotation consumes energy,[547] and leads to increased fuel consumption that could be avoided if the secondary axle components were completely disconnected and not rotating.

Light-duty AWD systems are often designed to divide variably torque between the front and rear axles in normal driving to optimize traction and handling in response to driving conditions. However, even when the secondary axle is not necessary for enhanced traction or handling, in traditional AWD systems it typically remains engaged with the driveline and continues to generate losses that could be avoided if the axle was instead disconnected. The SAX technology observed in the marketplace disengages one axle (typically the rear axle) for 2WD operation but detects changes in driving conditions and automatically engages AWD mode when it is necessary. The operation in 2WD can result in reduced fuel consumption. For example, Chrysler has estimated the SAX feature in the Jeep Cherokee reduces friction and drag attributable to the secondary axle by 80 percent when in disconnect mode.[548]

3.7.4.1 Secondary Axle Disconnect Technology Fleet Assignments

Observing SAX technology on actual vehicles is very difficult. Manufacturers do not typically identify the technology on technical specifications or other widely available information. We use an approach consistent with previous rulemaking in assigning this technology. Specifically, we assign SAX technology based on a combination of publicly available information and

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[546] Pilot Systems, "AWD Component Analysis," Project Report, performed for Transport Canada, Contract T8080-150132, May 31, 2016.
[547] Any time a drivetrain component spins it consumes some energy, primarily to overcome frictional forces.
[548] Brooke, L. "Systems Engineering a new 4x4 benchmark," *SAE Automotive Engineering*, June 2, 2014.

previously submitted confidential information. In the analysis fleet, we determine that 38 percent of the vehicles with AWD or 4WD have SAX technology. We skipped out SAX for all vehicles in the analysis fleet with front-wheel-drive (FWD) or rear-wheel-drive (RWD), since SAX technology is a way to emulate FWD or RWD in AWD and 4WD vehicles, respectively. The model cannot apply SAX technology to FWD or RWD vehicles because they do not have a secondary driven axle to disconnect.

3.7.4.2 Secondary Axle Disconnect Technology Adoption Features

The model can apply SAX technology to any vehicle in the analysis fleet, including those with a HEV or BEV powertrain that have AWD or 4WD. It does not supersede any technology or result in any other technology being excluded for future implementation for that vehicle. SAX technology can be applied during any refresh or redesign.

3.7.4.3 Secondary Axle Disconnect Technology Effectiveness Values

This analysis carries forward work on the effectiveness of SAX systems conducted in the Draft TAR and EPA Proposed Determination.[549] This work involved gathering information by monitoring press reports, holding meetings with suppliers and OEMs, and attending industry technical conferences. We do not simulate SAX effectiveness in the Autonomie modeling because, similar to LDB, IACC, and EFR, the fuel economy benefits from the technology are not fully captured on the two-cycle test. The SAX effectiveness values, for the most part, have been accepted as plausible based on the rulemaking record and absence of contrary comments. As such, we have prioritized its extensive Autonomie vehicle simulation work toward other technologies that are emerging or considered more critical for total system effectiveness. The resulting effectiveness estimates used in this analysis are shown below.

Table 3-134 – Fuel Consumption Improvement Values for Secondary Axle Disconnect

Tech Class	SAX
SmallCar	1.40%
SmallCarPerf	
MedCar	1.40%
MedCarPerf	
SmallSUV	1.40%
SmallSUVPerf	
MedSUV	1.30%
MedSUVPerf	
Pickup	1.60%
PickupHT	

[549] Draft TAR, at pp, 5–412; Proposed Determination TSD, at pp. 2–422.

3.7.4.4 Secondary Axle Disconnect Technology Costs

The cost estimates for SAX rely on previous work published as part of the rulemaking process, going back to the 2002 NAS report,[550] and carried through to the Draft TAR 208 NPRM, and 2020 final rule. The cost values were updated to 2018 dollars for this analysis. The learning rates for these technologies can be seen in Chapter 2.6.4.

Table 3-135 shows the absolute costs for SAX for select model years.

Table 3-135 – Absolute Costs for Secondary Axle Disconnect, including Learning Effects and Retail Price Equivalent (2018$)

Technology	2017	2021	2025	2029
SAX	$97.41	$86.69	$80.34	$75.98

3.8 Simulating Off-Cycle and AC Efficiency Technologies

Off-cycle and AC efficiency technologies can provide fuel economy benefits in real-world vehicle operation, but the traditional 2-cycle test procedures used to measure fuel economy cannot fully capture those benefits.[551] Off-cycle technologies include technologies like high efficiency alternators and high efficiency exterior lighting.[552] AC efficiency technologies are technologies that reduce the operation of or the loads on the compressor, which pressurizes AC refrigerant. The less the compressor operates or the more efficiently it operates, the less load the compressor places on the engine, resulting in better fuel efficiency.

Vehicle manufacturers have the option to generate credits for off-cycle technologies and improved AC systems under the EPA's CO_2 program and receive a fuel consumption improvement value (FCIV) equal to the value of the benefit not captured on the 2-cycle test under NHTSA's CAFE program. The FCIV is not a "credit" in the NHTSA CAFE program,[553] but the FCIVs increase the reported fuel economy of a manufacturer's fleet, which is used to determine compliance. EPA applies FCIVs during determination of a fleet's final average fuel economy reported to NHTSA.[554] We only calculate and apply FCIVs at a fleet level for a manufacturer, and the improvement is based on the volume of the manufacturer's fleet that contain qualifying technologies.[555]

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[550] National Research Council 2002. *Effectiveness and Impact of Corporate Average Fuel Economy (CAFE) Standards*. Washington, DC: The National Academies Press. https://doi.org/10.17226/10172. (Accessed: February 15, 2022).

[551] *See* 49 U.S.C 32904(c) ("The Administrator shall measure fuel economy for each model and calculate average fuel economy for a manufacturer under testing and calculation procedures prescribed by the Administrator. the Administrator shall use the same procedures for passenger automobiles the Administrator used for model year 1975 (weighted 55 percent urban cycle and 45 percent highway cycle), or procedures that give comparable results.").

[552] 40 CFR 86.1869-12(b) - Credit available for certain off-cycle technologies.

[553] Unlike, for example, the statutory overcompliance credits prescribed in 49 U.S.C. 32903.

[554] 49 U.S.C. 32904(c)-(e). EPCA granted EPA authority to establish fuel economy testing and calculation procedures. *See* preamble Section VII for more information.

[555] 40 CFR 600.510-12(c).

There are three pathways that manufacturers can use to determine the value of AC efficiency and off-cycle adjustments. First, manufacturers can use a predetermined list or "menu" of g/mi values that EPA established for specific off-cycle technologies.[556] Second, manufacturers can use 5-cycle testing to demonstrate off-cycle CO_2 benefit;[557] the additional tests allow emissions benefits to be demonstrated over some elements of real-world driving not captured by the 2-cycle compliance tests, including high speeds, rapid accelerations, hot temperatures, and cold temperatures. Third, manufacturers can seek EPA approval, through a notice and comment process, to use an alternative methodology other than the menu or 5-cycle methodology for determining the off-cycle technology improvement values.[558] For further discussion of the AC and off-cycle compliance and application process, see Section VII of the preamble.

We and EPA have been collecting data on the application of these technologies since implementing the AC and off-cycle programs.[559,560] Most manufacturers are applying AC efficiency and off-cycle technologies; in MY 2020, 17 manufacturers employed AC efficiency technologies and 20 manufacturers employed off-cycle technologies, though the level of deployment varies by manufacturer.[561]

Manufacturers have only recently begun including detailed information on off-cycle and AC efficiency technologies equipped on vehicles in compliance reporting data. For today's analysis, though, such information was not sufficiently complete to support a detailed representation of the application of off-cycle technology to specific vehicle model/configurations in the MY 2020 fleet. To account for the AC and off-cycle technologies equipped on vehicles and the potential that manufacturers will apply additional AC and off-cycle technologies in the rulemaking timeframe, we specify model inputs for AC efficiency and off-cycle fuel consumption improvement values in grams/mile for each manufacturer's fleet in each model year. We estimate future values based on an expectation that manufacturers already relying heavily on these adjustments would continue do so, and that other manufacturers would, over time, also approach the limits on adjustments allowed for such improvements.

The next sections discuss how the CAFE Model simulates the effectiveness and cost for AC efficiency and off-cycle technology adjustments.

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[556] *See* 40 CFR 86.1869-12(b). The TSD for the 2012 final rule for MYs 2017 and beyond provides technology examples and guidance with respect to the potential pathways to achieve the desired physical impact of a specific off-cycle technology from the menu and provides the foundation for the analysis justifying the credits provided by the menu. The expectation is that manufacturers will use the information in the TSD to design and implement off-cycle technologies that meet or exceed those expectations in order to achieve the real-world benefits of off-cycle technologies from the menu.

[557] *See* 40 CFR 86.1869-12(c). EPA proposed a correction for the 5-cycle pathway in a separate technical amendment rulemaking. *See* 83 Fed. Reg. 49344 (Oct. 1, 2019). EPA is not approving credits based on the 5-cycle pathway pending the finalization of the technical amendments rule.

[558] *See* 40 CFR 86.1869-12(d).

[559] *See* 77 Fed. Reg. 62832, 62839 (Oct. 15, 2012). EPA introduced AC and off-cycle technology credits for the CO_2 program in the MYs 2012-2016 rule and revised the program in the MY 2017-2025 rule and NHTSA adopted equivalent provisions for MYs 2017 and later in the MY 2017-2025 rule.

[560] Vehicle and Engine Certification. Compliance Information for Light-Duty Gas (GHG) Standards, https://www.epa.gov/ve-certification/compliance-information-light-duty-greenhouse-gas-ghg-standards. (Accessed: February 15, 2022).

[561] 2021 Automotive Trends Report., at pp. 90 and 92.

3.8.1 AC and Off-Cycle Effectiveness Modeling in the CAFE Model

In this analysis, the CAFE Model applies AC and off-cycle flexibilities to manufactures' CAFE regulatory fleet performance in a similar way to the regulation.[562] In the analysis and after the first MY, AC efficiency and off-cycle FCIVs apply to each manufacturer's regulatory fleet after the CAFE Model applies conventional technologies for a given standard. That is, conventional technologies are applied to each manufacturers' vehicles in each MY to assess the 2-cycle sales weighted harmonic average CAFE rating. Then, the CAFE Model assesses the CAFE rating to use for a manufacturer's compliance value after applying the AC efficiency and off-cycle FCIVs designated in the Market Data file. This assessment of adoption of conventional technology and the AC efficiency and off-cycle technology occurs on a year-by-year basis in the CAFE Model. The CAFE Model attempts to apply technologies and flexibilities in a way that both minimizes cost and allows the manufacturer to meet their standards without over or under complying.

To determine how manufacturers might adopt AC efficiency and off-cycle technologies in the rulemaking timeframe, we use data from EPA's 2021 Trends Report and CBI compliance material from manufacturers.[563,564] We use manufacturer's MY 2020 AC efficiency and off-cycle FCIVs as a starting point, and then extrapolate values in to each MY until MY 2026, for light trucks to the regulatory cap, for each manufacturer's fleets by regulatory class. For this analysis, we cap off-cycle values to 10 g/mi from MY2020 to MY2022 to align with EPA's program. Starting in MY2023, we allow manufacturers to reach the 15 g/mi cap.

To determine the rate at which to extrapolate the addition of AC and off-cycle technology adoption for each manufacturer, we use historical AC and off-cycle technology applications, each manufacturer's fleet composition (*i.e.*, breakdown between passenger cars (PCs) and light trucks (LTs)), availability of AC and off-cycle technologies that manufacturers could still use, and CBI compliance data. Different manufacturers show different levels of historical AC efficiency and off-cycle technology adoption; therefore, different manufacturers hit the regulatory caps for AC efficiency technology for both their PC and LT fleets, and different manufacturers hit caps for off-cycle technologies in the LT regulatory class. We did not extrapolate off-cycle technology adoption for PCs to the regulatory cap for a few reasons. First, past EPA Trends Reports show that many manufacturers did not adopt off-cycle technology to their passenger car fleets. Next, manufacturers limited PC offerings in MY 2020 as compared to historical trends. Last, CBI compliance data available to us indicate a lower adoption of menu item off-cycle technologies to PCs compared to LTs. We accordingly limit the application of off-cycle FCIVs to 10 g/mi for PCs but allowed LTs to apply 15 g/mi of off-cycle FCIVs starting in MY 2023. The inputs for AC efficiency technologies are set to 5 g/mi and 7.2 g/mi for PCs and LTs, respectively. We allow AC efficiency technologies to reach the regulatory caps by MY 2024, which is the first year of standards assessed in this analysis.

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562 49 CFR 531.6 and 49 CFR 533.6 Measurement and Calculation procedures.

563 Vehicle and Engine Certification. Compliance Information for Light-Duty Gas (GHG) Standards, https://www.epa.gov/ve-certification/compliance-information-light-duty-greenhouse-gas-ghg-standards. (Accessed: February 15, 2022).

564 49 U.S.C. 32907.

We apply FCIVs in this way because the AC and off-cycle technologies are generally more cost-effective than other technologies. The details of this assessment (and the calculation) are further discussed in the CAFE Model Documentation.[565]

Table 3-136 and Table 3-137 below shows the summary of adjustments for AC efficiency and off-cycle FCIVs used for this analysis.

Table 3-136 – AC Efficiency and Off-Cycle Adjustments Used for Passenger Car Regulatory Class (g/mi)

Manufacturer	Adjustment Type	Passenger Car MY						
		2020	2021	2022	2023	2024	2025	2026
BMW	AC Efficiency	4.9	5.0	5.0	5.0	5.0	5.0	5.0
	AC Leakage	13.6	13.8	13.8	13.8	13.8	13.8	13.8
	Off-Cycle Credits	7.6	7.6	8.3	9.0	10.0	10.0	10.0
Daimler	AC Efficiency	5.0	5.0	5.0	5.0	5.0	5.0	5.0
	AC Leakage	6.2	7.2	8.3	9.4	10.5	11.6	12.7
	Off-Cycle Credits	1.7	1.2	2.0	2.5	3.0	4.0	5.0
FCA	AC Efficiency	4.6	4.7	4.9	5.0	5.0	5.0	5.0
	AC Leakage	13.9	13.4	13.6	13.8	13.8	13.8	13.8
	Off-Cycle Credits	5.7	5.7	6.0	6.5	7.0	7.5	7.5
Ford	AC Efficiency	5.0	5.0	5.0	5.0	5.0	5.0	5.0
	AC Leakage	13.2	13.2	13.4	13.8	13.8	13.8	13.8
	Off-Cycle Credits	7.6	8.0	9.0	10.0	10.0	10.0	10.0
GM	AC Efficiency	4.0	4.3	4.8	5.0	5.0	5.0	5.0
	AC Leakage	12.1	12.7	13.0	13.8	13.8	13.8	13.8
	Off-Cycle Credits	7.2	7.9	8.5	9.0	9.5	10.0	10.0
Honda	AC Efficiency	3.8	3.8	4.0	4.5	5.0	5.0	5.0
	AC Leakage	13.1	13.5	13.8	13.8	13.8	13.8	13.8
	Off-Cycle Credits	4.8	5.7	6.0	6.5	7.0	10.0	10.0
Hyundai Kia-H	AC Efficiency	3.3	3.3	4.0	4.5	5.0	5.0	5.0
	AC Leakage	10.0	11.0	12.0	12.5	13.0	13.8	13.8
	Off-Cycle Credits	4.6	4.6	4.8	5.0	5.0	5.5	6.0

[565] CAFE Model Documentation, S5.

Manufacturer	Adjustment Type	Passenger Car MY						
		2020	2021	2022	2023	2024	2025	2026
Hyundai Kia-K	AC Efficiency	3.7	3.7	4.0	4.5	5.0	5.0	5.0
	AC Leakage	13.3	13.5	13.8	13.8	13.8	13.8	13.8
	Off-Cycle Credits	4.6	4.6	4.8	5.0	5.0	4.5	5.0
JLR	AC Efficiency	5.0	5.0	5.0	5.0	5.0	5.0	5.0
	AC Leakage	13.8	13.8	13.8	13.8	13.8	13.8	13.8
	Off-Cycle Credits	6.9	6.9	7.0	7.0	8.0	8.0	8.0
Mazda	AC Efficiency	1.2	2.0	3.0	4.0	5.0	5.0	5.0
	AC Leakage	1.8	3.8	5.0	7.0	9.0	11.0	12.0
	Off-Cycle Credits	2.9	3.0	4.0	4.5	5.0	5.5	6.0
Mitsubishi	AC Efficiency	4.4	4.4	4.7	5.0	5.0	5.0	5.0
	AC Leakage	13.8	13.8	13.8	13.8	13.8	13.8	13.8
	Off-Cycle Credits	2.5	2.5	2.5	2.5	2.7	3.0	3.2
Nissan	AC Efficiency	5.0	5.0	5.0	5.0	5.0	5.0	5.0
	AC Leakage	9.7	9.7	9.8	11.1	12.4	13.8	13.8
	Off-Cycle Credits	2.9	3.2	3.5	4.0	4.5	5.5	6.0
Subaru	AC Efficiency	4.0	4.2	4.6	5.0	5.0	5.0	5.0
	AC Leakage	7.6	8.4	9.0	11.0	13.0	13.8	13.8
	Off-Cycle Credits	2.6	3.3	3.6	4.1	4.4	5.6	6.2
Tesla	AC Efficiency	5.0	5.0	5.0	5.0	5.0	5.0	5.0
	AC Leakage	13.6	12.0	13.5	13.5	13.5	13.8	13.8
	Off-Cycle Credits	4.7	5.0	5.0	5.0	5.0	5.0	5.0
Toyota	AC Efficiency	4.4	5.0	5.0	5.0	5.0	5.0	5.0
	AC Leakage	9.6	10.3	12.0	13.8	13.8	13.8	13.8
	Off-Cycle Credits	5.1	5.6	6.0	7.0	8.5	9.0	10.0
Volvo	AC Efficiency	4.2	4.2	4.2	4.5	5.0	5.0	5.0
	AC Leakage	13.8	13.8	13.8	13.8	13.5	13.8	13.8
	Off-Cycle Credits	4.8	4.6	4.6	5.0	6.0	6.5	7.0

Manufacturer	Adjustment Type	Passenger Car MY						
		2020	2021	2022	2023	2024	2025	2026
VWA	AC Efficiency	3.9	3.9	4.5	5.0	5.0	5.0	5.0
	AC Leakage	13.6	13.6	13.8	13.8	13.8	13.8	13.8
	Off-Cycle Credits	5.8	5.8	6.0	6.5	7.0	7.5	8.0

Table 3-137 – AC Efficiency and Off-Cycle Adjustments Used for Light Truck Regulatory Class (g/mi)

Manufacturer	Adjustment Type	Light Truck MY						
		2020	2021	2022	2023	2024	2025	2026
BMW	AC Efficiency	7.2	7.2	7.2	7.2	7.2	7.2	7.2
	AC Leakage	17.0	17.2	17.2	17.2	17.2	17.2	17.2
	Off-Cycle Credits	10.0	10.0	10.0	13.5	14.0	15.0	15.0
Daimler	AC Efficiency	7.2	7.2	7.2	7.2	7.2	7.2	7.2
	AC Leakage	8.0	8.5	10.0	11.5	13.0	14.5	16.0
	Off-Cycle Credits	3.0	3.0	3.0	3.5	4.0	5.5	6.5
FCA	AC Efficiency	6.5	6.5	7.0	7.2	7.2	7.2	7.2
	AC Leakage	17.0	17.0	17.2	17.2	17.2	17.2	17.2
	Off-Cycle Credits	10.0	10.0	10.0	15.0	15.0	15.0	15.0
Ford	AC Efficiency	7.2	7.2	7.2	7.2	7.2	7.2	7.2
	AC Leakage	16.9	16.9	17.2	17.2	17.2	17.2	17.2
	Off-Cycle Credits	10.0	10.0	10.0	14.0	15.0	15.0	15.0
GM	AC Efficiency	6.7	7.0	7.1	7.2	7.2	7.2	7.2
	AC Leakage	16.7	16.8	17.2	17.2	17.2	17.2	17.2
	Off-Cycle Credits	10.0	10.0	10.0	13.0	14.0	15.0	15.0
Honda	AC Efficiency	6.2	6.5	7.2	7.2	7.2	7.2	7.2
	AC Leakage	16.9	17.2	17.2	17.2	17.2	17.2	17.2
	Off-Cycle Credits	10.0	10.0	10.0	14.0	15.0	15.0	15.0
Hyundai Kia-H	AC Efficiency	5.0	5.0	5.0	5.0	5.5	6.0	7.0
	AC Leakage	3.3	3.9	5.0	6.0	7.0	8.0	10.0
	Off-Cycle Credits	8.9	8.9	9.0	9.0	9.0	10.0	11.0
Hyundai Kia-K	AC Efficiency	4.3	5.4	6.0	6.5	7.0	7.2	7.2
	AC Leakage	15.2	16.0	17.0	17.2	17.2	17.2	17.2
	Off-Cycle Credits	8.8	8.8	9.0	9.9	9.0	9.0	10.0
JLR	AC Efficiency	7.2	7.2	7.2	7.2	7.2	7.2	7.2
	AC Leakage	17.2	17.2	17.2	17.2	17.2	17.2	17.2
	Off-Cycle Credits	10.0	10.0	10.0	12.0	13.0	14.0	15.0
Mazda	AC Efficiency	-	2.0	3.0	4.0	5.0	6.0	7.0
	AC Leakage	5.9	6.0	7.2	8.4	9.6	10.8	11.0
	Off-Cycle Credits	6.8	6.8	7.0	8.0	9.0	10.0	11.0
Mitsubishi	AC Efficiency	7.0	7.0	7.0	7.2	7.2	7.2	7.2

Manufacturer	Adjustment Type	Light Truck MY						
		2020	2021	2022	2023	2024	2025	2026
	AC Leakage	15.0	15.0	15.0	15.2	16.5	17.2	17.2
	Off-Cycle Credits	5.2	5.2	5.2	5.2	5.2	5.2	5.2
Nissan	AC Efficiency	4.9	5.8	6.5	7.2	7.2	7.2	7.2
	AC Leakage	6.0	6.1	7.1	9.1	11.1	13.1	15.1
	Off-Cycle Credits	6.1	7.1	8.0	8.5	9.0	10.0	11.0
Subaru	AC Efficiency	6.4	6.4	6.8	7.2	7.2	7.2	7.2
	AC Leakage	13.6	13.6	13.6	13.6	14.7	16.1	17.2
	Off-Cycle Credits	8.5	8.5	8.5	9.0	10.0	11.0	12.0
Tesla	AC Efficiency	5.0	5.0	5.0	7.2	7.2	7.2	7.2
	AC Leakage	13.7	14.0	15.0	16.0	17.0	17.2	17.2
	Off-Cycle Credits	4.8	5.0	6.0	7.0	8.0	9.0	9.0
Toyota	AC Efficiency	6.1	7.1	7.2	7.2	7.2	7.2	7.2
	AC Leakage	10.1	10.1	11.2	12.4	13.6	14.8	16.0
	Off-Cycle Credits	8.4	9.5	10.0	10.0	12.0	13.0	15.0
Volvo	AC Efficiency	6.1	6.4	7.0	7.2	7.2	7.2	7.2
	AC Leakage	17.2	17.2	17.2	17.2	17.2	17.2	17.2
	Off-Cycle Credits	8.3	9.0	9.3	10.0	11.0	12.0	13.0
VWA	AC Efficiency	6.2	6.2	6.6	7.2	7.2	7.2	7.2
	AC Leakage	17.6	16.0	16.5	17.2	17.2	17.2	17.2
	Off-Cycle Credits	10.0	10.0	10.0	13.5	14.0	14.5	15.0

3.8.2 AC Efficiency and Off-Cycle Costs

For this analysis, the model applies AC and off-cycle technologies independent of the decision trees using the extrapolated values shown above, so it is necessary to account for the costs of those technologies independently. Table 3-138 shows the costs used for AC and off-cycle FCIVs in this analysis. The costs are shown in dollars per gram of CO_2 per mile ($ per g/mi). The AC efficiency and off-cycle technology costs are the same costs used in the EPA Proposed Determination and described in the EPA Proposed Determination TSD.[566]

To develop these costs, we use the 2nd generic 3 gram/mile package estimated to cost $170 (in 2015$) to apply in this analysis in $ per gram/mile. We update the costs used in the Proposed Determination TSD from 2015$ to 2018$, adjust the costs for RPE, and apply a relatively flat learning rate.

Similar to off-cycle technology costs, we use the cost estimates from EPA Proposed Determination TSD for AC efficiency technologies.[567] We update these costs to 2018$ and adjust for RPE, and apply the same mature learning rate as off-cycle technologies.

[566] EPA PD TSD. EPA-420-R-16-021. November 2016. At 2-423 – 2-245. https://nepis.epa.gov/Exe/ZyPDF.cgi?Dockey=P100Q3L4.pdf. (Accessed: February 15, 2022).
[567] Joint NHTSA and EPA 2012 TSD, Chapter 5.1. These costs were first used in the 2012 rulemaking TSD.

For the purpose of cost accounting, when manufacturers adopt these off-cycle and AC efficiency technologies in given year, the added costs are not the direct product of the FCIV value multiplied by the cost. Instead, the CAFE Model only adds the cost of the difference between the MY 2020 baseline FCIVs and the analysis year that runs from MY 2021 to MY 2050.

Table 3-138 – AC and Off-Cycle FCIV Costs for this Analysis in Dollars per Gram of CO_2 per Mile (2018$)

Reg Class	Cost Type	2020	2021	2022	2023	2024	2025	2026
Passenger Car	AC Efficiency Costs	4.30	4.22	4.13	4.05	3.97	3.89	3.81
	AC Leakage Costs	10.76	10.54	10.33	10.12	9.92	9.72	9.53
	Off-Cycle Costs	83.79	82.21	81.16	79.58	78.52	77.47	76.31
Light Truck	AC Efficiency Costs	4.30	4.22	4.13	4.05	3.97	3.89	3.81
	AC Leakage Costs	10.76	10.54	10.33	10.12	9.92	9.72	9.53
	Off-Cycle Costs	83.79	82.21	81.16	79.58	78.52	77.47	76.31

4 Consumer Response to Manufacturer Compliance Strategies

4.1 Macroeconomic Assumptions that Affect and Describe Consumer Behavior

The comprehensive economic analysis of CAFE standards included in this rule requires a detailed and explicit explanation of the macroeconomic context in which regulatory alternatives are evaluated. NHTSA continues to rely on projections of future fuel prices to evaluate manufacturers' use of fuel-saving technologies, the resulting changes in fuel consumption, and various other benefits. Furthermore, the analysis includes modules projecting future aggregate travel demand (for light-duty vehicles), sales of new cars and light trucks, and the retirement of used vehicles under each regulatory alternative. Constructing these forecasts requires explicit projections of macroeconomic variables, including real U.S. GDP, consumer confidence, U.S. population, and real disposable personal income.

4.1.1 Gross Domestic Product and Other Macroeconomic Assumptions

The analysis employs forecasts of future fuel prices developed by NHTSA using the U.S. Energy Information Administration's (EIA's) National Energy Model System (NEMS). An agency within the U.S. Department of Energy (DOE), EIA collects, analyzes, and disseminates independent and impartial energy information to promote sound policymaking, efficient markets, and public understanding of energy and its interaction with the economy and the environment. EIA uses NEMS to produce its AEO, which presents forecasts of future fuel prices, among many other energy-related variables. AEO projections of energy prices and other variables are not intended as predictions of what will happen; rather, they are projections of the likely course of these variables that reflect their past relationships, specific assumptions about future developments in global energy markets, and the forecasting methodologies incorporated in NEMS. Each AEO includes a "Reference Case" as well as a range of alternative scenarios that each incorporate somewhat different assumptions from those underlying the Reference Case.

In addition to forecasts of future fuel prices, NHTSA's CAFE Model relies on forecasts of U.S. population, GDP, and disposable personal income to project both new vehicle sales in future model years and retirement rates for used vehicles. The CAFE Model also uses projections of consumer sentiment, as measured by the University of Michigan Index of Consumer Sentiment (http://www.sca.isr.umich.edu/) to forecast both new vehicle sales and aggregate demand for light-duty VMT. Forecasts of future values of all of these variables are developed by IHS Global Insight and published in March and October of each year.

In the course of updating its VMT forecasts to reflect the evolving pandemic and forecast recovery, the agency determined that macroeconomic projections from the more recent IHS Global Insight October 2021 Macroeconomic Outlook are likely to better reflect the most recent expectations for near-term performance of the U.S. economy than those from IHS' March 2021 Outlook, which the analysis presented in the proposed rule relied upon. Accordingly, we have updated the projections of U.S. population, GDP, consumer sentiment, and personal disposable income used in the CAFE Model to align with the more recent October 2021 forecast.

The U.S. Energy Information Administration also relies on the IHS Global Insight forecasts of these and other macroeconomic variables to develop the energy demand forecasts in NEMS, so the fuel price forecasts NHTSA obtains from EIA are also consistent with the IHS Global Insight economic forecasts (with the minor difference that the fuel price forecasts reported in AEO 2021 reflect the earlier March 2021 IHS Global Insight macroeconomic outlook). Table 4-1 presents the projections to 2050 for each of these macroeconomic inputs used for this rulemaking's central analysis.

Table 4-1 – Macroeconomic Assumptions

Year	GDP (Billion $2018)	Consumer Sentiment	U.S. Population (Millions)	Real Disposable Personal Income (Billion $2012)
2019	20,998	96.0	330.4	14,756
2020	20,283	81.5	331.5	15,676
2021	21,510	83.7	332.0	16,009
2022	22,448	88.7	333.1	15,606
2023	22,950	94.4	334.7	15,998
2024	23,496	96.0	336.4	16,447
2025	24,033	96.5	338.1	16,926
2026	24,586	97.2	340.0	17,426
2027	25,154	96.0	341.8	17,941
2028	25,721	94.4	343.6	18,464
2029	26,297	93.1	345.5	18,980
2030	26,879	93.0	347.3	19,482
2031	27,433	93.9	349.1	19,963
2032	28,009	94.2	350.9	20,447
2033	28,598	94.3	352.6	20,935
2034	29,180	94.2	354.3	21,421
2035	29,775	94.2	355.9	21,915
2036	30,360	94.5	357.5	22,418
2037	30,960	94.5	359.0	22,922
2038	31,571	94.7	360.5	23,426
2039	32,192	94.9	361.9	23,942
2040	32,834	95.0	363.3	24,478
2041	33,458	94.9	364.6	25,001
2042	34,098	94.8	366.0	25,542
2043	34,744	94.7	367.3	26,086
2044	35,403	94.8	368.5	26,636
2045	36,088	95.0	369.8	27,204
2046	36,786	95.1	371.0	27,782
2047	37,484	95.2	372.2	28,366
2048	38,197	95.2	373.4	28,960
2049	38,925	95.2	374.6	29,561
2050	39,671	95.0	375.8	30,179

As can be seen from an inspection of the forecasts in Table 4-1, 2020 was an unusual year. The table shows significant decreases in both real GDP and consumer confidence between 2019 and 2020, but an *increase* in real disposable personal income (RDPI). While the former reflects the reduction in employment and economic output during the early stages of the COVID-19 pandemic and the response of consumer sentiment to those developments, the increase in disposable income is a consequence of large-scale economic assistance from the U.S. government to households in an effort to aid them in coping with the consequences of the pandemic. Both real GDP and consumer confidence begin to climb again in 2021 and are projected to increase further during 2022 and grow steadily thereafter. In contrast, disposable income is anticipated to grow again in 2021 before declining to approximately its 2020 level during 2022—in response to the cessation of programs designed to boost household spending and support unemployed workers during the pandemic—and then to increase slowly starting in 2023.

Thus, the economic context of 2022 reflects a nation where GDP and consumer confidence are struggling to return to their 2019 levels, while disposable income is falling relative to the previous year. The first year simulated in this analysis is 2020, though the agency relies on observational data (rather than forecasts) for 2020 to the greatest extent possible. The elements of the analysis that rely most heavily on the macroeconomic inputs – aggregate demand for VMT, new vehicle sales, and used vehicle retirement rates – all reflect the economy's relatively rapid return to pre-pandemic growth rates.

4.1.2 Fuel Prices

Fuel prices influence a number of critical elements of the analysis. In particular, fuel prices determine the degree to which consumers demand additional fuel economy in the absence of regulatory pressure, influence the relative attractiveness of competing technologies available to manufacturers to improve fuel economy (which considers the value of fuel savings to buyers of new cars and trucks), the amount of travel in light-duty vehicles, and the value of each gallon saved from higher CAFE standards. In this analysis, NHTSA relies on the Reference Case fuel price forecast in AEO 2021, for all fuel types except hydrogen.[568] While fuel prices are one of the most critical inputs to the analysis, they are also one of the least certain – particularly over the extended lifetimes of the vehicles affected by this rulemaking.

NHTSA has actively engaged in CAFE rulemakings over the last decade, and in each of these actions, the forecasted fuel prices have borne little resemblance to observed fuel prices during the ensuing years. As Figure 4-1 illustrates, fuel price forecasts have generally declined in each successive rulemaking analysis but have still consistently overestimated the trajectory of real prices over the observed period. This is not a prediction that the current forecast will overestimate prices; instead, it is merely an indication that the results of CAFE analyses are vulnerable to uncertainty where future fuel prices are concerned.

EIA regularly produces a retrospective analysis that evaluates the performance of fuel price projections over time, measuring the degree of both under and over prediction and absolute prediction error.[569] The Congressional Budget Office recently compared the performance of

[568] NHTSA staff projected future prices for hydrogen based on discussions with hydrogen suppliers; the agency's current modeling shows fuel cell vehicles accounting for a negligible share of the on-road fleet through 2050, so this input does not critically affect the analysis.
[569] The most recent EIA retrospective analysis is available at https://www.eia.gov/outlooks/aeo/retrospective/pdf/retrospective.pdf. (Accessed: February 15, 2022).

various oil price forecasts and found, unsurprisingly, that most forecasts performed better over shorter periods of time.[570] In addition, NHTSA determined that assuming a fixed real price performed as well as EIA's reference case projections. However, this analysis requires fuel price projections that cover several decades, and EIA is generally recognized as an authoritative source for regulatory analysis. While we continue to use EIA's projections in this analysis, we recognize that future fuel prices may differ from those assumed here and address this possibility through sensitivity analysis.

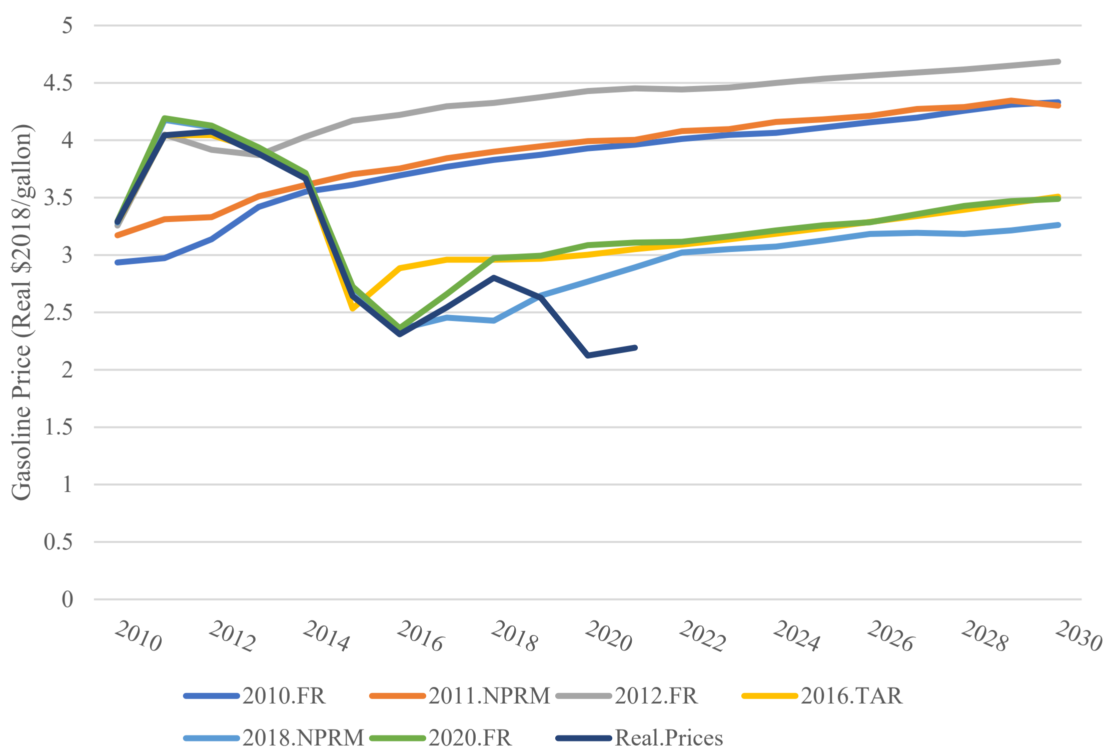

Figure 4-1 – Real Gasoline Price Forecasts in CAFE Rulemakings and Observed Prices

Figure 4-2 displays the High, Low, and Reference fuel price projections from AEO 2021 alongside historical, real gasoline prices dating back to the inception of the CAFE program. The supporting analysis uses the AEO 2021 Reference Case fuel price projections (for all fuel types except hydrogen), but we consider the AEO Low and High Oil price cases as bounding cases for sensitivity analyses. The purpose of the sensitivity analyses, discussed in greater detail in FRIA Chapter 7, is not to posit a more credible future state of the world than the central case assumes – we assume the central case is the most likely future state of the world – but rather to measure the degree to which important outcomes change under different assumptions about fuel prices.

570 Gecan, Ron, "CBO's Oil Price Forecasting Record," May 2020, Working Paper 2020-03, www.cbo.gov/publication/56356. (Accessed: March 26, 2022).

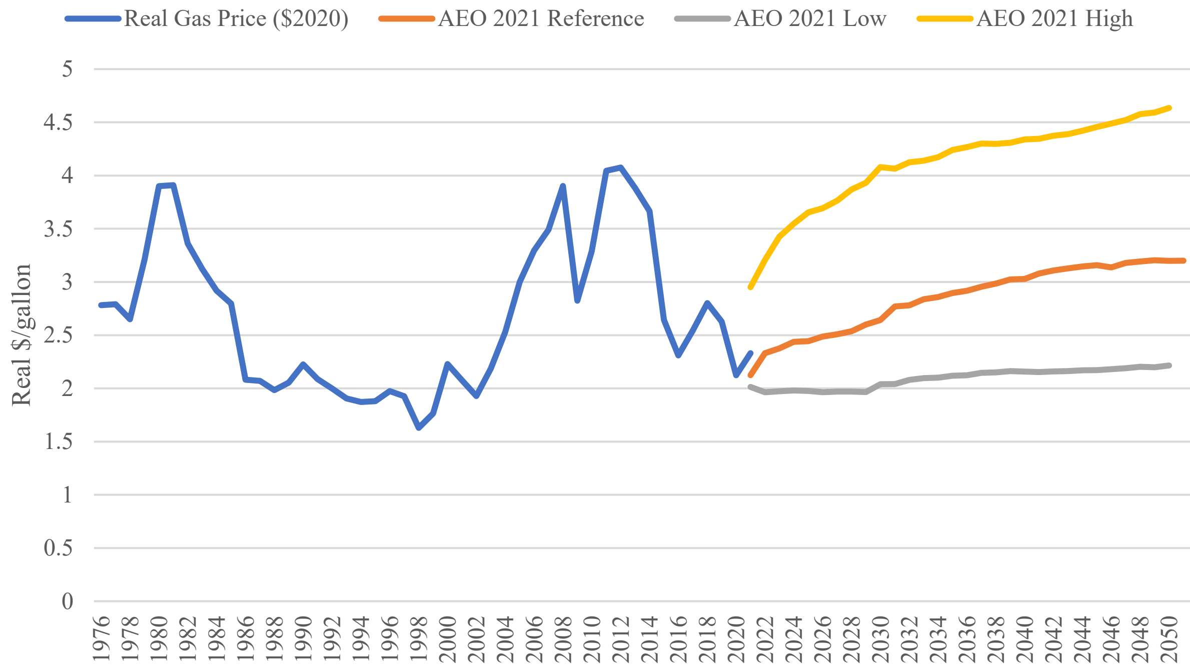

Figure 4-2 – Real Fuel Price Assumptions in Historical Context

4.2 Fleet Composition

The on-road fleet is a critical element of the analysis. It is dynamically simulated within the CAFE Model, and responds to regulatory alternatives, fuel prices, and macroeconomic conditions that determine its size, composition, and usage.

Until recently, all CAFE rulemaking analyses used static fleet forecasts that were based on a combination of manufacturer compliance data, public data sources, and proprietary forecasts (or product plans submitted by manufacturers). When simulating compliance with regulatory alternatives, those analyses assumed identical sales projections across the alternatives, for each manufacturer down to the make/model level—where the exact same number of each model variant was assumed to be sold in a given model year under both the least stringent alternative (typically the baseline) and the most stringent alternative considered (intended to represent "maximum technology application" scenarios in some cases), and that the rate of vehicle retirements, otherwise referred to as scrappage, would continue unabated.

To the extent that an alternative matched the assumptions made in the production of the proprietary forecast, using a static fleet based upon those assumptions may have been warranted. However, a fleet forecast is unlikely to be representative of a broad set of regulatory alternatives that produces significant variation in the cost and fuel economy of new vehicles. A number of commenters on previous regulatory actions encouraged consideration of the potential impact of fuel efficiency standards on new vehicle prices and sales, changes to compliance strategies that those shifts could necessitate, and the downstream impacts on vehicle retirement. In particular, the continued growth of the utility vehicle segment creates compliance challenges within some manufacturers' fleets: sometimes this growth shows up as higher sales of smaller- or larger-footprint vehicles, and sometimes it shows up as vehicles shifting from the passenger car to the light truck fleet but at the same footprint. These shifts, to the extent manufacturers have not anticipated them, create compliance uncertainties.

With higher fuel prices, moreover, the new vehicle market trends toward cars (and away from trucks), which has implications for aggregate VMT and the longevity of specific body-styles and model-year cohorts within the registered vehicle population. Logically, however, the stringency of fuel economy standards (and other regulations, such as CO_2 standards and ZEV mandates) could affect new sales and, consequentially, the retirement of older vehicles. In the peer review of the 2018 release of the CAFE Model, all reviewers encouraged the inclusion of a sales response to fuel economy regulations (albeit not necessarily the version of the response model that appeared in the CAFE Model at that time).

The following sections discuss how new vehicle sales – the annual addition of new vehicles to the fleet of registered population – of cars and light trucks are likely to evolve under the No-Action Alternative, and differ in response to the specific regulatory alternative that is adopted. They also discuss the influence of increasing durability of new cars and light trucks and of changing economic conditions on the rate at which used vehicles of different vintages and ages are retired from service under the No-Action Alternative, as well as the potential influence of the individual regulatory alternatives the agency considers on retirement rates and the population and use of older vehicles. Finally, the following sections address usage of the nation's fleet of new and used vehicles to satisfy households' and businesses' travel demands, and how the contributions of cars and light trucks of different ages and vintages are likely to differ among the baseline and regulatory alternatives.

The CAFE Model currently models sales and scrappage independently. As discussed in more detail in preamble Section III.E.2, some commenters have suggested that we need to account for interactions between the new and used vehicle markets. While we agree with the benefits that jointly modeling sales and scrappage would have, we are not implementing such an approach for the final rule because a functional model for our purposes is still hypothetical. While noting the benefits of modeling these two effects jointly, we believe our approach captures the independent sources of the change in fleet composition that is attributable to CAFE standards and allows policymakers to make informed opinions about CAFE stringency levels.

4.2.1 Changes in New Vehicle Sales

The CAFE Model currently operates as if all costs incurred by the manufacturer as a consequence of meeting regulatory requirements, whether those are the cost of additional technology applied to vehicles in order to improve fleetwide fuel economy or civil penalties paid when fleets fail to achieve their standard, are "passed through" to buyers of new vehicles in the form of price increases. The question of cost pass-through is one that academic and industry researchers have considered for decades—and two of the agencies' most recent peer reviewers addressed this issue in their comments. One of those recent peer reviewers argued that the assumption of complete cost pass through is defensible, and more likely in the short run than the long run.[571] Another reviewer suggested that costs would pass through to new vehicle buyers to

[571] CAFE Model Peer Review, DOT HS 812 590, Revised (July 2019), pp. B31-B33, available at http://downloads.regulations.gov/NHTSA-2018-0067-0055/attachment_2.pdf. (Accessed: March 3, 2022).

different degrees, depending upon the stringency of the standards.[572] It is possible that more stringent standards, which result in larger increases to the cost of production, would elicit greater efforts by manufacturers to pass those cost increases through to buyers in order to protect their profitability than would less stringent standards. In contrast, as some commenters have suggested in the past, manufacturers may be more able to absorb the smaller cost increases required to comply with less stringent standards in the form of lost profit. If the degree of cost pass-through varies with the stringency of the alternative in this way, the current version of the CAFE Model will systematically overestimate the increases in price under more stringent alternatives, —which would also lead it to overestimate the magnitude of sales changes for alternatives that require more stringent CAFE standards. This would have corresponding effects on the estimates of both costs and benefits.

Over the course of the last several rulemakings, some commenters have argued that manufacturers are able to compensate fully for the costs of fuel economy standards by increasing the prices of luxury vehicles—which would increase the average new vehicle price but leave large sections of the market unaffected by the increased cost of producing fleets that comply with the standards. While it seems likely that manufacturers employ pricing strategies that push regulatory costs (as well as increases in costs like pension obligations and health care costs for employees) into the prices of models and segments with less elastic demand, the extent to which any OEM can succeed at this is unknown by NHTSA. At some point, however, price increases on even luxury models will merely price more and more purchasers out of the new vehicle market (or shift them to down market models) and make competition with other manufacturers and market segments that much more difficult. The more that lower ends of the vehicle market are subsidized by luxury vehicles, the more either prices for luxury models would need to be increased, or (if moderately increasing prices) more of those luxury models would need to be sold to maintain historical profit levels. It is worth noting that luxury vehicles have tended to be more powerful and content-rich, and often have fuel economy levels below their targets on the curves (though the extent to which luxury vehicles adopt hybrid or electric technologies may shift this effect)—so that selling more of them to compensate for lost profit elsewhere further erodes the compliance levels of the fleets in which they reside.

While manufacturers could conceivably push some small cost increases into the prices of their vehicle segments that have less elastic demand to cover accordingly small increases in stringency, larger stringency increases would likely exhaust the ability of such segments to absorb additional costs. In addition, the analysis does not attempt to adjust the mix of vehicle models or footprints based on their own price elasticity of demand; doing so would require a pricing model that takes the compliance cost for each manufacturer (estimated in the CAFE Model) and apportions that cost to the prices of individual nameplates and trim levels. NHTSA has experimented with pricing models (when integrating vehicle choice models, pricing models are a necessity), but each manufacturer almost certainly has a unique pricing strategy that is unknown to NHTSA and involves both strategic decisions about competitive position within a segment and the volumes needed to fully amortize fixed costs associated with production. To the extent that we assume all regulatory costs are passed through and affect the average regulatory cost of each vehicle (which we believe is a more conservative approach) instead of being priced

[572] CAFE Model Peer Review, DOT HS 812 590, Revised (July 2019), pp. B54-B56, available at http://downloads.regulations.gov/NHTSA-2018-0067-0055/attachment_2.pdf. (Accessed: March 3, 2022).

in a fashion to minimize the impact on aggregate sales (which we are concerned would be speculative without more information about manufacturers' private business models), we note that more stringent alternatives are provided an artificial analytical advantage because manufacturers are better positioned to incorporate smaller price adjustments into their current strategic pricing models.

Finally, some commenters have argued that, even if regulations do increase the cost of producing vehicles and those costs are passed on to new vehicle buyers, it does not matter because sales have increased subsequent to the Great Recession – in a period characterized by both rising prices and rising standards. However, that argument assumes correlation means causation and ignores the counterfactual case. NHTSA contends that sales increased over that period, in large part, as a result of economic expansion following the great recession.[573] The counterfactual case that is relevant for regulatory analysis would attempt to answer the question, "would sales have been even higher if average prices had been lower?" The extent to which higher prices as a result of greater CAFE stringency suppresses sales that otherwise would have occurred is not settled in the literature, as described below. While higher prices in general would lead to fewer sales in theory, purchasers of new vehicles receive the benefit of greater fuel savings and lower total cost of ownership. For the purposes of today's analysis of sales effects, we conservatively assume that purchasers value only the first 30 months of fuel savings. For purposes of calculating benefits of standards, we assume that lifetime fuel savings are fully valued by society.

In order to isolate the impact of the standards, the CAFE Model breaks the sales response module into three discrete components. The first captures the effects of broader economic forces such as GDP growth. The second measures how changes in vehicle prices (and fuel economies) influence sales across regulatory alternatives. By modeling sales in the first step as a function of macroeconomic conditions, and then applying an independent own-price elasticity to estimate the change in sales across alternatives, the model is able to more clearly distinguish between absolute sales (in any given year) and incremental sales changes between alternatives. The third step determines how the change of vehicle sales influences the proportional market share of light trucks and passenger cars.

4.2.1.1 How do Fuel Economy Standards Impact Vehicle Sales?

How potential buyers value improvements in the fuel economy of new cars and light trucks is an important issue in assessing the benefits and costs of government regulation. If buyers fully value the savings in fuel costs that result from higher fuel economy, in a perfect market, manufacturers will presumably supply any improvements that buyers demand, and vehicle prices will fully reflect future fuel cost savings consumers would realize from owning—and potentially re-selling—more fuel-efficient models. Traditional economic theory implies that if consumers internalize fuel savings, more stringent fuel economy standards will impose net costs on vehicle owners and can only result in social benefits through correcting externalities, because consumers would already fully incorporate private savings into their purchase decisions, as discussed further below. If instead, consumers systematically undervalue future fuel savings because some market failure, such as an information asymmetry, or other differences between actual consumer

[573] Table 4-3 shows a large and statistically significant effect of GDP on sales.

decision making and theoretically rational decision-making leads to an underinvestment in fuel-saving technology, more stringent fuel economy standards will also lead manufacturers to adopt improvements in fuel economy that buyers might not choose despite the cost savings they offer and improve consumer welfare.

The potential for car buyers voluntarily to forego improvements in fuel economy that offer savings exceeding their initial costs is one example of what is often termed the "energy-efficiency gap." This appearance of such a gap, between the level of energy efficiency that would minimize consumers' overall expenses and what they actually purchase, is frequently based on engineering calculations that compare the initial cost for providing higher energy efficiency to the discounted present value of the resulting savings in future energy costs. However, the econometric literature is divided between support for full internalization of energy savings and substantial undervaluing, and manufacturers have consistently told NHTSA as well as National Academies committees that their customers severely undervalue expected fuel savings.

There has long been an active debate about why such a gap might arise and whether it actually exists. Economic theory predicts that, in a perfect market, individuals will purchase more energy-efficient products only if the savings in future energy costs they offer promise to offset their higher initial costs. However, the additional up-front cost of a more energy-efficient product includes more than just the cost of the technology necessary to improve its efficiency; because consumers have a scarcity of resources, it also includes the opportunity cost of any other desirable features that consumers give up when they choose the more efficient alternative. In the context of vehicles, whether the expected fuel savings outweigh any opportunity cost of purchasing a model offering higher fuel economy will depend, among other things, on how much its buyer expects to drive; his or her expectations about future fuel prices; financing options available (as studies suggest that consumers consider increases in monthly payments rather than total car price – which will be quite small for added fuel economy technology, and offset by lower fuel costs;) the discount rate he or she uses to value future expenses; the expected effect on resale value; and whether more efficient models offer equivalent attributes such as performance, carrying capacity, reliability, quality, or other characteristics. Importantly, consumer information through window stickers, education by dealers or other sources of information may cause a consumer to place greater value on the benefit of fuel savings at the time of purchase. Likewise, advertising, financing options and incentives will also impact vehicle choice and a consumer's willingness to purchase.

Published literature has offered little consensus about consumers' willingness-to-pay for greater fuel economy, and whether it implies over-, under- or full-valuation of the expected discounted fuel savings from purchasing a model with higher fuel economy. Most studies have relied on car buyers' purchasing behavior to estimate their willingness-to-pay for future fuel savings; a typical approach has been to use "discrete choice" models that relate individual buyers' choices among competing vehicles to their purchase prices, fuel economy, and other attributes (such as performance, carrying capacity, and reliability), and to infer buyers' valuation of higher fuel economy from the relative importance of purchase prices and fuel economy.[574] Empirical estimates using this approach span a wide range, extending from substantial undervaluation of fuel savings to significant overvaluation, thus making it difficult to draw solid conclusions about the influence of fuel economy on vehicle buyers' choices.[575] Because a vehicle's price is often correlated with its other attributes (both measured and unobserved), analysts have often used instrumental variables or other approaches to address endogeneity and other resulting concerns.[576]

Despite these efforts, more recent research has criticized these cross-sectional studies; some have questioned the effectiveness of the instruments they use,[577] while others have observed that coefficients estimated using non-linear statistical methods can be sensitive to the optimization algorithm and starting values.[578] Collinearity (i.e., high correlations) among vehicle attributes—most notably among fuel economy, performance or power, and vehicle size—and between vehicles' measured and unobserved features also raises questions about the reliability and interpretation of coefficients that may conflate the value of fuel economy with other attributes (Sallee, et al., 2016; Busse, et al., 2013; Allcott & Wozny, 2014; Allcott & Greenstone, 2012; Helfand & Wolverton, 2011).

In an effort to overcome shortcomings of past analyses, three studies published fairly recently rely on panel data from sales of individual vehicle models to improve their reliability in identifying the association between vehicles' prices and their fuel economy (Sallee, et al. 2016; Allcott & Wozny, 2014; Busse, et al., 2013). Although they differ in certain details, each of these analyses relates changes over time in individual models' selling prices to fluctuations in fuel prices, differences in their fuel economy, and increases in their age and accumulated use, which affects their expected remaining life, and thus their market value. Because a vehicle's future fuel costs are a function of both its fuel economy and expected gasoline prices, changes in fuel prices have different effects on the market values of vehicles with different fuel economy; comparing these effects over time and among vehicle models reveals the fraction of changes in fuel costs that is reflected in changes in their selling prices (Allcott & Wozny, 2014). Using very large samples of sales enables these studies to define vehicle models at an extremely disaggregated level, which enables their authors to isolate differences in their fuel economy from the many other attributes, including those that are difficult to observe or measure, that affect their sale prices.[579]

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[574] In a typical vehicle choice model, the ratio of estimated coefficients on fuel economy — or more commonly, fuel cost per mile driven — and purchase price is used to infer the dollar value buyers attach to slightly higher fuel economy.

[575] *See* Greene et al. (2018), Helfand & Wolverton (2011) and Greene (2010) for detailed reviews of these cross-sectional studies.

[576] *See, e.g.,* Barry, et al. (1995).

[577] *See* Allcott & Greenstone (2012).

[578] *See* Knittel & Metaxoglou (2014).

[579] These studies rely on individual vehicle transaction data from dealer sales and wholesale auctions, which includes actual sale prices and allows their authors to define vehicle models at a highly disaggregated level. For instance, Allcott & Wozny (2014) differentiate vehicles by manufacturer, model or nameplate, trim level, body type,

These studies point to a somewhat narrower range of estimates than suggested by previous cross-sectional studies; more importantly, they consistently suggest that buyers value a large proportion—and perhaps even all—of the future savings that models with higher fuel economy offer.[580] Because they rely on estimates of fuel costs over vehicles' expected remaining lifetimes, these studies' estimates of how buyers value fuel economy are sensitive to the strategies they use to isolate differences among individual models' fuel economy, as well as to their assumptions about buyers' discount rates and gasoline price expectations, among others. Since Anderson et al. (2013) found evidence that consumers expect future gasoline prices to resemble current prices, the agency uses this assumption to compare the findings of the three studies and examine how their findings vary with the discount rates buyers apply to future fuel savings.[581]

As Table 4-2 indicates, Allcott & Wozny (2014) found that consumers incorporate 55 percent of future fuel costs into vehicle purchase decisions at a six percent discount rate, when their expectations for future gasoline prices are assumed to reflect prevailing prices at the time of their purchases. With the same expectation about future fuel prices, the authors report that consumers would fully value fuel costs only if they apply discount rates of 24 percent or higher. However, these authors' estimates are closer to full valuation when using gasoline price forecasts that mirror oil futures markets, because the petroleum market expected prices to fall during this period (this outlook reduces the discounted value of a vehicle's expected remaining lifetime fuel costs). With this expectation, Allcott & Wozny (2014) find that buyers value 76 percent of future cost savings (discounted at six percent) from choosing a model that offers higher fuel economy, and that a discount rate of 15 percent would imply that they fully value future cost savings. Sallee et al. (2016) begin with the perspective that buyers fully internalize future fuel costs into vehicles' purchase prices and cannot reliably reject that hypothesis; their base specification suggests that changes in vehicle prices incorporate slightly more than 100 percent

fuel economy, engine displacement, number of cylinders, and "generation" (a group of successive model years during which a model's design remains largely unchanged). All three studies include transactions only through mid-2008 to limit the effect of the recession on vehicle prices. To ensure that the vehicle choice set consists of true substitutes, Allcott & Wozny (2014) define the choice set as all gasoline-fueled light-duty cars, trucks, SUVs, and minivans that are less than 25 years old (i.e., they exclude vehicles where the substitution elasticity is expected to be small). Sallee et al. (2016) exclude diesels, hybrids, and used vehicles with less than 10,000 or more than 100,000 miles.

[580] Killian & Sims (2006) and Sawhill (2008) rely on similar longitudinal approaches to examine consumer valuation of fuel economy except that they use average values or list prices instead of actual transaction prices. Since these studies remain unpublished, their empirical results are subject to change, and they are excluded from this discussion.

[581] Each of the studies makes slightly different assumptions about appropriate discount rates. Sallee et al. (2016) use five percent in their base specification, while Allcott & Wozny (2014) rely on six percent. As some authors note, a five to six percent discount rate is consistent with current interest rates on car loans, but they also acknowledge that borrowing rates could be higher in some cases, which could be used to justify higher discount rates. Rather than assuming a specific discount rate, Busse et al. (2013) directly estimate implicit discount rates at which future fuel costs would be fully internalized; they find discount rates of six to 21 percent for used cars and one to 13 percent for new cars at assumed demand elasticities ranging from -2 to -3. Their estimates can be translated into the percent of fuel costs internalized by consumers, assuming a particular discount rate. To make these results more directly comparable to the other two studies, we assume a range of discount rates and uses the authors' spreadsheet tool to translate their results into the percent of fuel costs internalized into the purchase price at each rate. Because Busse et al. (2013) estimate the effects of future fuel costs on vehicle prices separately by fuel economy quartile, these results depend on which quartiles of the fuel economy distribution are compared; our summary shows results using the full range of quartile comparisons.

of changes in future fuel costs. For discount rates of five to six percent, the Busse et al. (2013) results imply that vehicle prices reflect 60 to 100 percent of future fuel costs. As Table 4-2 suggests, higher private discount rates move all of the estimates closer to full valuation or to over-valuation, while lower discount rates imply less complete valuation in all three studies.

Table 4-2 – Percent of Future Fuels Costs Internalized in Used Vehicle Purchase Price using Current Gasoline Prices to Reflect Expectations (for Base Case Assumptions)

Authors (Pub. Date)	Discount rate			
	3%	5%	6%	10%
Busse, et al. (2013)*	54%-87%	60%-96%	62%-100%	73%-117%
Allcott & Wozny (2014)	48%		55%	65%
Sallee, et al. (2016)		101%		142%

*Note: The ranges in the estimates from Busse et al. (2013) depend on which quartiles of the fuel economy distribution are compared. With no prior on which quartile comparison to use, this table presents the full quartile comparison range.

The studies also explore the sensitivity of the results to other parameters that could influence their results. Busse et al. (2013) and Allcott & Wozny (2014) find that relying on data that suggest lower annual vehicle use or survival probabilities, which imply that vehicles will not last as long, moves their estimates closer to full valuation, an unsurprising result because both reduce the changes in expected future fuel costs caused by fuel price fluctuations. Allcott & Wozny's (2014) base results rely on an instrumental variables estimator that groups miles-per-gallon (MPG) into two quantiles to mitigate potential attenuation bias due to measurement error in fuel economy, but they find that greater disaggregation of the MPG groups implies greater undervaluation (for example, it reduces the 55 percent estimated reported in Table 4-2 to 49 percent). Busse et al. (2013) allow gasoline prices to vary across local markets in their main specification; using national average gasoline prices, an approach more directly comparable to the other studies, results in estimates that are closer to or above full valuation. Sallee et al. (2016) find modest undervaluation by vehicle fleet operators or manufacturers making large-scale purchases, compared to retail dealer sales (i.e., 70 to 86 percent).

Since they rely predominantly on changes in vehicles' prices between repeat sales, most of the valuation estimates reported in these studies apply most directly to buyers of used vehicles. Only Busse et al. (2013) examine new vehicle sales; they find that consumers value between 75 to 133 percent of future fuel costs for new vehicles, a higher range than they estimate for used vehicles. Allcott & Wozny (2014) examine how their estimates vary by vehicle age and find that fluctuations in purchase prices of younger vehicles imply that buyers whose fuel price expectations mirror the petroleum futures market value a higher fraction of future fuel costs: 93

percent for one- to three-year-old vehicles, compared to their estimate of 76 percent for all used vehicles assuming the same price expectation.[582]

Accounting for differences in their data and estimation procedures, the three studies described here suggest that car buyers who use discount rates of five to six percent value at least half—and perhaps all—of the savings in future fuel costs they expect from choosing models that offer higher fuel economy. Perhaps more important, one study (Busse et al., 2013) suggests that buyers of *new* cars and light trucks value three-quarters or more of the savings in future fuel costs they anticipate from purchasing higher-MPG models, although this result is based on more limited information.

Based on a meta-analysis of the literature from 1995-2015, including the papers discussed above, Greene et al. (2018) concluded that the economic literature over that period did not support a consensus estimate of consumers' willingness to pay for fuel economy. The National Academies (NASEM, 2021) fuel economy committee agreed, observing that, "Many papers found undervaluation, and many have found full or even overvaluation. Both earlier studies and more recent ones have found undervaluation. Studies using both methodologies (discrete choice or otherwise) have found undervaluation." (NASEM, 2021, p. 11-351). More recently, Gillingham et al. (2021) analyzed the effects of changes in fuel economy ratings of 1.6 million vehicles and concluded that consumers were willing to pay only 16-39 cents per dollar of fuel savings, assuming an annual discount rate of 4 percent.[583] Analyzing a data set of more than half a million vehicles purchased by households between 2009 and 2014, Leard et al. (2021) found a willingness to pay for $1 of discounted expected fuel savings of $0.54.[584]

What analysts assume about consumers' vehicle purchasing behavior, particularly about potential buyers' perspectives on the value of increased fuel economy, clearly matters a great deal in the context of benefit-cost analysis for fuel economy regulation. One possible approach would be to use a baseline scenario where fuel economy levels of new cars and light trucks reflected full (or nearly so) valuation of fuel savings by potential buyers in order to reveal whether setting fuel economy standards above market-determined levels could produce net social benefits. Another might be to assume that, unlike previous analyses where buyers were assumed to greatly undervalue higher fuel economy under the baseline but to value it fully under the standards, buyers value improved fuel economy identically under both the baseline scenario and with stricter CAFE standards in place.

Behavioral economics offers yet another possible explanation, namely that consumers' decision making about fuel economy is affected by the context of the choice. Choices framed in terms of paying more or not paying more for uncertain future fuel savings may be viewed as a risky bet

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[582] Allcott & Wozny (2014) and Sallee, et al. (2016) also find that future fuel costs for older vehicles are substantially undervalued (26-30 percent). The pattern of Allcott and Wozny's results for different vehicle ages is similar when they use retail transaction prices (adjusted for customer cash rebates and trade-in values) instead of wholesale auction prices, although the degree of valuation falls substantially in all age cohorts with the smaller, retail price based sample.

[583] Gillingham, K., S. Houde, and A. van Benthem. 2021. "Consumer Myopia in Vehicle Purchases: Evidence from a Natural Experiment." *American Economic Journal: Economic Policy* 13(3): 207–38.

[584] Leard, B., J. Linn, and Y. Zhou,. 2021. "How Much Do Consumers Value Fuel Economy and Performance? Evidence from Technology Adoption." *The Review of Economics and Statistics:* 1–45.

and induce a response that severely undervalues future fuel savings (e.g., Greene, 2019). On the other hand, when the fuel economy of all new vehicles is increasing as a consequence of fuel economy standards, consumers might approximately fully value expected fuel savings (see, e.g., NASEM, 2021, Ch. 11.3.4). Of course, given that CAFE standards apply to manufacturers' overall new vehicle fleets rather than to specific vehicle models, nothing guarantees that manufacturers will distribute fuel economy improvements evenly across their respective product lines. One thing is clear—the analysis must include some estimate of consumers' valuation of fuel economy, in part because fuel prices are uncertain, and buyers and manufacturers would certainly make different decisions if they expected future fuel prices to be very low than if they anticipated much higher future fuel prices. While we acknowledge the uncertainty around the estimates in the literature, a consumer willingness to pay of zero is not supported by the literature and we believe that assuming a value between zero and full valuation is better than omitting consumers' willingness to pay for fuel economy from our analysis.

The analysis supporting this final rule accounts for the value of fuel economy in several places, though it uses a more conservative value than is suggested by the majority of the literature summarized above. Manufacturers have consistently told the agencies that new vehicle buyers will pay for about 2 or 3 years' worth of anticipated fuel savings before the price increase associated with providing those improvements begins to affect sales. It is, of course, possible that manufacturers are incorrect in their assumptions; the same manufacturers, for example, long assumed that consumers would not pay extra for safety features. And manufacturers play a role in shaping consumer preferences. Otherwise, they would not spend large sums on advertising.

Nevertheless, in this rulemaking NHTSA assumes the same valuation, 2.5 years (i.e., 30 months) of undiscounted fuel savings, in all components of the analysis that reflect consumer decisions regarding vehicle purchases and retirements.[585] This analysis explicitly assumes that: 1) consumers are willing to pay for fuel economy improvements that pay back within the first 2.5 years of vehicle ownership (at average usage rates); 2) manufacturers know this and will provide these improvements even in the absence of regulatory pressure; 3) the amount of technology for which buyers will pay rises (or falls) with rising (or falling) fuel prices; 4) consumer willingness to pay is the same with or without higher fuel economy standards; and 5) these fuel savings are considered when evaluating the impact of new vehicle prices on vehicle retirement decisions.

The agency's analysis assumes that potential car and light truck buyers value only the savings in fuel costs from purchasing a higher-MPG model they expect to realize over the first 30 months they own it. Depending on the discount rate buyers are assumed to apply, this amounts to 25-30 percent of the expected savings in fuel costs over its entire lifetime. These savings would offset only a fraction of the expected increase in new car and light truck prices that the agency estimates will be required for manufacturers to recover their increased costs for making required improvements to fuel economy. If this is the case, sales of new cars and light trucks will decline, prices for used vehicles are likely to increase, and the retirement of older cars and light trucks and their replacement by newer models will slow.

[585] When accounting for social benefits and costs associated with an alternative, the full lifetime value of (discounted) fuel savings is included.

Because we assume, 1) that consumers are willing to pay for only 30 months of expected fuel savings and 2) that in all regulatory alternatives manufacturers will voluntarily adopt fuel economy technologies that pay for themselves in 30 months, our model will necessarily predict that fuel economy standards will decrease vehicle sales somewhat and slow down stock turnover. As discussed above, there is a high degree of both empirical and theoretical uncertainty about how consumers value fuel economy in their car buying decisions. We are aware that the future magnitude of such sales and scrappage effects is highly uncertain, and we are seeking ways to improve the state of knowledge and more fully represent the uncertainties in our assessments. We are also aware that assuming full valuation of future fuel savings could lead to the conclusion that fuel economy regulations would increase sales and accelerate stock turnover in cases where the fuel value of fuel savings exceeded the increased vehicle cost.[586]

One explanation for such "undervaluation" of the savings from purchasing higher-MPG models is that potential buyers view the prospect of the future savings those models appear to offer as uncertain, in contrast to the more immediate and certain increase in the prices buyers face for purchasing them. This situation could arise because they are unsure of the fuel economy the vehicle will achieve on the road under their driving conditions, how long they will own a new vehicle, whether they will drive it enough to realize the promised savings or have difficulty predicting the future course of fuel prices. As a consequence, they may view choosing a more fuel-efficient model as a risky purchase; widespread aversion to the prospect of financial losses may lead many to view the already uncertain future savings even more skeptically, and thus to choose more modest levels of fuel economy. For these same reasons, car and light truck producers may be unwilling to improve their models' fuel economy, because they believe few consumers will be likely to purchase them. We note that an individual's purchase decision, that is whether they purchase a marginally more expensive vehicle with lifetime fuel savings that exceeds the cost, is different than collective consumer purchases of a fleet of more efficient vehicles. It is the latter that drives analysis of regulatory impacts.

From this perspective, it is possible that requiring manufacturers to improve the fuel economy of most or all of their models by raising CAFE standards will change the way potential buyers assess future savings from choosing models with higher fuel economy. It is also possible that when all models are required to provide higher fuel economy as a result of regulation, consumer choice is affected differently. It would effectively require producers to offer higher-MPG cars and light trucks and consumers to experience first-hand the benefits from owning them. This would change the context of consumers' fuel economy choices from buy or do not buy a fuel economy technology to one in which the fuel economy of virtually all new vehicles increased. Over time, this might reduce buyers' uncertainty about the prospect of future savings and soften (or even eliminate) their usual aversion to potential losses from investing in higher fuel economy.[587]

By doing so, raising standards could thus increase potential buyers' valuation of improved fuel economy to the point where it offsets the accompanying increases in new car and light truck

[586] There is the additional question of whether consumers' willingness to pay for other vehicles attributes that could have been produced by technologies used to increase fuel economy might be greater than the full present value of fuel savings.
[587] If buyers primarily learn about the benefits of improved fuel economy through vehicle ownership, it does raise the question of the utility of the fuel economy label, but such questions are beyond the scope of this rulemaking.

prices, thus raising their sales and hastening the retirement of older cars and light trucks as newer models gradually replaced them. Of course, CAFE standards apply to manufacturers' overall fleets, such that it is not obvious how NHTSA could actually require that manufacturers apply fuel economy improvements evenly throughout their respective product lines. Nevertheless, NHTSA has been steadily increasing CAFE standards for passenger cars for the last decade, and light trucks for almost 15 years, so data are accumulating that will help us evaluate this perspective. We will continue to monitor the market and assess the evolving nature of consumer demand for fuel economy in the new vehicle market.

4.2.1.2 Modeling the Sales Response

For the purposes of regulatory evaluation, the relevant sales metric is the difference between alternatives rather than the absolute number of sales in any of the alternatives. As such, the sales response model currently contains three parts: a nominal forecast that provides the level of sales in the baseline (based upon macroeconomic inputs, exclusively), a price elasticity that creates sales differences relative to that baseline in each year, and a fleet share model that produces differences in the passenger car and light truck market share in each alternative. The nominal forecast does not include price and is merely a (continuous) function of several macroeconomic variables that are provided to the model as inputs. The price elasticity is also specified as an input, but this analysis assumes a response of -0.4—meaning that a ten percent increase in the average price of a new vehicle produces a four percent decrease in total sales.[588] Unlike a conventional price elasticity, the price change on which the elasticity acts is calculated net of some portion of the future fuel savings that accrue to new vehicle buyers (2.5 years' worth, in this analysis, as discussed in the previous section).

The current sales module reflects the idea that total new vehicle sales are primarily driven by conditions in the economy that are exogenous to the automobile industry. Over time, new vehicle sales have been cyclical – rising when prevailing economic conditions are positive (periods of growth) and falling during periods of economic contraction. While the kinds of changes to vehicle offerings that occur as a result of manufacturers' compliance actions exert some influence on the total volume of new vehicle sales, they are not determinative. Instead, they drive the kinds of marginal differences between regulatory alternatives that the current sales module is designed to simulate – more expensive vehicles, generally, reduce total sales but only marginally. Greater availability of fuel-efficient light truck body styles increases their share of the new vehicle market, but only on the margin – and does so in the context of the current market shares prior to that model year's changes.

The first component of the sales response model is the nominal forecast, which is a function (with a small set of inputs) that determines the size of the new vehicle market in each calendar year in the analysis for the baseline. It is of some relevance that this statistical model is intended only as a means to project a baseline sales series. Past peer reviewers expressed concerns about the possibility of econometrically estimating an industry average price elasticity in a way that isolates the causal effect of new vehicle prices on new vehicle sales (and properly addresses the issue of endogeneity between sales and price). The nominal forecast model does not include

[588] The "price increase" in this case represents the new vehicle price net of a portion of fuel savings, described further in this section.

prices and is not intended for statistical inference around the question of price response in the new vehicle market.

The forecast is derived from a statistical model (described in Equation 4-1) that accounts for a set of exogenous factors related to new light-duty vehicle sales. In particular, the model accounts for the number of households in the United States, recent number of new vehicles sold, GDP, and consumer confidence. The structure of the forecast model is a time series autoregressive distributed lag specification. To reflect the fact that households are the primary unit of demand for new vehicles, the dependent variable is defined as new vehicles sold per household.[589] While this variable still exhibits the cyclical behavior that new vehicle sales exhibit over time, the trend shows the number of new vehicles sold per household declining since the 1970s, as shown in Figure 4-32, where the dotted line is the trend over time. As this time series is non-stationary,[590] a lagged variable (the value in the previous year) is included on the right-hand side of the regression equation. In addition, the model includes a lagged variable that represents the three-year running sum of new vehicle sales, divided by the number of households in the previous year. This variable attempts to capture the potential that some households may "overshoot" their desired vehicle ownership levels by purchasing additional cars or light trucks during periods of robust income growth, and then avoid making additional purchases for some period. As vehicles' durability and prices have increased over time, and the average length of initial ownership has increased similarly, this variable puts downward pressure on sales after successive years of high sales (particularly during extrapolation).

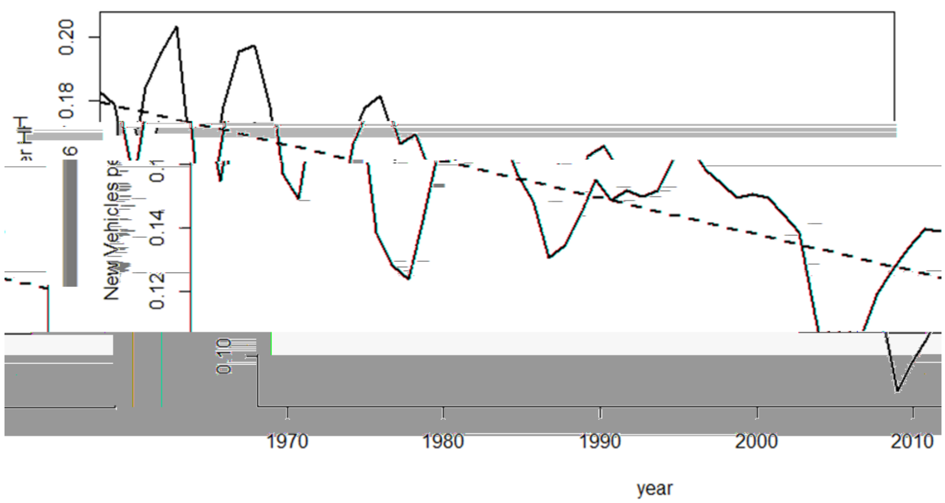

Figure 4-3 – New Light-Duty Vehicle Sales per Household in the United States, 1970 – 2016

The forecast model includes the natural logarithm of real U.S. GDP and consumer sentiment, as measured by the University of Michigan survey of consumers.[591] As both of these series are non-stationary (determined by applying augmented Dickey-Fuller unit root tests to the time

[589] Number of U.S. households is taken from Federal Reserve Economic data, https://fred.stlouisfed.org/series/TTLHH. (Accessed: February 15, 2022).
[590] The series contains a unit root (i.e., it is integrated of order one), based on the augmented Dickey-Fuller test.
[591] http://www.sca.isr.umich.edu/tables.html. (Accessed: February 15, 2022).

series), lagged versions of the variables are included to ensure stationarity in the residuals. The functional form appears below in Equation 4-1.

$$
\begin{aligned}
New\_Veh\_per\_HH_t \\
&= C + \beta_1 New\_Veh\_per\_HH_{t-1} + \beta_2 3YrSumPerHH_{t-1} + \beta_3 LN(GDP_t) \\
&+ \beta_4 LN(GDP_{t-1}) + \beta_5\ Consumer\_sentiment_t \\
&+ \beta_6 Consumer\_sentiment_{t-1}
\end{aligned}
$$

Equation 4-1 – Statistical Model Used to Generate Nominal Forecast

The model fit is described in Table 4-3. The included lag term of the dependent variable and both GDP variables are statistically significant at nearly zero, while both the lagged three-year sum term and consumer sentiment are both marginally significant. Being a time series model, the Breusch-Godfrey test for serial correlation is (0.65) at order 1. The signs of the coefficients are all consistent with expectations.

Table 4-3 – Summary of Forecast Regression Function

Predictors	Estimates	CI	p
(Intercept)	0.21	0.10 – 0.32	<0.001
lag(new.veh.per.HH)	0.70	0.45 – 0.95	<0.001
lag(3yrSum.per.HH)	-0.08	-0.16 – 0.01	0.070
LN.Real.GDP	0.44	0.25 – 0.62	<0.001
lag(LN.Real.GDP)	-0.45	-0.63 – -0.28	<0.001
Cons.sentiment	0.0003	-0.00 – 0.00	0.136
lag(Cons.sentiment)	0.00001	-0.00 – 0.00	0.948
Observations	47		
R2 / R2 adjusted	0.919 / 0.907		

Because the dependent variable is the number of new vehicles sold per household, it is necessary to multiply by the number of households to produce an estimate of new vehicle sales. This model is used to produce a forecast of new vehicle sales out to 2050, so it is also necessary to have projections of each variable used in Equation 4-1 through calendar year 2050. As indicated previously, NHTSA relies on forecasts of U.S. GDP from the recent IHS Global Insight October 2021 Macroeconomic Outlook, and projections of future growth in the number of U.S. households are also obtained from this source.

While the analysis could have relied on a forecast of new vehicle sales taken from a published source (AEO 2021, for example), using a function is an attractive option because it allows the CAFE Model to dynamically adjust the forecast in response to input changes. If a sensitivity case requires a forecast that is consistent with a set of specific, possibly unlikely, assumptions, a forecast of new vehicle sales that is consistent with those assumptions may not exist in the public domain. Using a functional form also allows the user to vary some of the assumptions to the analysis without creating inconsistencies with other elements of the analysis. However, it is incumbent upon the user to ensure that any set of assumptions is logically consistent.

This function and the set of assumptions contained in the central analysis produces a projection that is comparable in magnitude to the forecast in AEO 2021's Reference case, although there are some important differences. The two forecasts, as well as the AEO 2020 Reference case forecast, which is included for context, project new light vehicle sales to be relatively flat over the coming decades. However, the baseline forecast in this analysis projects a temporary increase in new sales occurring as the economy recovers from the COVID-19 pandemic. Prior to the pandemic, some recent model years had new light vehicle sales in excess of 17 million units. The baseline forecast shows a brief return to that level before returning to the long-run average, which is closer to 15 million units per year.

As the AEO 2020 forecast illustrates, the pandemic has had a significant influence on sales projections through the 2020s. The baseline forecast, which uses manufacturer compliance data to measure MY 2020 production (and, thus, sales in this analysis) introduces a discrepancy with the projection in AEO 2021. However, we treat the compliance data as an authoritative source. After the effects of the pandemic recede toward the end of the 2020s, differences between all three forecasts shrink to about 5 percent (or less) in most years. Obviously, the economic response to the pandemic has created considerable near-term uncertainty about the pace at which the market for new automobiles will recover – and the scale and timing of the recovery's peak – before returning to its long-term trend.

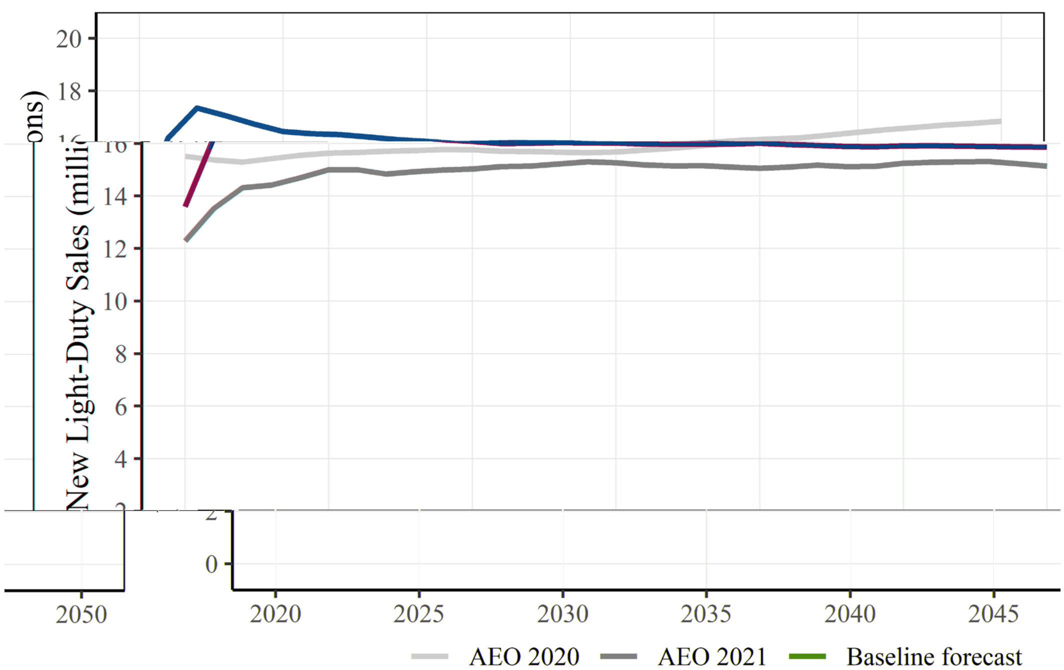

Figure 4-4 – Comparison of Projected New Vehicle Sales with Annual Energy Outlook

Although the forecast produces the total number of new vehicle sales in the baseline, an elasticity is imposed on price differences to produce sales changes between alternatives.

In previous rules, while the agency produced analyses that qualitatively considered sales and employment impacts, the agency acknowledged that fuel economy standards were likely to increase vehicle prices, while simultaneously reducing operating costs, and that estimating how consumers would choose to balance those two factors in the new vehicle market was challenging.[592] For the final rule, the agency revisited the price elasticity assumption and selected a central case price elasticity of vehicle demand equal to -0.4. An extended discussion of this choice is contained in preamble Section III.E.

Because the elasticity assumes no perceived change in the quality of the product, and the vehicles produced under different regulatory scenarios have inherently different operating costs, the price metric must account for this difference. The price to which the unit elasticity is applied in this analysis represents the residual price change *between scenarios* after accounting for 2.5 years' worth of fuel savings to the new vehicle buyer. Like that applied in the 2020 FRIA, this approach is consistent with the 2012 FRIA analysis of sales impacts, which considered several payback periods over which the value of fuel savings was subtracted from the change in average new vehicle price.

The price elasticity is applied to the percentage change in average price (in each year). As discussed below the price change does not represent an increase/decrease over the last observed year, but rather the percentage change relative to the baseline. In the baseline, the average price is defined as the observed new vehicle price in 2019 (the last historical year before the simulation begins) plus the average regulatory cost associated with the baseline. The central analysis for the final rulemaking analysis simulates multiple programs simultaneously (CAFE final standards, EPA final greenhouse gas standards, ZEV, and the California Framework Agreements), and the regulatory cost includes both technology costs and civil penalties paid for non-compliance (with CAFE standards) in a model year.[593] So the change in sales for alternative *a* in year *y* is:

$$\Delta Sales_{y,a} = \frac{(\Delta RegCost_{y,a-0} - \Delta FuelCosts_{t,a-0})}{MSRP_{2019} + RegCost_{y,0}} \cdot PriceElasticity \cdot NominalSales_y$$

Equation 4-2 – Calculation of Change in Sales

ΔRegCost is the difference in average regulatory cost between alternative *a* and the baseline scenario in year *y* to make a vehicle compliant with the standards, $MRSP_{2019}$ is the average transaction price of a new vehicle in 2019, *NominalSales* is the forecasted sales (in the baseline) in year *y,* ΔFuelCosts is the change in average fuel costs over 2.5 years relative to the baseline in year *y* and *PriceElasticity* is -0.4

$$\Delta FuelCosts_{t,a-0} = \left(\frac{FuelPrice_t}{NewVehFE_{t,a}} - \frac{FuelPrice_t}{NewVehFE_{t,0}}\right) * 35000$$

Equation 4-3 – Change in Fuel Costs Used to Compute Sales Differences

[592] Final Regulatory Impact Analysis, Corporate Average Fuel Economy for MY 2017-MY 2025 Passenger Cars and Light Trucks, August 2012, at p. 821.

[593] The baseline regulatory costs include all of the costs associated with fuel economy technology assumed to be applied to vehicles in the baseline scenario. If a technology is estimated to have a payback period within 30 months, the model will apply it within the baseline and that cost would be incorporated into the baseline's regulatory cost.

Where 35,000 miles is assumed to be equivalent to 2.5 years of vehicle usage.[594]

NHTSA assumes that consumers behave as if the fuel price faced at the time of purchase is the fuel price that they will face over the first 2.5 years of ownership and usage. Essentially, consumers behave as if fuel prices follow a random walk, where the best prediction of (near) future prices is the price today. Scrappage rates in the first few years of ownership are close to zero, so buyers can reasonably expect to travel the full annual mileage in each of the first three years of ownership. Total sales in each alternative (that is not the baseline) will equal $NominalSales_y + \Delta Sales_{a,y}$ for alternative *a* in year *y*. This implementation produces total sales estimates that vary among alternatives and over time. Sales effects are discussed in detail in the accompanying FRIA Section 6.3.3.

4.2.1.3 Dynamically Modeling Changes in Fleet Mix

The first two modules described above (the forecast function and applied elasticity) determine the total industry sales in each model year from 2021 (in this analysis, 2020 is based on certified compliance data) to 2050. A third module, the dynamic fleet share, acts to distribute the total industry sales across two different body-types: "cars" and "light trucks." While there are specific definitions of "passenger cars" and "light trucks" that determine a vehicle's regulatory class, the distinction used in this phase of the analysis is more simplistic. All body-styles that are obviously cars—sedans, coupes, convertibles, hatchbacks, and station wagons—are defined as "cars" for the purpose of determining fleet share. Everything else—SUVs, smaller SUVs (crossovers), vans, and pickup trucks—are defined as "light trucks"—even though they may not be treated as such for compliance purposes. In the case of SUVs, in particular, many models may have sales volumes that reside in both the passenger car and light fleets for regulatory purposes, but the dynamic fleet share does not make this distinction. All crossovers are considered light trucks for the purposes of fleet share, even though they may be 2WD crossovers treated as passenger cars for compliance purposes. So, while the number may increase overall for a given scenario, the proportion of crossovers sold as 4WD, rather than 2WD, does not. This means that the number of vehicles regulated as passenger cars is less affected by changes in fleet share because many SUVs are regulated as cars – and the portion of a given SUV nameplate that is regulated as a passenger car in the MY 2020 fleet is carried forward into future years.

Even if the fleet share model (described in greater detail below) increases the share of light trucks (for example), the inherent price difference between passenger cars and light trucks does not pass through to the average price—only the relative difference in compliance costs associated with the vehicle types. Despite the fact that light trucks have generally higher transaction prices than passenger cars, there is no guarantee that regulatory costs will be higher for light-trucks than for cars (which depend upon the mix of footprints, their distance from the relevant curve, and the technology cost needed to bring each fleet into compliance). Thus, the average price differences used in the sales calculations are relatively unaffected by the fleet share model.

[594] Based on odometer data, 35,000 miles is a good representation of typical new vehicle usage in the first 2.5 years of ownership and use—though the distribution of usage is large.

The dynamic fleet share (DFS) represents two different equations that independently estimate the share of passenger cars and light trucks, respectively, given average new market attributes (fuel economy, horsepower, and curb weight) for each group and current fuel prices, as well as the prior year's market share and prior year's attributes.[595] The two independently estimated shares are then normalized to ensure that they sum to one. As with the Sales Response model, the DFS utilizes values from one and two years preceding the analysis year when estimating the share of the fleet during the model year being evaluated. For the horsepower, curb weight, and fuel economy values occurring in the model years before the start of analysis, the DFS model uses the observed values from prior model years. After the first model year is evaluated, the DFS model relies on values calculated during analysis by the CAFE Model. The DFS model begins by calculating the natural log of the new shares during each model year, independently for each vehicle class, as specified by Equation 4-4.

$$\ln\left(Share_{VC,MY}\right) = \begin{pmatrix} \beta_C \times (1 - \beta_{Rho}) + \beta_{Rho} \times \ln\left(Share_{VC,MY-1}\right) \\ +\beta_{FP} \times \left(\ln\left(Price_{Gas,MY}\right) - \beta_{Rho} \times \ln\left(Price_{Gas,MY-1}\right)\right) \\ +\beta_{HP} \times \left(\ln\left(HP_{VC,MY-1}\right) - \beta_{Rho} \times \ln\left(HP_{VC,MY-2}\right)\right) \\ +\beta_{CW} \times \left(\ln\left(CW_{VC,MY-1}\right) - \beta_{Rho} \times \ln\left(CW_{VC,MY-2}\right)\right) \\ +\beta_{MPG} \times \left(\ln\left(FE_{VC,MY-1}\right) - \beta_{Rho} \times \ln\left(FE_{VC,MY-2}\right)\right) \\ +\beta_{Dummy} \times (\ln(0.423453) - \beta_{Rho} \times \ln(0.423453)) \end{pmatrix}$$

Equation 4-4 – Dynamic Fleet Share

Where:

$\beta_C - \beta_{Dummy}$: set of coefficients, as defined by Table 4-4 below, used for tuning the Dynamic Fleet Share model,

$Share_{VC,MY-1}$: the share of the total industry new sales classified as vehicle class *VC*, in the year immediately preceding model year *MY*,

$Price_{Gas,MY}$: the fuel price of gasoline fuel, in cents per gallon, in model year *MY*,[596]

$Price_{Gas,MY-1}$: the fuel price of gasoline fuel, in cents per gallon, in the year immediately preceding model year *MY*,

$HP_{VC,MY-1}$: the average horsepower of all vehicle models belonging to vehicle class *VC*, in the year immediately preceding model year *MY*,

[595] NHTSA explored alternatives to this DFS model. Preliminary results of this exploration are discussed in Exploration of alternate fleet share module" in Docket No. NHTSA-2021-0053 and primary output measures are presented in Chapter 7 of the accompanying FRIA.
[596] Model year and calendar year are assumed to be equivalent in the simulation—as they always have been in all prior rulemaking analyses.

$HP_{VC,MY-2}$: the average horsepower of all vehicle models belonging to vehicle class *VC*, in the year preceding model year *MY* by two years,

$CW_{VC,MY-1}$: the average curb weight of all vehicle models belonging to vehicle class *VC*, in the year immediately preceding model year *MY*,

$CW_{VC,MY-2}$: the average curb weight of all vehicle models belonging to vehicle class *VC*, in the year preceding model year *MY* by two years,

$FE_{VC,MY-1}$: the average on-road fuel economy rating of all vehicle models (excluding credits, adjustments, and petroleum equivalency factors) belonging to vehicle class *VC*, in the year immediately preceding model year *MY*,

$FE_{VC,MY-2}$: the average on-road fuel economy rating of all vehicle models (excluding credits, adjustments, and petroleum equivalency factors) belonging to vehicle class *VC*, in the year preceding model year *MY* by two years,

0.423453 : a dummy coefficient, and

$\ln(Share_{VC,MY})$: the natural log of the calculated share of the total industry fleet classified as vehicle class *VC*, in model year *MY*.

In the equation above, the coefficients, β_C through β_{Dummy}, are provided in the following table. The coefficients differ depending on the vehicle class for which the fleet share is being calculated.

Table 4-4 – DFS Coefficients for Cars and Light Trucks

Coefficient	Car Value	Light Truck Value
β_C	3.4468	7.8932
β_{Rho}	0.8903	0.3482
β_{FP}	0.1441	0.4690
β_{HP}	-0.4436	1.3607
β_{CW}	-0.0994	1.5664
β_{MPG}	-0.5452	0.0813
β_{Dummy}	-0.1174	0.6192

Once the initial car and light truck fleet shares are calculated (as a natural log), obtaining the final shares for a specific vehicle class is simply a matter of taking the exponent of the initial value, and normalizing the result at one (or 100 percent). This calculation is demonstrated by the following:

$$Share_{VC,MY} = \frac{e^{\ln(Share_{VC,MY})}}{e^{\ln(Share_{LDV,MY})} + e^{\ln(Share_{LDT1/2a,MY})}}$$

Equation 4-5 – Normalizing Individual Fleet Shares

Where:

ln$(Share_{VC,MY})$: the natural log of the calculated share of the total industry fleet classified as vehicle class *VC*, in model year *MY*,

ln$(Share_{LDV,MY})$: the natural log of the calculated share of the total industry fleet classified as light duty passenger vehicles (LDV), in model year *MY*,

ln$(Share_{LDT1/2a,MY})$: the natural log of the calculated share of the total industry fleet classified as class 1/2a light duty truck (LDT1/2a), in model year *MY*, and

$Share_{VC,MY}$: the calculated share of the total industry fleet classified as vehicle class *VC*, in model year *MY*.

These shares are applied to the total industry sales derived in the first stage of the sales response. This produces total industry volumes of car and light truck body styles. Individual model sales are then determined from there based on the following sequence: 1) individual manufacturer shares of each body style (either car or light truck) times the total industry sales of that body style, then 2) each vehicle within a manufacturer's volume of that body-style is given the same percentage of sales as appear in the 2020 fleet. This implicitly assumes that consumer preferences for particular styles of vehicles are determined in the aggregate (at the industry level), but that manufacturers' sales shares of those body styles are consistent with MY 2020 sales. Within a given body style, a manufacturer's sales shares of individual models are also assumed to be constant over time. This approach implicitly assumes that manufacturers are currently pricing individual vehicle models within market segments in a way that maximizes their profit. Without more information about each OEM's true cost of production and operation, fixed and variables costs, and both desired and achievable profit margins on individual vehicle models, there is no basis to assume that strategic shifts within a manufacturer's portfolio will occur in response to standards.

Some commenters to the current rule as well as previous rules have noted that the market share of SUVs continues to grow, while conventional passenger car body-styles continue to lose market share. The CAFE Model includes the DFS model in an attempt to address these market realities. In the 2012 final rule, the agencies projected fleet shares based on the continuation of the baseline standards (MY 2012-2016) and a fuel price forecast that was much higher than the realized prices since that time. As a result, that analysis assumed passenger car body-styles comprising about 70 percent of the new vehicle market by 2025, which was internally consistent. The reality, however, has been quite different.

NHTSA reviewed the DFS model and explored alternative specifications. As discussed in detail in preamble Section III.E.2, the agency determined that use of the preliminary, alternative DFS model in the central analysis should be deferred to future rulemakings. This exploration is documented in "Exploration of alternate fleet share module" in Docket No. NHTSA-2021-0053. Results using this DFS model candidate are presented as part of the sensitivity analysis in preamble Section V.E and discussed in detail in the accompanying FRIA, Chapter 7.

The coefficients of the DFS model as implemented in the central analysis show passenger car styles gaining share with higher fuel prices and losing them when prices decline. Similarly, as fuel economy increases in light truck models, which offer consumers other desirable attributes beyond fuel economy (ride height or interior volume, for example) their relative share increases. However, this approach does not suggest that consumers *dislike* fuel economy in passenger cars, but merely recognizes the fact that fuel economy has diminishing returns to consumers. As the fuel economy of light trucks increases, the tradeoff between passenger car and light truck purchases increasingly involves a consideration of other attributes. The coefficients also show a relatively stronger preference for power improvements in cars than light trucks because that is an attribute where trucks have typically outperformed cars, like cars have outperformed trucks for fuel economy.

Rather than estimate new functions to determine relative market shares of cars and light trucks, the CAFE Model applied existing functions from the transportation module of the National Energy Modeling System (NEMS) that was used to produce the 2017 AEO.[597] The functions above appear in the "tran.f" input file to that version of NEMS, and were embedded (in their entirety) in the CAFE Model. NEMS uses the functions to estimate the percent of total light vehicles less 8,500 GVW that are cars/trucks. In addition to better reflecting market shifts over time, this approach also enables consistent sensitivity cases—where higher fuel prices produce fleets with more traditional passenger car body styles, for example—and ensures that the starting point (MY 2020) evolves in response to both fuel economy improvements and fuel prices in a way that is internally consistent.

While NEMS intended the fleet shares to be defined by regulatory classes, vehicles are defined much more coarsely in NEMS than in the CAFE Model, and manufacturers are not differentiated at all. In order to produce well-behaved fleet share projections with this model, the CAFE Model applies the share functions to body-styles rather than regulatory classes. For many years, there was little overlap between nameplates in a manufacturer's passenger car regulatory class and its light truck regulatory class. However, with the recent emergence of smaller FWD SUVs and crossovers, it is increasingly common to have nameplates with model variants in both the passenger car and light truck regulatory classes, and it is also common for there to be only minor differences (like the presence of 4WD or AWD) between versions regulated as cars and versions regulated as light trucks. The CAFE Model applies the fleet share equations to focus on body-style, rather than regulatory class, in recognition of the increased ambiguity between the regulatory class distinction for popular models like the Honda CR-V and Toyota RAV4, that sell more than 100K units in each regulatory class (typically using the same powertrain configuration). This trend has only continued in recent years under favorable fuel prices and improving fuel economy among light truck offerings. Applying the fleet share at the body-style level preserves the existing regulatory class splits for nameplates that straddle the class definitions. It also serves to minimize the deviation from the observed MY 2020 regulatory class shares over time. Our implementation allows the passenger car regulatory class to continue evolving toward crossover-type cars, if that is what economic and policy conditions favor.

[597] The share equation is described in the 2016 NEMS model documentation (see Equation 82), available at: https://www.eia.gov/outlooks/aeo/nems/documentation/archive/pdf/m070(2016).pdf. (Accessed: February 15, 2022).

4.2.1.4 Using Vehicle Choice Models in Rulemaking Analysis

For years, some commenters encouraged DOT to consider vehicle attributes beyond price and fuel economy when estimating a sales response to fuel economy standards and suggested that a more detailed representation of the new vehicle market would allow the agency to simulate strategic mix shifting responses from manufacturers and diverse attribute preferences among consumers. Doing so would require a discrete choice model.

There are a number of practical challenges to using estimates of consumer attribute preferences to simulate market responses. Discrete choice models typically rely on fixed effects (or alternative-specific constant terms) to account for the unobserved characteristics of a given model that influence purchasing decisions, such as styling,[598] but are not captured by independent variables that represent specific vehicle attributes (horsepower, interior volume, or safety rating, for example). Ideally, these constant terms would contribute relatively little to the fit and performance of the model, assuming that the most salient characteristics are accounted for explicitly. In practice, this is seldom the case. While the fixed effects at the model level are statistically sound estimates of consumer preferences for the unobserved vehicle characteristics of the individual models, the estimates are inherently historical—based on observed versions of the specific vehicle models to which they belong. However, once the simulation starts, and new technologies are added to each manufacturer's product portfolio over successive generations, it is no longer obvious that those constant terms would still be valid in the context of those changes.

Another complication is that discrete choice models are highly dependent on their inputs and are unable to account for future market changes. For example, the Draft TAR relied on a MY 2014 market (for EPA's analysis) and a MY 2015 market (for NHTSA's analysis), while the 2020 final rule used a MY 2017 fleet, and this rulemaking uses a characterization of the MY 2020 fleet. A discrete choice model estimated on any of those model years would probably produce different fixed effects estimates for each model variant in the fleet. Even assuming that no new variants of a given model are offered over time, new nameplates emerge as others are retired—and for those new nameplates and all of their model variants, no constant terms would exist. They would have to be imputed (either from comparable vehicles in the market, some combination of their attributes, or both). Some studies have attempted to estimate fixed effects for a single new entrant to the market,[599] but none have attempted to do so at the scale required to migrate a discrete choice model operating at the vehicle level that was fit on an earlier model year to a newer model year for simulation.

Figure 4-5 shows the cumulative percentage of nameplates in the 2017 new vehicle market by year of introduction. About ten percent of nameplates in 2017 have been around since the 1970s, but another ten percent have only existed since about 2010. This fact illustrates the likely necessity of constructing vehicle model fixed effects for the inevitable new entrants between the estimating fleet and the rulemaking fleet. But it also suggests another challenge. New model entrants are driven by the dynamics of the market, where some vehicle models succeed and others fail, but a simulated market with a discrete choice model can only simulate failure—where

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[598] Aesthetics such as styling are difficult, if it not impossible, to define in a manner that allows meaningful comparison between choices.

[599] Berry, Steven, James Levinsohn, and Ariel Pakes (2004). Differentiated products demand systems from a combination of micro and macro data: The new car market. Journal of Political Economy 112(1): 68-105.

consumer demand for specific nameplates erode to the point that the nameplate volumes trend toward zero. It has no mechanism to generate new nameplates to replace those nameplates whose sales it estimates will erode beyond some minimal practical level of production. Even if the CAFE Model can generate sufficiently different technology content that modified variants could be thought of as "new" market entrants, there would be no way to associate valid fixed effects with these vehicles in the discrete choice model.

Consumer choice models are typically fit on a single year of data (a cross-section of vehicles and buyers), but this approach misses relevant trends that build over time, such as rising GDP or shifting consumer sentiment toward emerging technologies. If such a model is used to estimate total sales, but lacks trends in GDP growth or employment, etc., it will have the wrong set (likely a smaller set) of new vehicle buyers and exaggerate price responses and attribute preferences. Consumer preferences change over time in response to any number of factors—given manufacturers' recent investments in electric powertrains, they are counting on this fact. But a choice model estimated on observed consumer preferences for EVs—or other vehicle attributes with comparatively little experience in the market—would necessarily disadvantage a technology that is currently (or only recently) unpopular, but gaining popularity. While these are problems that may not matter in the estimation process, where a researcher is attempting to measure revealed consumer preference for given attributes at a single point in time, they become material once that model is integrated into the simulation and dynamically carried forward for three decades. We note that models that examine aggregate trends, such as the one utilized in this analysis, are able to side-step this issue by not placing a value on unique vehicle attributes.

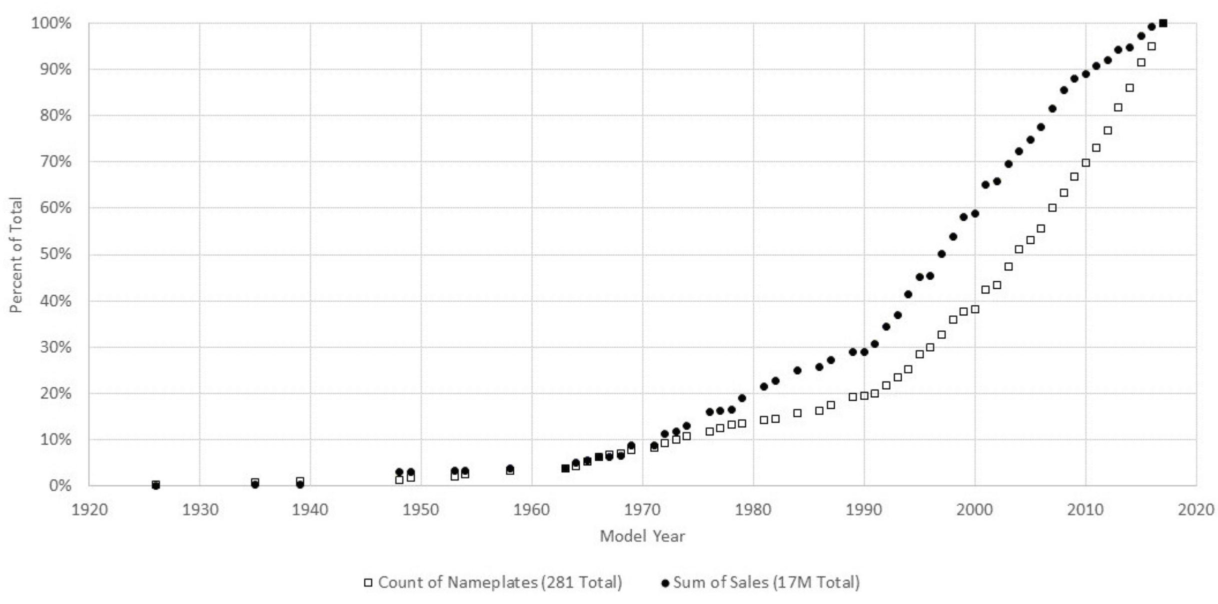

Figure 4-5 – Nameplate Introduction and Attrition; Cumulative Portion of MY 2017 Nameplate Count and Sales by Year of Introduction to the U.S. Market

DOT's compliance simulation model estimates the additional cost of technology required to achieve compliance, or to satisfy market demand for additional fuel economy. While it necessarily calculates these costs on a per-vehicle basis, estimating the cost of additional technologies as they are applied to each specific model in order to bring an entire fleet into compliance, it is agnostic about how these costs are distributed to buyers. Manufacturers have strategic, complex pricing models that rely on extensive market research and reflect each company's strategic interests in each market segment. Automobile companies attempt to maximize profit from the sale of their vehicles, rather than solely focusing on minimizing the cost of compliance, as the CAFE Model simulates. Lacking reliable data for each manufacturer on production costs and profit margins for each vehicle model in their portfolios, the most reasonable course of action is to simulate compliance as if OEMs are attempting to minimize costs, and, worth noting, this approach is also the one NHTSA takes in its rulemakings related to the Federal Motor Vehicle Safety Standards (FMVSS).

However, it is obvious that some market segments and individual models are much less elastic than others.[600] As reflected in the prices of those models, consumers are able to bear a greater share of the total cost of compliance before negatively affecting sales and manufacturer profits.

Several recent commenters on CAFE rules have suggested that the agency should employ a pricing model that allows manufacturers to vary prices in response to heterogeneous consumer preferences and different levels of willingness to pay for fuel economy, and other attributes, in the new vehicle market. Fundamentally, this would require the agency to model strategic pricing for each manufacturer individually—no single pricing model would be appropriate for every manufacturer. There is no reasonable expectation that the agency could embed and utilize each manufacturer's pricing strategy, as this is an essential feature of competitive corporate behavior and automakers closely hold pricing strategy information. Furthermore, models in the academic literature that commenters to past rules have suggested are superior because they allow prices to adjust, merely demonstrate that the mechanics of those adjustments work; they do not imply that the resulting prices are reasonable or realistic. Given the burden to estimate each manufacturer's standard under the attribute-based system, where the mix of vehicles sold defines not only the achieved fuel economy of each fleet but also the standard to which it is compared, NHTSA is understandably reluctant to implement models that might drastically shift a manufacturer's mix of vehicles sold within a market segment.

Some past commenters have also suggested that the agency should use a joint model of household vehicle holdings and sales that encompasses decisions to purchase new vehicles, retain existing ones, or reduce or augment current holdings of vehicles of all types and vintages in each period. Manufacturers would modify either new vehicle content, prices, or both to produce a supply of new vehicles that allowed them each to comply with standards. And, subsequently, households and manufacturers would iteratively interact until the market reached equilibrium. Such a model would face many of the same issues outlined above. There are significant econometric challenges associated with estimating a household's decision to buy a new vehicle instead of a used vehicle (of some vintage), or to maintain its current set. And integrating such a model would require the agency to simulate the dynamics of the used vehicle market—hundreds of unique nameplates for each of dozens of vintages—in order to provide the correct choice set in each simulated year. Such a model is beyond the scope of the current analysis.

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[600] *See*, for example, Kleit, A.N. (2004), Impacts of Long-Range Increases in the Fuel Economy (CAFE) Standard. Economic Inquiry, 42: 279-294. doi:10.1093/ei/cbh060.

While the agency believes that these challenges provide a reasonable basis for not employing a discrete choice model in the current CAFE Model, the agency also believes these challenges are not insurmountable, and that some suitable variant of such models may yet be developed for use in future fuel economy rulemakings. The agency has not abandoned the idea and plans to continue experimenting with econometric specifications that address heterogeneous consumer preferences in the new vehicle market as they further refine the analytical tools used for regulatory analysis.

Operating at the level of individual auto and light truck model variants—the same level at which compliance is, necessarily, simulated—may not be tractable for rulemaking analyses. However, market shares for brands and manufacturers within market segments are more stable over time—even if the volumes of segments across the industry fluctuate. In the 2012 final rule, the analysis showed a new vehicle market where the share of passenger car body styles—sedans, coupes, hatchbacks—reached about 70 percent of the new vehicle market by 2025, while light trucks, including many crossovers, accounted for the remaining 30 percent. Those results were consistent with the assumptions made in 2012, but the combination of low fuel prices and decreasing differences in fuel consumption between body styles has instead reduced the market share of those body styles significantly and thus eroded the value of the 2012 analysis to inform current decisions. Including a choice model that operated on existing market shares, albeit at a higher level of aggregation than specific nameplates, such as brand/segment/powertrain, may improve internal consistency with the interaction of assumptions about fuel prices and regulatory alternatives. DOT will continue to engage with the academic community and other stakeholders to ensure that future work on this question improves our analysis of regulatory alternatives.

4.2.2 Modeling Changes in Vehicle Retirement Rates

The effects of this rulemaking on the fuel economy, prices, and other features of new cars and light trucks will affect not only their sales, but also the demand for used vehicles. This is because used cars and light trucks—especially those produced more recently—are a close substitute for new models, so changes in prices and other attributes of new cars and light trucks will affect demand for used models. In turn, this will affect their market value as well as the number of used vehicles remaining in service.

Changes in the number of used vehicles in service, and by extension how much they are driven, have important consequences for fuel consumption, emissions of CO_2 and criteria air pollutants, and safety. The average age of a registered light-duty vehicle in the United States has already risen by more than 40 percent since 1995, and topped 12 years old for the first time in 2021 (see Figure 4-5, from IHS Markit).[601] In light of this trend, it is important to capture the changes to vehicle usage and retirement in the used market that may be caused by regulation of the new vehicle market.

[601] https://ihsmarkit.com/research-analysis/average-age-of-cars-and-light-trucks-in-the-us-rises.html. (Accessed: February 15, 2022).

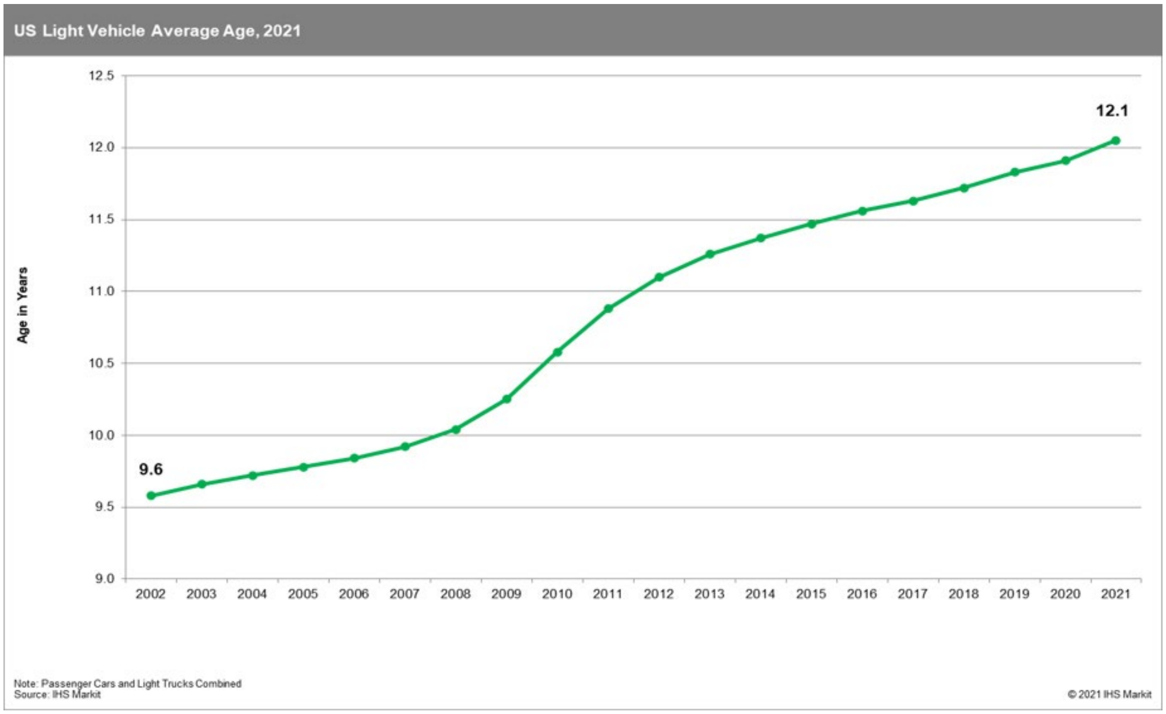

Figure 4-6 – Average Age of a Registered Light-Duty Vehicle in United States

This section discusses the basis for the scrappage effect of higher CAFE standards, traces each of these effects in detail, and explains how the magnitude of this effect is estimated for this action. Like many of the effects estimated in this analysis, the magnitude of the simulated standards' effect on scrappage rates is subject to uncertainty. As a consequence of our assumptions about how consumers value fuel economy and when manufacturers will voluntarily adopt fuel economy technology, the direction of the scrappage effect is unambiguous.

4.2.2.1 Foundation of the Scrappage Effect

Fuel economy standards increase the cost of acquiring new vehicles, but also improve the quality of those vehicles by increasing their fuel economy. The CAFE analysis assumes that consumers value the first 30 months of fuel savings at the time of purchase, so that the quality-adjusted change in new vehicle prices is the increase in regulatory costs less 30 months of fuel savings. Because the CAFE analysis also assumes that in the No-Action Alternative manufacturers will adopt fuel economy technologies with a payback period of 30 months or less, it follows that there will be net price increases in any regulatory scenario. Higher CAFE standards make it costlier for manufacturers to produce vehicles and, as a result, prices of new vehicles increase. As long as the quality-adjusted price increases,[602] sales of new vehicles are likely to decline, on the margin. Through the lens of supply and demand curve interactions, the quality-adjusted price increase equates to a shift inward of the supply curve for new vehicles. All else equal, this movement corresponds to an increase in the equilibrium price, and decrease in equilibrium quantity, of new vehicles purchased.

[602] The quality adjusted price is considered higher when regulatory compliance costs exceed 30 months of fuel savings.

New and used vehicles are substitutes. When the price of a good's substitute increases, the demand curve for that good shifts outward and the equilibrium price and quantity supplied both increase. Thus, increasing the quality-adjusted price of new vehicles will result in an increase in equilibrium price and quantity of used vehicles. Since, by definition, used vehicles are not being "produced" but rather "supplied" from the existing fleet, the increase in quantity must come via a reduction in their retirement rates. Practically, when new vehicles become more expensive, demand for used vehicles increases (and these used vehicles become more expensive). Because used vehicles are more valuable in such circumstances, they are scrapped at a lower rate, and just as rising new vehicle prices push marginal prospective buyers into the used vehicle market, rising used vehicle prices force marginal prospective buyers of used vehicles to acquire older vehicles or vehicles with fewer desired attributes.

See FRIA Chapter 4.5 for a more detailed theoretical discussion of the effects of higher CAFE standards on the used car market.

4.2.2.2 Model Development

The unintended consequence of emissions standards on scrappage rates was first observed by Gruenspecht shortly after the inaugural CAFE standards were promulgated in 1978.[603] Gruenspecht identified criteria pollutant standards as a form of differentiated regulation; a regulation that affected some vehicles but not others – in this case, new vehicles but not used vehicles. CAFE standards are another form of differentiated regulation, regulating the fuel economy of new, but not used, vehicles and so may produce the same kind of scrappage effect in the used vehicle population. Since then, the relationship between fuel economy standards and scrappage has been a growing topic of academic literature. In preparation of the previous rule—which marked the first CAFE rulemaking to dynamically model scrappage—the agency performed a detailed review of the literature on this topic.[604] The principal conclusion from the literature review was that, among the studies that have attempted to estimate this effect directly, there is consensus about both its existence and direction (i.e., higher used vehicle prices lead to slower retirement rates) but estimates of the magnitude of the effect vary. The agency used the literature and other regulatory scrappage models—mainly CARB's 2004 CARBITS vehicle transaction choice model[605]—as a springboard to create a scrappage model that would be internally consistent with the broader CAFE Model.[606]

While the agency did not use any particular model from the literature, the agency retained the framework outlined by Greenspan and Cohen to construct the CAFE Model's scrappage model. Greenspan and Cohen identified two types of scrappage - engineering scrappage and cyclical scrappage.[607] Engineering scrappage represents the physical wear on vehicles which results in their being scrapped. Cyclical scrappage represents the effects of macroeconomic conditions on

[603] Gruenspecht, H. "Differentiated Regulation: The Case of Auto Emissions Standards." American Economic Review, Vol. 72(2), pp. 328–31 (1982).
[604] *See* 83 Fed. Reg. 43093-94 (Aug. 24, 2018).
[605] Id.
[606] There were four elements identified as being necessary. The agency noted that none of the existing scrappage models in literature met all four criteria.
[607] Greenspan, A. & Cohen, D. "Motor Vehicle Stocks, Scrappage, and Sales." Review of Economics and Statistics, vol. 81, no. 3, 1999, pp. 369–83., doi:10.1162/003465399558300.

the relative value of new and used vehicles—under economic growth the demand for new vehicles increases and the value of used vehicles declines, resulting in increased scrappage and more rapid fleet turnover. In addition to allowing new vehicle prices to affect cyclical vehicle scrappage à la the Gruenspecht effect, Greenspan and Cohen also note that engineering scrappage seemed to increase where EPA vehicular-criteria pollutant emissions standards also increased; as more costs went towards compliance technologies, scrappage increased. In this way, Greenspan and Cohen identify two ways that fuel economy standards could affect vehicle scrappage: 1) through increasing new vehicle prices, thereby increasing used vehicle prices, and finally, reducing on-road vehicle scrappage, and 2) by shifting resources towards fuel-saving technologies—potentially reducing the durability of new vehicles. Under this framework, CAFE standards influence only engineering scrappage, but do so in the context of macroeconomic conditions that influence cyclical scrappage. The current implementation of the scrappage model is relatively unchanged from the scrappage model used in the 2020 final rule, which had made a variety of improvements as compared to the model used for the prior NPRM and addressed other substantive comments.

4.2.2.2.1 Variables and Data Used to Estimate Scrappage

Many competing factors influence the decision to scrap a vehicle, including the cost to maintain and operate it, the household's demand for VMT, the cost of alternative means of transportation, and the value that be attained through reselling or scrapping the vehicle for parts. A car owner will decide to scrap a vehicle when the value of the vehicle is less than the value of the vehicle as scrap metal, plus the cost to maintain or repair the vehicle. In other words, the owner gets more value from scrapping the vehicle than continuing to drive it, or from selling it. Typically, the owner that scraps the vehicle is not the first owner. For the purposes of this exercise, any vehicle that disappears from the U.S. population is considered to be retired or "scrapped," despite the fact that many of them are neither dismantled nor actually retired from service. Many vehicles, whose value has declined to a point where continuing to operate and maintain them in the United States no longer makes economic sense, are merely exported to other countries (typically sold at auction) where they continue their lives for some number of years. Others disappear as a result of collisions or irreparable mechanical failures, but present the same way for our purposes here – they fail to appear in the registration roles and, for our purposes, are assumed to be scrapped.

While scrappage decisions are made at the household level, the agency is unaware of sufficient household data to capture scrappage at that level. Instead, NHTSA uses aggregate data measures which capture broader market behavior.

The agency is interested in how changes in new vehicle prices and fuel economy impact the retirement rate of the on-road fleet *over time.* In order to isolate this effect, NHTSA needed multi-period data on the scrappage rates of used vehicles and prices of new vehicles. Scrappage, itself, is a phenomenon inherently defined over multiple time periods; it represents a change in a vehicle (or model year cohort's) registration status between one period and the next. As such, the potential scrappage effect can only be measured through time series data. The data contain information about national vehicle registrations in each calendar year from 1975 to 2017.[608] 1975 was the earliest year where all data were available.

4.2.2.2.1.1 Age and Durability

The most predictive element of vehicle's scrappage in a given year is the influence of 'engineering scrappage.' This source of scrappage is largely determined by the age of a vehicle and the durability of a specific model year vintage. For a model year cohort, vehicle scrappage typically follows a roughly logistic function with age — that is, instantaneous scrappage increases to some peak, and then declines, with vehicle age until all (or nearly all) of the vehicles produced in a given year have been retired (which is illustrated in Figure 4-6).

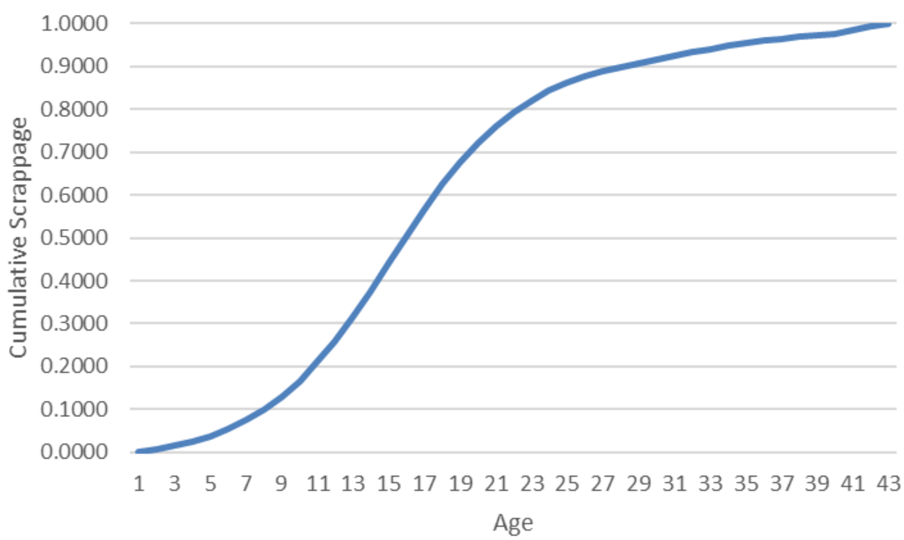

Figure 4-7 – Cumulative Scrappage for a Model Year Cohort

NHTSA uses proprietary vehicle registration data from IHS-Polk, the National Vehicle Population Profile (NVPP), to collect vehicle age and estimate durability. While the agency gives preference to publicly accessible data whenever possible, the NVPP represents the most comprehensive and complete source of vehicle registration information the agency has identified to date.

The data cover the following regulatory classes as defined by NHTSA - passenger cars, light trucks (classes 1 and 2a), and medium and heavy-duty trucks (classes 2b and 3). Polk separates these vehicles into finer market segments based on body style and gross vehicle weight rating. In order to build scrappage models to support this action, it was important to aggregate these vehicle types in a way that is compatible with the existing CAFE Model.

Since for the purposes of this analysis, vans/SUVs are sometimes classified as passenger cars and sometimes as light trucks for regulatory purposes, survival schedules were developed to vary by body style. Separate models were developed for cars, vans/SUVs, and pickup trucks. This

[608] The analysis begins in 1975 as this is the earliest year all required input data were available.

approach is preferable to alternative methods—such as dividing vehicles by regulatory class—because VMT schedules are calculated based on body style in the analysis. Furthermore, these vehicle body styles are assumed to serve different purposes and, as a consequence, likely result in different lifetime scrappage patterns.

Once stratified into body style buckets, the data are aggregated into population counts by vintage (model year) and age. These counts represent the population of vehicles of a given body style and vintage in a given calendar year. How many vehicles remaining in the fleet can be viewed as the durability of a particular model and the difference between the counts of a given vintage and body style from one calendar year to the next is assumed to represent the number of vehicles of that vintage and style scrapped in a given year.

One issue with using snapshots of registration databases as the basis for computing scrappage rates is that vehicles are not removed from registration databases until the last valid registration expires. For example, if registrations are valid for a year, vehicles will still appear to be registered in the calendar year in which they are scrapped. To correct for the scrappage that occurs during a calendar year, a similar correction as that in Greenspan and Cohen (1996) is applied to the Polk registration data. We assume that the real on-road count of vehicles of a given model year registered in a given calendar year (CY) is best represented by the Polk count of the vehicles of that model year in the succeeding calendar year ($Polk_{CY+1}$). For example, the vehicles scrapped between CY 2000 and CY 2001 will still remain in the Polk snapshot from CY 2000 ($Polk_{CY2000}$), as they will have been registered at some point in that calendar year, and therefore exist in the database. Using a simplifying assumption that all States have annual registration requirements,[609] vehicles scrapped between July 1st, 1999 and July 1st, 2000 will not have renewed registration between July 1st, 2000 and July 1st, 2001, and will not show up in $Polk_{CY2001}$. The vehicles scrapped during CY2000 are therefore represented by the difference in count from the CY 2000 and CY 2001 Polk datasets: $Polk_{CY2001}$ - $Polk_{CY2000}$.

For new vehicles (vehicles where model year is greater than or equal to calendar year), the count of vehicles will be smaller than the count in the following year—not all of the model year cohort will have been sold and registered. For these new model years, Greenspan and Cohen assume that the Polk counts will capture all vehicles which were present in the given calendar year and that approximately one percent of those vehicles will be scrapped during the year. Importantly, this analysis begins modeling the scrappage of a given model year cohort in: $CY = MY + 2$,[610] so that the adjustment to new vehicles is not relevant in the modeling because it only considers scrappage after the point where the on-road count of a given MY vintage has reached its maximum.

609 In future analysis, it may be possible to work with State-level information and incorporate State-specific registration requirements in the calculation of scrappage, but this correction is beyond the initial scope of this rulemaking analysis. Such an approach would be extraordinarily complicated as States can have very different registration schemes, and, further, the approach would also require estimates of the interstate and international migration of registered vehicles.

610 Calculating scrappage could begin at CY=MY+1, as for most model year the vast majority of the fleet will have been sold by July 1st of the succeeding CY, but for some exceptional model years, the maximum count of vehicles for a vintage in the Polk data set occurs at age 2.

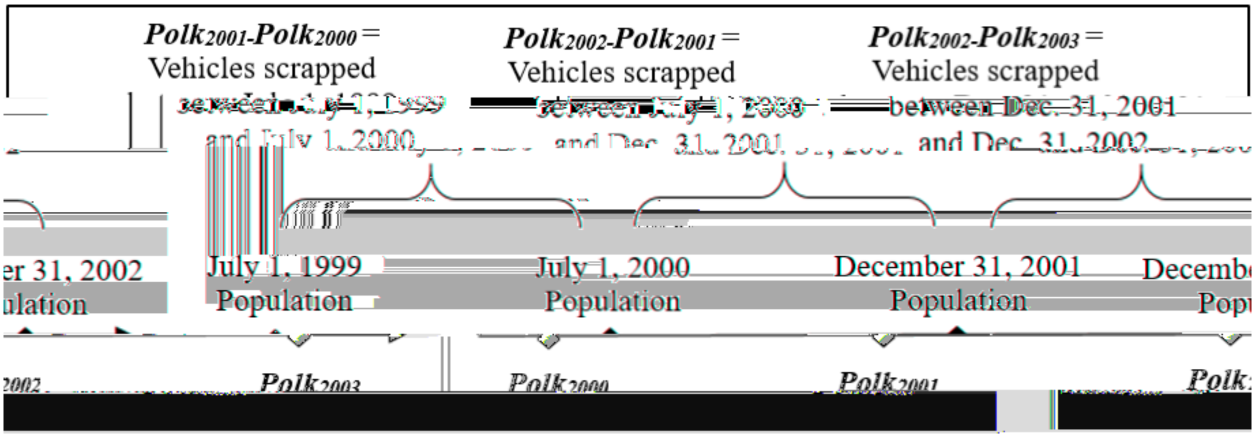

Figure 4-8 – Visualization of Greenspan-Cohen Adjustment and Polk Data Collection Change

There is a discontinuity between 2001 and 2002 data due a change in data collection.[611] Scrappage computed for calendar year 2001 represents the difference between the vehicle count reported in $Polk_{CY2002}$ and $Polk_{CY2001}$. $Polk_{CY2001}$ represents all vehicles on the road as of July 1st, 2000, and $Polk_{CY2002}$ represents all vehicles on the road as of December 31, 2001. For this one timespan, the scrappage will represent vehicles scrapped over a 17-month time period, rather than a year. For this reason, the CY 2001 scrappage data point is dropped, and because of the difference in the time period of vehicles scrapped under the old and new collection schemes, an indicator for scrappage measured before and after CY 2001 was considered; however, this indicator is not statistically significant, and is dropped from the preferred model. Variations in the resolution of state registration data over time have caused some calendar years to contain a larger number of vintages than others – the trend being that the oldest calendar years contain the fewest ages. The number of observations for each range of vehicle ages (across the set of calendar year snapshots) is summarized in Table 4-5.

[611] Prior to calendar year 2002, Polk vehicle registration data were collected as a single snapshot on July 1st of every calendar year. For calendar years 2002 and later, Polk changed the timing of the data collection process to a rolling collection ending on December 31. That is, they consider information from other data sources to remove vehicles from the database that have been totaled in crashes before December 31st, but may still be active in State registration records. The switch to a partially rolling dataset means that some of the vehicles scrapped in a calendar year will not appear in the dataset and their scrappage will wrongly be attributed to the year prior to when the vehicle is scrapped. While this is less than ideal, these records represent only some of the vehicles scrapped during crashes and scrappage rates due to crashes should be relatively constant over the 2001 to 2002-time period. For these reasons, NHTSA expects the potential bias from the switch to a partially rolling dataset to be limited. Thus, the Greenspan and Cohen adjustment applied does not change for the dataset complied from Polk's new collection procedures.

Table 4-5 – Summary Vehicle Age and Vintage

Ages	Calendar Years	Count
0-15	1975-2017	43
16	1994-2017	24
17	1995-2017	23
18	1996-2017	22
19	1997-2017	21
20	1998-2017	20
21	1999-2017	19
22	2000-2017	18
23	2001-2017	17
24	2001-2017	17
25	2001-2017	17
26	2001-2017	17
27-39	2001-2017	17

4.2.2.2.1.2 New Vehicle Prices

As discussed earlier, new and used vehicles are substitutes. Therefore, the price of new vehicles will have a strong effect on the value of used vehicles and, thus, their scrappage rates. This is the primary mechanism by which higher CAFE standards affect retirement rates of used vehicles. For historical data on new vehicle transaction prices, NHTSA uses data from the National Automobile Dealers Association (NADA).[612] The data consist of the average transaction price of all light-duty vehicles; since the transaction prices are not broken-down by body style, the model may miss unique trends within a particular vehicle body style. The transaction prices are the amount consumers paid for new vehicles and exclude any trade-in value credited towards the purchase. This may be particularly relevant for pickup trucks, which have experienced considerable changes in average price as luxury and high-end options entered the market over the past decade. Future models will further consider incorporating price series that consider the price trends for cars, SUVs and vans, and pickups separately.

NHTSA considered using the Bureau of Labor Statistics (BLS) New Vehicle Consumer Price Index (CPI). The purpose of BLS data is to show how prices of similar goods and services change over time. As such, the BLS New Vehicle CPI adjusts prices based on vehicle features—such as safety and fuel economy improvements. While this is good for some purposes, it incorporates into the price assumptions that are controlled for elsewhere in today's analysis.

As further justification, Park (1977) cites a discontinuity found in the amount of quality adjustments made to the series so that more adjustments are made over time.[613] This could further limit the ability for the BLS New Vehicle CPI to predict changes in vehicle scrappage.

612 The data can be obtained from NADA. For reference, the data for MY 2020 may be found at https://www.nada.org/nadadata/. (Accessed: February 15, 2022).

613 Parks, R. W. "Determinants of Scrapping Rates for Postwar Vintage Automobiles." Econometrica, vol. 45, no. 5, 1977, at p. 1099.

However, in order to ensure consistency with the sales response mechanism in the CAFE Model, the observed transaction prices have been modified for estimation (and subsequent simulation inside the CAFE Model). In the tables that follow, *New Price - FS* represents the average price of new vehicles minus 30 months of fuel savings for all body styles. The final specification treats the coefficient on the age interactions for this term as zero for all body styles, but alternative specifications were tested that allow the elasticity of scrappage to vary with age.

4.2.2.2.1.3 Fuel Prices, Fuel Economy, and Cost Per Mile

Instantaneous vehicle scrappage rates are also influenced by fuel economy and fuel prices. Historical data on the fuel economy by vehicle style from model years 1979-2016 were obtained from the 2016 EPA Fuel Economy Trends Report.[614] The van/SUV fuel economy values represent a sales-weighted harmonic average of the individual body styles. Fuel prices were obtained from Department of Energy (DOE) historical values, and future fuel prices within the CAFE Model use the AEO 2021 Reference Case fuel price projections.[615] Fuel price assumptions in this analysis are described further in Chapter 4.1.2. From these values the average cost per 100 miles of travel for the cohort of new vehicles in a given calendar year and the average cost per 100 miles of travel for each used model year cohort in that same calendar year are computed.[616] The agency expects that as the new vehicle fleet becomes more efficient (holding all other attributes constant), it will be more desirable, and the demand for used vehicles should decrease (increasing their scrappage). As a given model year cohort becomes more expensive to operate due to increases in fuel prices, it is expected the scrappage rate of vehicles from that model year will increase. It is perhaps worth noting that more efficient model year vintages will be less susceptible to changes in fuel prices, as absolute changes in their cost per mile will be smaller. The functional forms of the cost per mile measures are further discussed in the model specification section below.

4.2.2.2.1.4 Macroeconomic Data

To capture the cyclical effects of scrappage, the model must include a variable accounting for economic conditions. The agency uses the growth rate of real GDP for the analysis. GDP growth rates are sourced from AEO 2021 through 2050, and extrapolated at the final (stable) growth rate through 2090. Because the purpose of building this scrappage model is to project vehicle survival rates under different fuel economy alternatives, and the current fuel economy

[614] Environmental Protection Agency, Light-Duty Automotive Technology, Carbon Dioxide Emissions, and Fuel Economy Trends - 1975 through 2016, EPA-420-R-16-010, November 2016.

[615] Note - The central analysis uses the AEO reference fuel price case, but sensitivity analysis also considers the possibility of AEO's low and high fuel price cases.

[616] Work by Jacobsen & van Bentham suggests that these initial average fuel economy values may not represent the average fuel economy of a model year cohort as it ages — mainly, they find that the most fuel-efficient vehicles scrap earlier than the least fuel-efficient models in a given cohort. This may be an important consideration in future endeavors that work to link fuel economy, VMT, and scrappage. Studies on "the rebound effect" suggest that lowering the fuel cost per driven mile increases the demand for VMT. With more miles, a vehicle will be worth less as its perceived remaining life will be shorter; this will result in the vehicle being more likely to be scrapped. A rebound effect is included in this analysis, but expected lifetime VMT is not included within the current dynamic scrappage model.

projections go as far forward as calendar year 2050, using a data set that encompasses projections at least through 2050 is essential.

NHTSA considered using U.S. unemployment rate and per capita personal disposable income as alternatives to GDP growth rate to capture the cyclical component of the macro-economy. Since these three variables are highly correlated, the model may only contain one of these indicators. The agency tested the scrappage model with unemployment and per capita personal disposable income data, gathered from BEA. The results showed evidence of autocorrelation in the error terms that is absent when GDP is used instead.

4.2.2.2.1.5 Cash for Clunkers

On June 14, 2009, the Car Allowance Rebate System (CARS) became law, with the intent to stimulate the economy through automobile sales and accelerate the retirement of older, less fuel efficient and less safe vehicles. The program offered a \$3,500 to \$4,500 rebate for vehicles traded-in for the purchase of a new vehicle. Vehicles were subject to several program eligibility criteria: first, the vehicle had to be drivable and continuously registered and insured by the same owner for at least one year; second, the vehicle had to be less than 25 years old; third, the MSRP had to be less than \$45,000; and finally, the new vehicle purchased had to be more efficient than the trade-in vehicle by a specified margin. The fuel economy improvement requirements by body style for specific rebates are presented in Table 4-6.

Table 4-6 – CARS Fuel Economy Improvement Required for Rebates by Regulatory Class

	\$3,500 Rebate Eligibility	**\$4,500 Rebate Eligibility**
Passenger Car	4-9 MPG Improvement	10+ MPG Improvement
Light Truck	2-5 MPG Improvement	5+ MPG Improvement

By August 25, 2009, the program spent its \$2.85 billion budget on 678,359 eligible transactions. As a condition of the program, the vehicles were scrapped at the point of trade-in by destroying the engine. The CARS program arguably had two transitory effects on scrappage. First, some vehicles may have been prematurely scrapped in exchange for the trade-in credit. Second, the trade-in incentive likely increased demand for new vehicles, which in-turn increased new vehicle prices. Both of these effects would accelerate scrappage for the duration of the program. The Polk data support this hypothesis as vehicle scrappage rates spiked in 2009. Figure 4-8 shows the impact of the program from another perspective. It shows the observed instantaneous scrappage rate of MYs 1977-2015 by age for CYs 1980-2015. The black stars represent observed scrappage rates for calendar years where the CARS program was not in effect, the red stars represent CY 2009 when the CARS program was in effect, and the blue dots represent the mean value of the scrappage when CARS was not in effect.

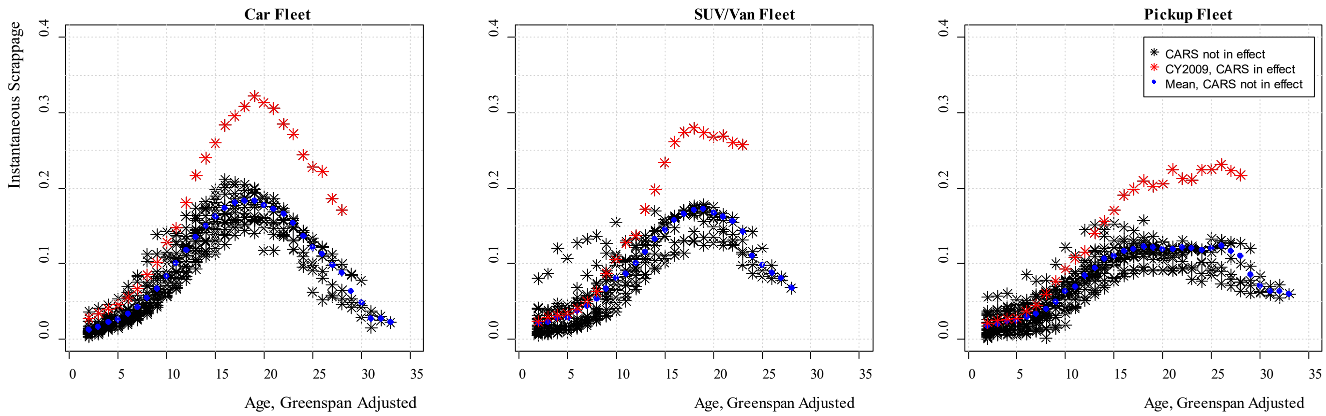

Figure 4-9 – Impacts of the 2009 CARS by Body Style

Li, Linn, and Spiller (2010) used Canada as a counterfactual example to identify the portion of CARS trade-ins attributable to the policy, i.e., trade-ins that would not have happened anywhere if the program were not in place.[617] They argued that the Canadian market is largely similar to the U.S. market, in part based upon the fact that 13 to 14 percent of households purchased new vehicles one year pre-recession in both countries. They also argued that the economic crisis affected the Canadian economy in a similar manner as it affected the U.S. economy. They noted that when Canada offered a small rebate of $300 to vehicles traded in during January 2009, only 60,000 vehicles were traded in under that program. Using those assumptions, Li, et al., applied a difference-in-difference methodology to isolate the effect of the CARS program on the scrappage of eligible vehicles. Li, et al., found a significant increase in the scrappage only for eligible U.S. vehicles, suggesting they isolated the effect of the policy. They conclude that of the 678,359 trade-ins made under the program, 370,000 of those would not have happened during July and August 2009.

The agency finds the evidence from Li, et al., persuasive toward the inclusion of a control for the CARS program during calendar year 2009. Notable from Figure 4-8 is that the effect of CARS on instantaneous scrappage is largest around the point that the average scrappage peaks for all other calendar years for each body style. For cars the effect of the program increases until around age 20 and then decreases, for vans/SUVs the effect increases until just after age 15 and then decreases at a much slower rate, and finally, for trucks the effect increases steadily until around age 17 and then nearly levels off for all observed ages. For this reason, a dummy variable for CY 2009 was interacted with linear and non-linear age variables to represent the effect of the CARS program. The analysis confirmed that modeling as a constant dummy variable is sufficient to capture the nonlinear effect and accurately predict the spikes in scrappage under the CARS program.

[617] Li, S. et al. "Evaluating Cash-for-Clunkers - Program Effects on Auto Sales and the Environment." Journal of Environmental Economics and Management, vol. 65, no. 2, 2013, pp. 175–93., doi:10.1016/j.jeem.2012.07.004.

4.2.2.3 Model Specification

4.2.2.3.1 Stationary Testing

As discussed earlier, the scrappage model utilizes panel data. Panel data observe multiple individuals or cohorts over time. The data employed by the scrappage model observes the scrappage rates of individual model year cohorts between successive calendar years. The model allows for the isolation of trends over time and across individuals.[618] Since the scrappage model uses aggregate model year cohorts to estimate scrappage rates by age and time-dependent variables (new vehicle prices, fuel prices, GDP growth rate, etc.), panel data are necessary to estimate the model. A major challenge to using panel data is that the data structure requires consideration of potential violations of econometric assumptions necessary for consistent and unbiased estimates of coefficients both across the cross-section and along the time dimension. The cross-section of the scrappage data introduces potential heterogeneity bias—where model year cohorts may have cohort-specific scrappage patterns.[619] Stated differently, each model year may have its own inherent durability. The time dimension of a panel introduces a set of potential econometric concerns present in time series analysis.

Before devising the scrappage model, the agency needs to determine which, if any, of the variables are non-stationary. The agency uses the Augmented Dickey-Fuller test to test the variables.[620] The logistic form of the instantaneous scrappage rate is stationary in levels. As such, there are no long-term trends within the scrappage rates that need to be captured and the scrappage model does not require lagged dependent variables to produce stationary residuals. However, to estimate unbiased estimators, the independent variables must also be stationary. The following table summarizes the order of integration of each of the considered regressions; the regression forms represent the form of the variable that is included in the considered models. All the variables considered are either I(0) or I(1), meaning that they should be run in either levels or first differences, respectively. This significantly simplifies the regressions.

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[618] Cambridge University Press. (1989). *Analysis of Panel Data*. New York, NY.
[619] Cambridge University Press. (1989). *Analysis of Panel Data*. New York, NY.
[620] Lupi, Claudio (2019, September 7). Package 'CAFtest.' Retrieved from https://cran.r-project.org/web/packages/CADFtest/CADFtest.pdf. (Accessed: February 15, 2022).

Table 4-7 – Summary of Order of Integration of Considered Scrappage Variables

Scrappage Factor	Considered Measure	Source	Integration Order	Regression Form	Expected Sign
Scrappage Rate	Logistic of inter-annual scrappage rate for a model year/body style cohort	NVPP (IHS/Polk)	I(0)	Levels	N/A
Age	Age defined by the Greenspan and Cohen adjustment	NVPP (IHS/Polk)	N/A	Levels	Polynomial[621]
Model year	Model year as defined from dataset	NVPP (IHS/Polk)	N/A	Levels	See MY Projections[622]
Business cycle indicator	Growth in GDP from previous year (annual, %)	BEA	I(0)	Levels	(+)
Prices of purchase	Average used vehicle prices by age in current year	No source; endogenous	N/A	N/A	(-)
Maintenance/repair costs	Maintenance/repair CPI (fixed to 2016)	BLS	I(1)	Difference	(+)
Prices supply of substitutes	Average new vehicle prices less 30 months fuel savings in current year ($2018)	NADA, EIA, EPA trends	I(1)	Difference	(-)
Prices of usage	Cost-per-mile of model year/body style cohort in current year ($2018/100 mile)	EIA, EPA trends	I(1)	Difference	(+)
Prices of usage	Fuel share weighted fuel prices for model year/body style cohort in current year ($2018)	EIA, EPA trends	I(1)	Difference	(-)[623]

4.2.2.3.2 Modeling Durability of Model Year Cohorts Over Time

As explained in Chapter 4.2.2.2.1.1, engineering scrappage is largely determined by the age of a vehicle and the durability of a specific model year vintage. Because vehicle scrappage typically follows a roughly logistic function with age, the analysis uses a logistic function to capture the trend of vehicle scrappage with age, but allows non-linear terms to capture any skew to the

[621] The effect of age on scrappage is an 'inverted-U' shape; the scrappage rate increases with age up to some age, after which the scrappage rate declines with age.
[622] *See* the section on modeling durability trends over time. Generally, scrappage rates will decrease with successive model years.
[623] Since we include the cost-per-mile, we would expect that the change in fuel prices should capture only a capital constraint where increasing fuel prices will result in less capital to scrap a used vehicle and replace it.

logistic relationship. The durability of successive model years generally increases over time. However, this trend is not constant with vehicle age—the instantaneous scrappage rate of vehicles is generally lower for later vintages up to a certain age, but increases thereafter so that the final share of vehicles remaining converges to a similar share remaining for historically observed vintages. Figure 4-9 to Figure 4-11 shows the survival and scrappage patterns of different vintages with vehicle age for cars, SUVs/vans and pickups, respectively. Cars have the most pronounced durability pattern. Figure 4-9 shows that newer vintages scrap slower at first, but then scrap more heavily so that the final share remaining of cars is relatively constant by age 25 for all vintages.

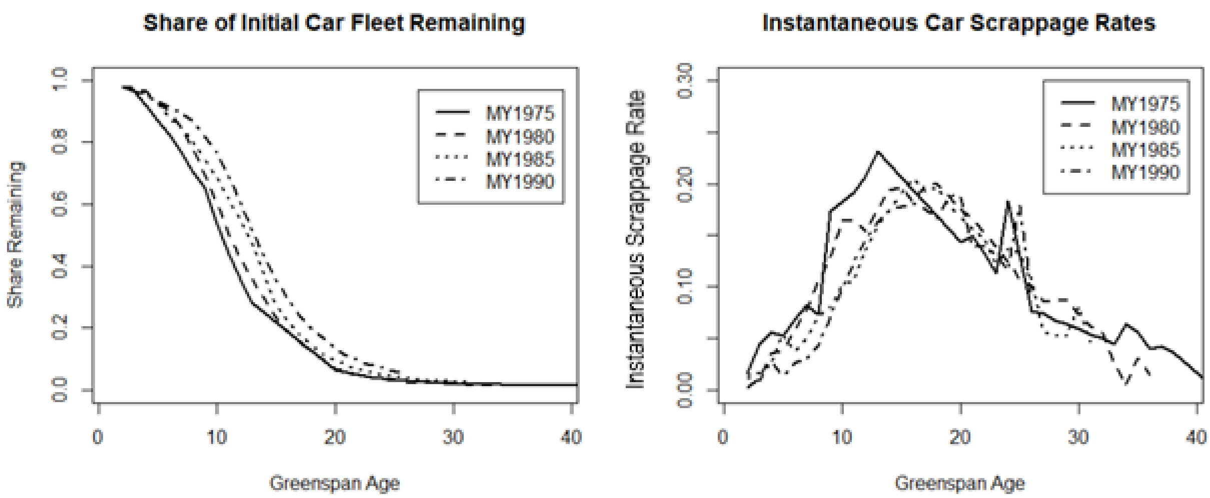

Figure 4-10 – Survival and Scrappage Patterns of Cars by Greenspan Age

SUVs/vans have a less pronounced durability pattern. Model year 1980 actually lives longer than model years 1985 and 1990. This is likely due to a switch of SUVs/vans to be based on car chassis rather than pickup chasses over time. However, through the later model years, the durability trend is more like that of cars. The lack of a continuous trend in durability of SUVs/vans makes the way this trend is captured particularly important.

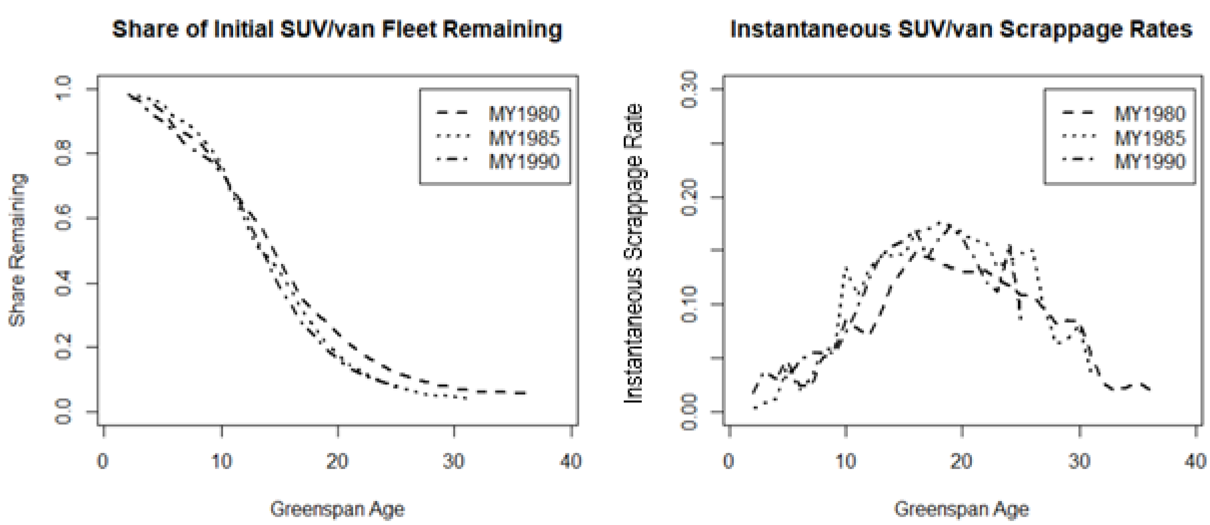

Figure 4-11 – Survival of Scrappage Patterns of SUVs/Vans by Greenspan Age

There is no clear trend in durability for pickups. Like SUVs/vans, this makes parameterizing by using a form of vintage as a continuous variable problematic. Such a parametric form does not allow for each model year to have its own durability pattern.

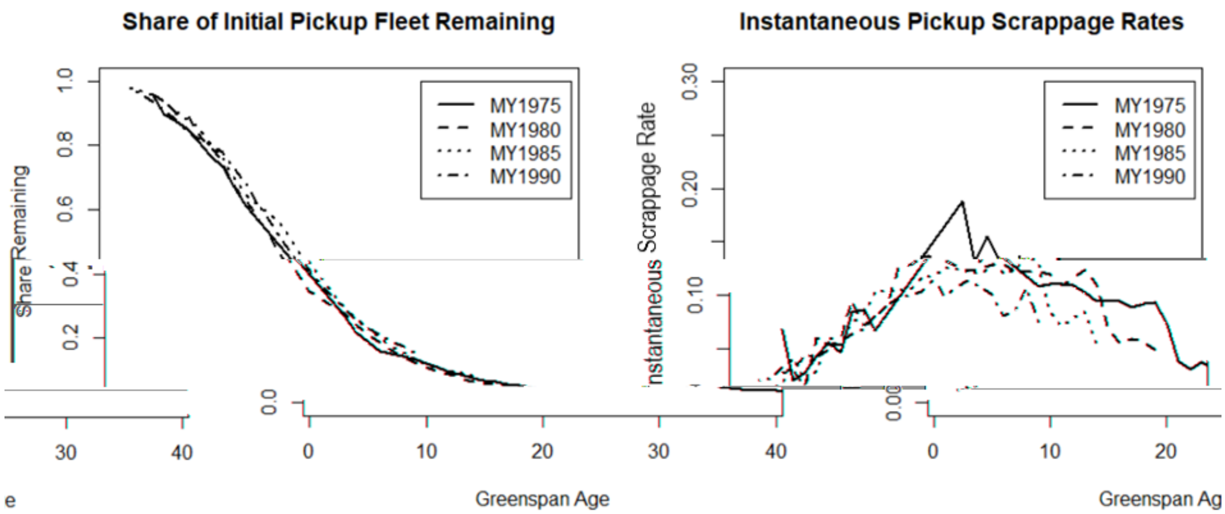

Figure 4-12 – Survival and Scrappage Patterns of Pickups by Greenspan Age

NHTSA attempted to model the natural log of model year as a continuous variable interacted with age to capture an increasing but diminishing trend of vehicle durability for the younger ages. However, enforcing a parametric form on a continuous model year excluded the possibility of including model year specific fixed effects and required that durability to have a parametric trend with successive vintages. As seen above, SUVs/vans and pickups certainly do not follow such a trend, so that this constraint was too restrictive, at least for these body styles.

Instead of regressing the natural log of the vintage share in the remaining models, the agency tried several forms of the share remaining from the previous period as an independent variable, as seen in Table 4-8 through Table 4-10, below. Since the logistic instantaneous scrappage rate is stationary (it is independent of the previous periods' logistic instantaneous scrappage rate), the share remaining should not be endogenous. The specifications that include variables for the share remaining also include model year specific fixed effects, as well as the additional variables that were selected to capture the effect of economic cycles, changes in average new vehicle prices, and other non-engineering considerations on instantaneous scrappage rates.

4.2.2.3.3 Estimating the Scrappage Models

Below is the logistic scrappage equation used in the analysis supporting this final rule.

$$\ln\left(\frac{S_{MY,CY}}{1-S_{MY,CY}}\right) = \beta_0 * Age_{MY,CY} + \beta_1 * {Age^2}_{MY,CY} + \beta_2 * {Age^3}_{MY,CY} +$$

$$\beta_3 * Share\ Remaining_{MY,CY} + \beta_4 * (Age_{MY,CY}\ *\ Share\ Remaining_{MY,CY}) + \beta_5 * ({Age^2}_{MY.CY}\ *\ Share\ Remaining_{MY,CY}) + \beta_6 * Diff(New\ Price - FS)_{CY} +$$

$$\beta_7 * Diff(Fuel\ Price)_{CY} + \beta_8 * Diff(CPM_{MY})_{CY} + \beta_9 * GDP\ Growth_{CY} +$$

$$* I[\quad] + \beta_{11} * (I[CY2009] * I[Age \geq 25]) + (\beta_{12} * I[CY2010] + \beta_{13} * (I[CY2020] *$$
$$* I[Age \geq 25]) + FixedEeffects_{MY}$$

Equation 4-6 – Scrappage Logistic Form

S represents the instantaneous scrappage rate in a period, so that the dependent variable is the logit form of the scrappage rates. Throughout the equation, *Diff* refers to the first difference of a given variable. As discussed in Chapter 4.2.2.3.1, above, it is important to ensure that the statistical properties of a variable do not change with time or else the variable will introduce statistical bias into the analysis. Because several of the variables considered in Table 4-7 were integrated of order 1, it is necessary to use the first difference (the calculated difference in its observed value from time *t* to time *t + 1*) in order to ensure stationarity.

Age represents the age of the model year cohort in a specific calendar year. The coefficient on the cubic age term is assumed to be zero for the van/SUV and pickup specifications as this term is not necessary to capture the general scrappage trend for these body styles. *Share Remaining* represents the share of the original cohort remaining in that calendar year. These two components represent the engineering portion of scrappage—the inherent durability of a model year and the natural life cycle of how vehicles scrap out of a model year cohort as the cohort increases in age.

New Price—FS represents the average price of new vehicles minus 30 months of undiscounted fuel savings for all body styles. The central analysis assumes the coefficient on the age interactions for this term are zero for all body styles, but NHTSA considered alternative specifications that allow the elasticity of scrappage to vary with age. *Fuel Price* is the real fuel prices, weighted by fuel share (across all fuel types, but is overwhelming skewed toward gasoline in the historical data) of the model year cohort being scrapped. *CPM* represents the cost per 100 miles of travel for the specific body style of the model year cohort being scrapped under the current period fuel prices and using fuel shares for that model year cohort. These measures capture the response of scrappage rates to new vehicle prices, fuel savings, and to changes in fuel prices that make the used model year cohort more or less expensive to operate. Because these measures are all I(1), as discussed above in Table 4-7, the first difference of all of these variables is used in modelling.

GDP Growth represents the (real) GDP growth rate for the period. This captures the cyclical components of the macro-economy. Chapter 4.2.2.2.1.4, above, discusses how this specific measure was chosen, and what other measures were considered as alternative or additional independent variables.

I[CY2009] and *I[CY2010]* represent calendar year dummies for 2009 and 2010 when the CARS program was in effect; this controls for the impact of the program.

I[Age ≥ 25] represents an indicator for vehicles 25 years and older. The interaction of the calendar year dummies with this indicator allows for the effect of the CARS program to be different for vehicles under 25 versus vehicles 25 and older. Since only vehicles under 25 were eligible for the program, this flexibility is important to correctly control for the program.

FixedEffects represents a set of model year fixed effects used to control for heterogeneity across different model years. This is related to the durability and engineering scrappage.

Solving for instantaneous scrappage yields the following:

$$S = \frac{e^{\sum \beta_i X_i}}{1 + e^{\sum \beta_i X_i}}$$

Equation 4-7 – Instantaneous Scrappage

In the equation above, $\sum \beta_i X_i$ represents the right-hand side of the above model specification.

Table 4-8 – Car Specifications with Alternative Durability Constructions

Variable	Share Remaining, Quadratic	Preferred Share Remaining, Linear	Share Remaining, Constant
Age	0.0578317*** (0.0070468)	0.0951732*** (0.0058835)	0.4360045*** (0.0021804)
Age2	-0.0019635*** (0.0003689)	-0.0063290*** (0.0002880)	-0.0205609*** (0.0001130)
Age3	-0.0000414*** (0.0000061)	0.0000472*** (0.0000047)	0.0002313*** (0.0000025)
Share Remaining	-3.1435300*** (0.0414626)	-3.4186938*** (0.0343009)	-1.4338395*** (0.0256165)
Age *Share Remaining	0.3120942*** (0.0072003)	0.1806424*** (0.0026794)	
Age2 *Share Remaining	-0.0121010*** (0.0005793)		
Diff(New Price - Fuel Savings)	-0.0000951*** (0.0000013)	-0.0001009*** (0.0000014)	-0.0000912*** (0.0000020)
Diff(Real Gas Price)	-0.4458118*** (0.0200234)	-0.5176484*** (0.0166983)	-0.6428521*** (0.0220153)
Diff(Used Cost Per 100 miles)	0.0524257*** (0.0038726)	0.0620020*** (0.0034245)	0.0714549*** (0.0045965)
GDP Growth Rate	0.0456642*** (0.0008774)	0.0469495*** (0.0010729)	0.0563901*** (0.0010643)
CY2009	0.0732048*** (0.0190192)	0.2075985*** (0.0094498)	0.0839103*** (0.0121392)
CY2009, Ages 25+	0.4512855*** (0.0314314)	0.4920502*** (0.0218911)	0.4029622*** (0.0252641)
CY2010	0.2273621*** (0.0135031)	0.3150729*** (0.0089111)	0.4052745*** (0.0169191)
CY2010, Ages 25+	0.2995697*** (0.0238203)	0.2372077*** (0.0122188)	0.1398496*** (0.0233336)
Adj-R2	0.8989188	0.9001046	0.8957709
AIC	213	201	231
Woodridge AC P-Value[624]	0.0026154	0.0145811	0.0010401

*** p < 0.001, ** p < 0.01, * p < 0.05, . p < 0.1

[624] Note: Wooldridge Test For AR(1) Errors In FE Panel Models implemented as 'pwartest' from the R Package 'plm'. The null hypothesis is that there is serial correlation in the errors, so that a p-value<0.05 suggests that the errors are not serially correlated.

Table 4-9 – SUVs/Vans Specifications with Alternative Durability Constructions

Variable	Share Remaining, Quadratic	Preferred Share Remaining, Linear	Share Remaining, Constant
Age	0.2466527*** (0.0063507)	0.0460123*** (0.0055806)	0.4015673*** (0.0015458)
Age2	-0.0065623*** (0.0001252)	-0.0029204*** (0.0001212)	-0.0095063*** (0.0000358)
Share Remaining	0.0297029 (0.0901657)	-3.3452757*** (0.0554430)	0.7119660*** (0.0222985)
Age *Share Remaining	-0.0621384*** (0.0073936)	0.1825513*** (0.0030923)	
Age2 *Share Remaining	0.0112131*** (0.0003223)		
Diff(New Price - Fuel Savings)	-0.0000228*** (0.0000013)	-0.0000356*** (0.0000013)	-0.0000299*** (0.0000011)
Diff(Real Gas Price)	-0.2764171*** (0.0257452)	-0.4362834*** (0.0278925)	-0.2895806*** (0.0231274)
Diff(Used Cost per 100 Miles)	0.0524134*** (0.0043595)	0.0717750*** (0.0043034)	0.0531272*** (0.0034518)
GDP Growth Rate	0.0695386*** (0.0012301)	0.0657111*** (0.0009900)	0.0795823*** (0.0010000)
CY2009	0.4353784*** (0.0155607)	0.1828926*** (0.0129064)	0.6678445*** (0.0236451)
CY2009, Ages 25+	0.3581448*** (0.0206753)	0.6247703*** (0.0191476)	0.3282078*** (0.0248535)
CY2010	0.0924318*** (0.0167183)	0.2424634*** (0.0126816)	0.3936159*** (0.0158770)
CY2010, Ages 25+	0.3022435*** (0.0215352)	0.1385811*** (0.0298242)	-0.0734390** (0.0223489)
R2	0.9033051	0.9049046	0.8845334
AIC	173	160	288
Woodridge AC P-Value[625]	0.0035220	0.0486846	0.0000051

*** p < 0.001, ** p < 0.01, * p < 0.05, . p < 0.1

[625] Note: Wooldridge Test For AR(1) Errors In FE Panel Models implemented as 'pwartest' from the R Package 'plm'. The null hypothesis is that there is serial correlation in the errors, so that a p-value<0.05 suggests that the errors are not serially correlated.

Table 4-10 – Pickup Specifications with Alternative Durability Constructions

Variable	Share Remaining, Quadratic	Preferred Share Remaining, Linear	Share Remaining, Constant
Age	0.0776425*** (0.0064930)	0.0528728*** (0.0055778)	0.2629608*** (0.0015738)
Age2	-0.0023773*** (0.0001126)	-0.0018482*** (0.0000995)	-0.0057176*** (0.0000225)
Share Remaining	-1.5573629*** (0.1003296)	-1.9174078*** (0.0731793)	0.5012308*** (0.0306657)
Age *Share Remaining	0.1049521*** (0.0054214)	0.1310775*** (0.0034927)	
Age2 *Share Remaining	0.0012152*** (0.0002025)		
Diff(New Price - Fuel Savings)	-0.0000674*** (0.0000019)	-0.0000816*** (0.0000018)	-0.0000581*** (0.0000017)
Diff(Real Gas Price)	-0.2864880*** (0.0334947)	-0.5001835*** (0.0334884)	0.0798291** (0.0299877)
Diff(Used Cost per 100 Miles)	0.0441250*** (0.0056864)	0.0646677*** (0.0057105)	-0.0097471 (0.0052524)
GDP Growth Rate	0.0736057*** (0.0011368)	0.0582337*** (0.0012998)	0.0602333*** (0.0009533)
CY2009	0.5757490*** (0.0170277)	0.5752367*** (0.0170742)	0.5852774*** (0.0205956)
CY2009, Ages 25+	0.0705278* (0.0354674)	-0.0770359* (0.0343983)	0.1636518*** (0.0337895)
CY2010	0.1908829*** (0.0074929)	0.2808360*** (0.0070026)	0.2236518*** (0.0129120)
CY2010, Ages 25+	0.3659284*** (0.0136404)	0.4057619*** (0.0129972)	0.2123575*** (0.0153148)
R2	0.9228605	0.9193500	0.9170718
AIC	-45	-48	-32
Woodridge AC P-Value[626]	0.6073232	0.6683055	0.0516705

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, . $p < 0.1$

As Table 4-8 shows, the linear form of the interaction of age and share remaining does not show evidence of autocorrelation and also has the lowest Akaike Information Criterion (AIC – an estimator of prediction error and measure of model quality) and highest adjusted R-squared. For these reasons, this is the preferred specification of the durability effect. Since the share remaining coefficient is negative and larger than the positive coefficient on the share remaining

[626] Note: Wooldridge Test For AR(1) Errors In FE Panel Models implemented as 'pwartest' from the R Package 'plm'. The null hypothesis is that there is serial correlation in the errors, so that a p-value<0.05 suggests that the errors are not serially correlated.

interacted with age, a cohort that has a higher share remaining at an early age will have a lower instantaneous scrappage rate in this period until a certain age and then a higher scrappage rate after that age. To find the age where the sign of the share remaining coefficient will switch from predicting a lower instantaneous scrappage rate to a higher one, one must take the ratio of the coefficient on the share remaining variable to the share remaining interacted with age—this suggests that at age 19, the sign of the share remaining variable flips. That is, the instantaneous scrappage rate of cars is predicted to be lower if the share remaining is higher until age 18, after which a higher share remaining predicts a higher instantaneous scrappage rate.

Table 4-9 shows, the linear interaction of age and share remaining is the only specification of the durability effect for SUVs/vans that do not show autocorrelation in the error structure. The linear interaction of age and share remaining has the lowest AIC and highest R-squared; for this reason, this is the preferred specification of the durability effect for SUVs/vans. The signs for share remaining and share remaining interacted with age show a similar trend as that to cars. Taking the ratio again of the share remaining to the share remaining interacted with age, for ages 0 to 18 a higher share remaining predicts lower instantaneous scrappage, and for ages beyond 18 it predicts a higher instantaneous scrappage rate.

Table 4-10 shows, all specifications of the durability effect for pickups do not show autocorrelation in the error structures. However, similar to cars and SUVs/vans, the linear interaction of age and share remaining has the lowest AIC and highest adjusted R-squared. For this reason, this is the preferred specification for all body styles. Taking the ratio of the coefficient on share remaining to share remaining interacted with age shows that a higher share remaining will predict a lower instantaneous scrappage rate in the next period for ages 0 through 14, but a higher instantaneous scrappage rate for ages 15 and older.

4.2.2.3.3.1 Projecting Durability in the CAFE Model

The left graphs in Figure 4-12 through Figure 4-14 show the fixed effects for the preferred scrappage specifications for cars, vans/SUVs, and pickups, respectively. For all body styles there is a general downward trend in the fixed effects. This suggests an increase in the durability over successive model years. However, since the panel datasets are unbalanced, there is likely potential bias for the fixed effects that include only certain ages. This makes projecting the durability increase from the fixed effects a little more complicated than merely fitting to all fixed effects. First, NHTSA determined what part of this trend is likely due to increases in vehicle durability (and should be projected forward) and which part of the trend may conflate other factors.

The right graphs in Figure 4-12 through Figure 4-14 show the average observed logistic scrappage rates by model year for all ages where data exist. As can be seen, the average observed scrappage rates decline dramatically for model years after 1996 for all body styles. There are two reasons this trend exists. First, as the figures show, the instantaneous scrappage rate generally follows an inverted u-shape with respect to vehicle age. The instantaneous scrappage rates generally peak between ages 15 and 20 for all body styles. Model year 1996 is the first model year which will be at least age 20 at the most recent year of data used to estimate the scrappage models (calendar year 2016). This means that all model years newer than 1996 have likely not yet reached the age where the instantaneous scrappage rate will be the highest for the cohort. Accordingly, the fixed effects could be biased downwards (consistent with the sharper downward slope in the fixed effects for most body styles for model years beyond 1996) because of the unbalanced nature of the panel, and not because of an actual increase in inherent vehicle durability for those model years.

The second reason the average logistic scrappage rates for model years before 1996 is more stable is because each data point in the average has increasingly less effect on the average as more data exist. For model years 1996 and older there are at least 18 data points (we start the scrappage at age 2, by which point effectively all of a model year has been sold), and each will have a smaller effect on the average than for newer model years with fewer observations. For these reasons, the average observed logistic scrappage rate is more constant for model years before 1996. As a result, we do not consider the trend in fixed effects after model year 1996 to rely on enough historical data to represent a trend in vehicle durability, as opposed to a trend in the scrappage rate with vehicle age.

In considering which model year fixed effects should be considered in projecting durability trends forward, another important factor is whether there are discrete shifts in the types of vehicles that are in the market or category of each body style over time. For cars, an increasing market share of Japanese automakers which tend to be more durable over time might result in fixed effects for earlier model years being higher. This trend is shown in the fixed effects in Figure 4-12, which follow a steeper trend before model year 1980.

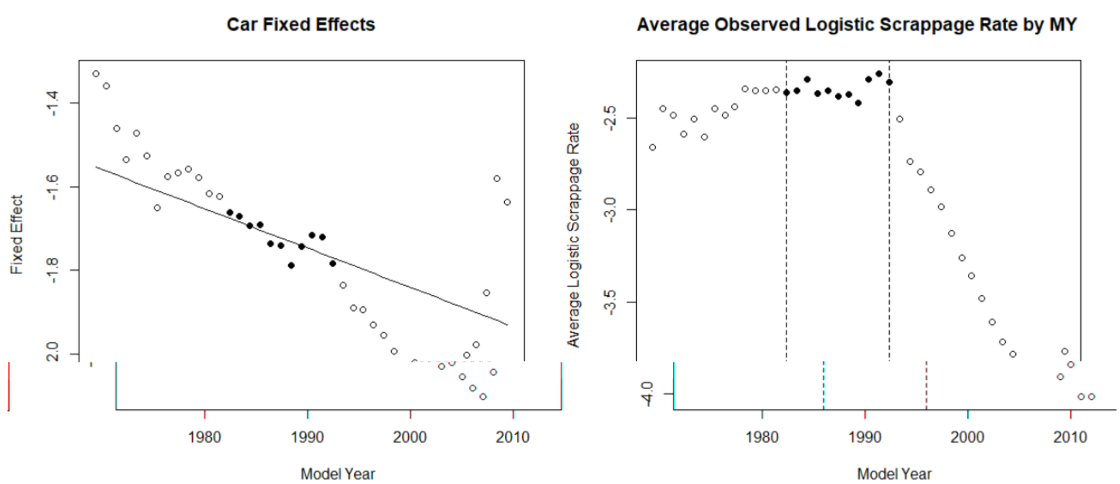

Figure 4-13 – Trends in Fixed Effects for Preferred Car Specification

For vans/SUVs, earlier model years are more likely to be built on truck chassis (body-on-frame construction) instead of car chassis (unibody construction). Since pickups tend to be more durable, the earlier fixed effects are likely to be lower for vans/SUVs for earlier model years. The 1984 Jeep Cherokee was the first unibody construction SUV.[627] As Figure 4-13 shows, the fixed effects before 1986 show inconsistent trends; these are likely due to changes in what was

[627] https://www.autoguide.com/auto-news/2018/01/10-interesting-facts-from-the-history-of-the-jeep-cherokee.html. (Accessed: February 15, 2022).

considered a van/SUV over time. For this reason, NHTSA builds the trend of fixed effects from model years 1986 to 1996.

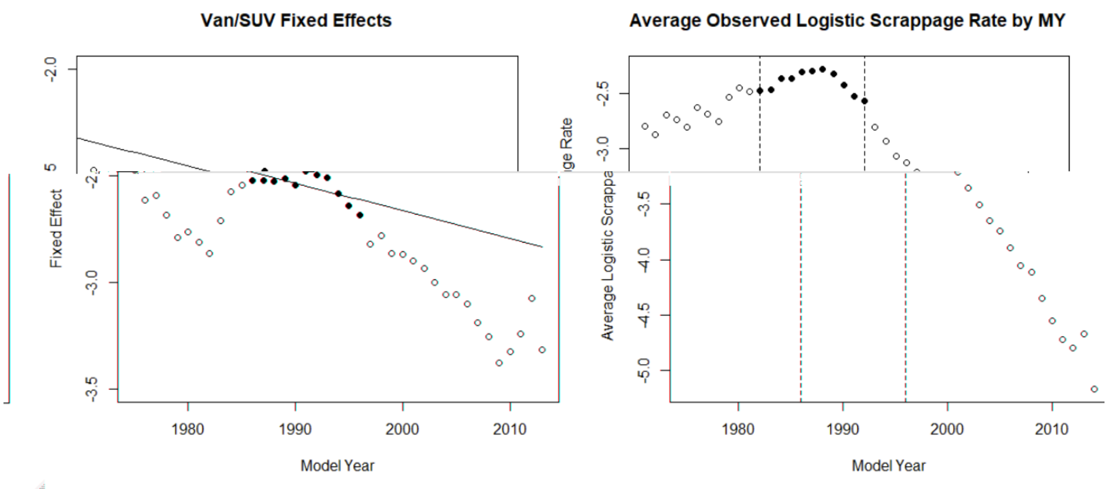

Figure 4-14 – Trends in Fixed Effects for Preferred Van/SUV Specification

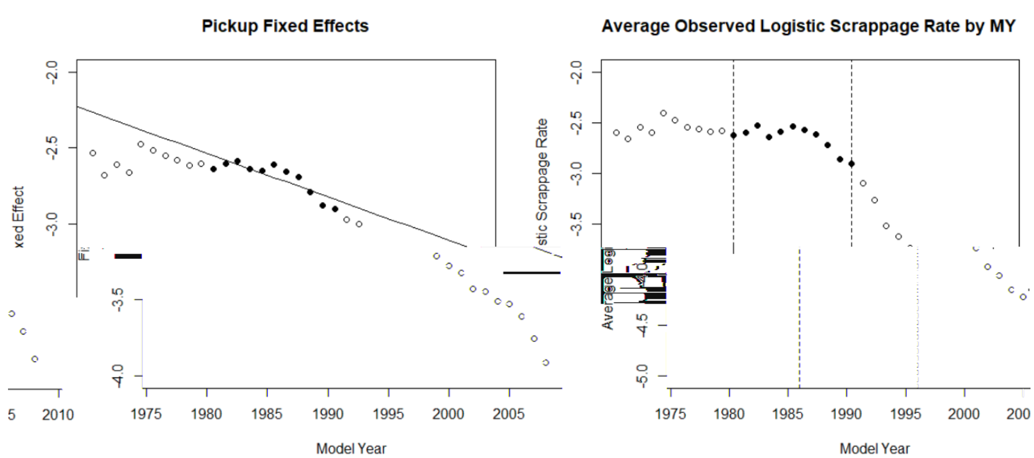

Figure 4-15 – Trends in Fixed Effects for Preferred Pickup Specification

While the trend for pickups and cars could be extrapolated before 1986, NHTSA opted to keep the fixed effects included constant for all body styles. Thus, the projections are built from model year 1986 to model year 1996 fixed effects. Table 4-11 below shows the linear regressions shown as the line on the left side of Figure 4-12 through Figure 4-14. The durability cap represents the last model year where the durability trend is assumed to persist. The agency caps the durability impacts at model year 2005, as data beyond this point do not exist for enough ages to determine if durability has continued to increase since this point. This cap implies that model years after 2005 are assumed to have the same initial durability as model year 2005 vehicles. Since there is a limit to the potential durability of vehicles, this acts as a bound on this portion of the scrappage model (which, in turn impacts simulated fleet size and average age).

Table 4-11 – Durability Inputs in the CAFE Model

Coefficients	Inputs	Cars	Vans/SUVs	Pickups
β_{12}	Intercept	21.13195	25.488	54.52891
β_{13}	MY	-0.01141	-0.01364	-0.02879
β_{14}	MY Durability Cap	2005	2005	2005

The durability projections enter the scrappage equation in the CAFE Model simulations in accordance with the following equation:

$$\ln\left(\frac{S_{MY,CY}}{1-S_{MY,CY}}\right) = \beta_0 * Age_{MY,CY} + \beta_1 * {Age^2}_{MY,CY} + \beta_2 * {Age^3}_{MY,CY} +$$

$$Share\ Remaining_{MY,CY} * (\beta_3 + \beta_4 * Age_{MY,CY}) +$$

$$Diff(New\ Price - FS)_{CY} * (\beta_5 + \beta_6 * Age_{MY.CY} + \beta_7 * {Age^2}_{MY.CY} + \beta_8 * {Age^3}_{MY,CY}) +$$

$$\beta_9 * Diff(Fuel\ Price)_{CY} + \beta_{10} * Diff(CP100M_{MY})_{CY} +$$

$$\beta_{11} * GDP\ Growth_{CY} + \beta_{12} + \beta_{13} * MY_{MY} - \text{ifelse}(MY_{MY} > \beta_{14}, \beta_{13} * (MY_{MY} - \beta_{14}), 0)$$

Equation 4-8 – Durability Projections and Scrappage Equation

The intercept enters as a constant added to the predicted logistic of the instantaneous scrappage rate. The model year slope enters as the model year for all model years older than 2005 and enters as 2005 for all model years 2005 and newer.

Once the predicted logistic scrappage rate is calculated in the CAFE Model (including the projections of the fixed effect portion of the equation), the future population of model year cohorts can be predicted. The instantaneous scrappage can be calculated directly from S. It identifies the share of remaining vehicles in each calendar year that are scrapped in the next year. The population of vehicles in the next calendar year can be calculated as follows:

$$Population_{MY,CY+1} = Population_{MY,CY} * (1 - s_{MY,CY})$$

Equation 4-9 – Calculation of Population of Vehicles in the Next Calendar Year

This process iterates at the end of the CAFE Model simulation to determine the projected population of each model year in each future calendar year. This allows the calculation of VMT, fuel usage, pollutant and CO_2 emissions, and associated costs and benefits. The CAFE Model documentation released with this final rule further details how the scrappage model is projected within the simulations.

4.2.2.3.3.2 Decay Function for Oldest Ages

Nearly six percent of the MY 2015 van/SUV fleet and eight percent of the pickup fleet is projected to persist until age 40. This is unrealistic, and likely due to the fact that the agency does not observe enough model years for those ages and over-predicts the impact of durability increases for those ages. For this reason, the agency uses a scrappage curve with an accelerated decay function to predict instantaneous scrappage beyond age 30 for all classes. Table 4-12 below, shows the inputs used for this analysis.

Table 4-12 – Decay Function Inputs

Coefficients	Inputs	Cars	Vans/SUVs	Pickups
β_{15}	Decay Age	30	30	30
β_{16}	Final Survival Rate	0.01	0.025	0.025

The agency selected to have the decay function begin operating at age 30 as the observed historical trends run through age 30.

The decay function is implemented in the model using the following conditions for the coefficients in Table 4-12:

$$\text{If (age}<\beta_{15}\text{)}, S = \frac{e^{\sum \beta_i X_i)}}{1+e^{\sum \beta_i X_i)}}$$

$$\text{And: } Population_{MY,CY+1} = Population_{MY,CY} * (1 - S_{MY,CY}).$$

$$\text{If (age}>=\beta_{15}\text{)},$$

$$Population_{MY,CY+1} = Population_{MY,CY=\beta_{15}} * exp^{rate*t}$$

$$\text{Where:} t = (age + 1 - \beta_{15})$$

$$\text{And: } rate = \frac{ln\left(\frac{(\beta_{16})}{Population_{MY,CY=\beta_{15}}}\right)}{40-\beta_{15}}$$

Here, the population for ages beyond the start age of the decay function depends on the population of the cohort at that start age and the final share expected for that body style at age 40. Then the model calculates and applies the rate of decay necessary to make the final population count equal that observed in the historical data.

4.2.2.3.4 Other Variables Considered

In addition to the variables included in the scrappage model, the agency considered several other variables that likely—either directly or indirectly—influence scrappage in the real world. As explained in more detail in the forthcoming paragraphs, these variables were excluded from the model either because of a lack of underlying data or due to modeling constraints. Their exclusion from the model is not intended to diminish their importance, but rather highlights the practical constraints of modeling decisions like complex behavior like vehicle scrappage in both an econometric and (subsequently) simulation context.

As noted earlier, households will retire used vehicles when their market value drops below the cost of maintenance necessary to keep them in service longer. As such, maintenance costs play a critical role in determining when vehicles are scrapped. The agency encountered several issues when attempting to incorporate maintenance into the analysis. First, there is a lack of comprehensive data sources for used vehicle maintenance. By far the most comprehensive and complete data set is the BLS maintenance and repair data. However, the BLS data do not measure the cost of maintenance for individual model year cohorts, but instead measures average maintenance cost per calendar year, which limits the usefulness of the data in a panel model. Despite this inherent shortcoming, the agency tried including maintenance as a calendar year effect, but this resulted in poorer model fit. For these reasons, the agency excluded maintenance from the model. If model year specific repair costs become available, the agency will reconsider including maintenance in future model specifications.

The market value of a vehicle at the time of scrappage is equal to a combination of the price of the parts that can be salvaged and the value of the recoverable scrapped metal. The agency considered including the value of steel and iron to capture the scrappage value of vehicles. However, the material composition and mass of vehicles has changed over time meaning that the absolute amount of recoverable scrap steel is not constant. To appropriately estimate the value to scrap a vehicle, the agency would need to know the average weight of recoverable steel by vintage *and* the quantity and value of other recoverable materials. The agency is unaware of any data granular enough to provide estimates of these values. Further, projecting the future value of the recoverable scrap metal would involve computing the amount of recoverable steel under all scenarios of fuel economy standards, where mass and material composition are assumed to vary across all alternatives. The agency attempted to use a coarse approximation of scrappage value by using the BLS scrap steel CPI; similar to maintenance, including the variable diminished the fit of the model. It is also a consideration that, over time, vehicles leave U.S. registration rolls for reasons other than true scrappage (typically export to less wealthy nations where the vehicle still represents a positive value proposition to potential buyers), which would not be as strongly affected by the price of scrap steel.

The scrappage model controls for vehicle characteristics across model years through fixed effects. As an alternative, the agency considered a more granular approach of estimating the impact of discrete vehicle traits, such as horsepower to weight, zero to sixty acceleration time, and average curb weight. However, including these individual traits produced a poorer fit than the model with fixed effects, and showed evidence of autocorrelation in the errors. Similarly, the agency considered using terms that would more directly capture the value of improved fuel economy in newer vehicles, such as the CPM of new vintages, than subtracting the first 30 months of undiscounted fuel prices from the price of new vehicles.[628] These variables did not

[628] The scrappage model cannot include both independent variables on the fuel economy and cost-per-mile of new vehicles, and adjust the new vehicle prices by the value of fuel savings considered at the time of purchase, which would account for the improvement of the fuel economy of new vehicles twice.

improve the fit of the model and would be inconsistent with how the agency approaches consumer valuation of fuel economy throughout the rest of the analysis.

The quantity of new vehicles purchased and scrappage rates seem intuitively interconnected; when new vehicle sales increase, demand for older vehicles decreases, leading to higher scrappage rates. When the agency tested new vehicle sales in the model, the model's fit decreased and the direction of the coefficient was counterintuitive. It also introduced evidence of autocorrelation in the error structure for cars and reduced the effect of the change in fuel prices by two orders of magnitude for vans/SUVs. It seems quite unlikely that fuel price sensitivities would differ so vastly between model types. For these reasons, the scrappage model excludes the change in new vehicles sales. The agencies also considered including changes in vehicle stock, but this similarly did not improve the fit of the scrappage models—and doing so limited the ability to link the sales and scrappage models in future versions of the model.

Higher interest rates increase the cost to purchase new vehicles, which should increase the incentive for households to hold onto existing vehicles. For some households, higher interest rates could act as a barrier to entry; however, the households excluded from the new vehicle market because of a modest change in interest rates are much more likely to be in the market for a used vehicle and their purchasing decision is unlikely to be heavily influenced by interest rates. The agency tested interest rates in the model using the average real interest rate on social security trust public-debt obligations. While this is not a perfect measure of auto loan interest rates, the two are correlated so that that most of the effect of auto loan rates should be captured by using the interest rate facing the federal government. For vans/SUVs the model with interest rates had a poorer fit and showed evidence of autocorrelation in the error structures. For pickups, including interest rates changed the sign on CPM. Interest rates do not affect CPM as CPM measures only the post-sale operating cost.

4.3 Estimating Total Vehicle Miles Traveled

4.3.1 Overview of the Process

The likely future course of car and light truck use directly influences many of the various effects of fuel economy standards that decision-makers consider in determining what levels of standards to set. For example, the value of fuel savings is a function of vehicle's 'fuel efficiency, the number of miles they are driven, and future fuel prices. Similarly, factors like criteria pollutant emissions, congestion, and fatalities are direct functions of vehicle use (usually measured by average or total vehicle-miles traveled, or "VMT.") In the CAFE Model, total VMT is the product of average usage per vehicle in the fleet and the composition of the entire light-duty vehicle fleet, itself a function of new vehicle sales and vehicle retirement (or "scrappage") decisions. In conjunction with the composition of the vehicle fleet by type (cars, SUVs/vans, and pickups) and age at the outset of the analysis period, these three components—average annual use, of vehicles of different ages and body styles sales of new vehicle sales, and scrappage of older vehicles—jointly determine total VMT projections for future years under each alternative.

CAFE Model simulations provide aggregate estimates of light-duty VMT comparable to other well-regarded VMT estimates. However, because decisions about alternative stringencies look at the incremental costs and benefits across alternatives, it is more important that the analysis capture the variation of VMT across the baseline and regulatory alternatives than to accurately predict total VMT for a specific scenario. To accomplish this, the CAFE Model incorporates a model of aggregate VMT developed by the U.S. Department of Transportation's Volpe Center to produce the Federal Highway Administration's (FHWA) official annual VMT forecasts. and constrains the CAFE Model's internally constructed forecasts of total VMT under different regulatory alternatives in each future year to be identical to those produced by the FHWA model[629]

The CAFE Model first uses the FHWA model to develop a forecast of total light-duty VMT for each future calendar year spanned by the analysis (currently 2020 through 2050) that reflects forecasts of the U.S. population, future economic conditions, fuel prices and fleet average fuel economy, and consumer confidence levels. As described in more detail below, this forecast of total VMT is interpreted as "non-rebound" VMT travel and is constrained to be identical for all regulatory alternatives being considered. This produces the desired effect of making the only differences in VMT among regulatory alternatives during any future calendar year a consequence of the rebound effect associated with the specific improvements in fuel economy required by each regulatory alternative.

NHTSA's CAFE Model uses a combination of each year's "top-down" forecast of total light-duty VMT generated by the FHWA model and "bottom-up" forecasting to represent the composition of total VMT. In the latter approach, the composition of the fleet among cars and light truck cohorts of different vintages and ages the average utilization of each cohort determines a base distribution and level of VMT in each calendar year. This "bottom up" forecast is then adjusted to match the "top down" forecast of total VMT for that same calendar year while preserving its distribution of total vehicle use among the car and light truck model year cohorts comprising that year's fleet.

While NHTSA believes that a joint household consumer choice model—if one could be developed adequately and reliably to capture the myriad circumstances under which families and individuals make decisions relating to vehicle purchase, use, and disposal—would better reflect vehicle ownership and use decisions that are made at the household level, it is not necessarily appropriate, to model the national program at that level of disaggregation in order to produce meaningful results that can usefully inform policy decisions. The most useful information for policymakers relates to national-scale impacts of potential policy choices. No other element of the rulemaking analysis is represented or modeled at the household level, and the error associated with allocating specific vehicles to specific households over the course of three decades would easily dwarf any error associated with the estimation of these effects in aggregate.

NHTSA has attempted to incorporate estimates of changes to the new and used vehicle markets at the highest practical levels of aggregation and worked to ensure that these effects produce fleetwide VMT estimates that are consistent with the best, current projections reflecting our economic assumptions. While future work will always continue to explore approaches to

[629] There is a minor and consistent discrepancy between the forecasts of light-duty VMT issued by FHWA and those generated using the CAFE Model, because the former include class 2b and 3 light-duty vehicles while the CAFE Model and analysis exclude them.

improve the realism of CAFE policy simulation, there are important differences in the objectives and design of small-scale econometric research and the kind of flexibility that is required to assess the impacts of a broad range of regulatory alternatives over multiple decades.

4.3.2 Developing the Mileage Accumulation Schedules

To account properly for the values of consumer and societal costs and benefits associated with vehicle usage under various CAFE alternatives, it is necessary to estimate the portion of these costs and benefits occurring during each calendar year that are attributable to the ownership and use of vehicles from each model year cohort. Doing so requires some estimate of how many miles the average vehicle of each body type is expected to be driven during each year (i.e., at each age) throughout its life. We refer to these as “mileage accumulation schedules.” As described in greater detail below, these mileage accumulation schedules represent an initial estimate of average annual vehicle use at each age during some base year, and are subsequently adjusted in each future calendar year based on forecasted fuel prices and the aggregate travel demand determined by a separate forecasting model. For this analysis, NHTSA is relying on a set of mileage accumulation schedules that were constructed from a statistical analysis of millions of unique vehicles followed over their lives, during which odometer readings were recorded at uneven intervals.

4.3.2.1 Data Used to Develop the Schedules

Unlike cross-sectional data, which provide a “snapshot” of the usage of vehicles of different ages at a single point in time, panel data track the use of vehicles over time as they reach different ages and accumulate mileage. Including this temporal dimension resolves many of the limitations imposed by cross-sectional data., which restricted some of the agency’s earlier rulemakings. The data source used to construct the current mileage accumulation schedules contains sequential odometer readings for a very large sample of individual vehicles tracked at the Vehicle Identification number (VIN) level over time. The data vendor, IHS Markit – Polk, accumulates odometer readings for individual vehicles from state inspection programs, title changes, and maintenance events, among other sources. The IHS-Polk dataset includes observations of a specific vehicle’s odometer readings over the course of many years, capturing its accumulated lifetime mileage at multiple ages.

By using the observation date and accumulated miles (represented by the odometer reading), NHTSA computed the rate of driving (miles per year, or month) between observations for each vehicle. This method provides more reliable estimates of variation in vehicle use with increasing age than assuming that the rate of mileage accumulation, over all ages, is simply the ratio of odometer reading to age, as schedules built from cross-sectional data implicitly assume.[630] In particular, calculating the rates of mileage accumulation using successive observations of the same vehicle explicitly resolves the attrition bias (where some vehicles disappear from a cross-sectional data sample because of the intensity with which they were used) and matches the approach to estimating driving rates with panel data in other studies.

[630] Lu, S., “Vehicle Survivability and Travel Mileage Schedules”, DOT HS 809 952, January 2006.

The panel dataset has another advantage over other sources: because it tracks individual vehicles over time, the agencies have more precise and reliable information about each vehicle's age. In previous analyses, we were forced to assume that a vehicle's "age" was equal to the calendar year minus the model year in which the vehicle was produced (for example, all MY 2010 vehicles were assumed to be five years old in calendar year 2015.) It is common for vehicles produced in a given model year to be sold and registered over the course of multiple calendar years. Thus, a MY 2010 vehicle assumed to be five years old in 2015, could have been purchased and registered for the first time in CY 2012 any calendar year from 2009 through (or in rare cases, even later), so its "effective" age could range from 3 to 6 years. The IHS-Polk data allows us to identify the first registration date of each vehicle in the sample and to compute its "true" driving age at each point in time. This not only improves the precision of the mileage accumulation rate in the first year, but in subsequent years and thus at later ages as well.

The agency also considered using the 2017 National Household Travel Survey to develop mileage accumulation schedules. However, it suffers from the same flaws as data sources used to develop previous schedules. It represents a cross section of odometer readings at a single point in time, requiring the assumption that the rate of usage is simply the reported odometer divided by the vehicle's age, or an extrapolation of respondents' daily travel behavior into representative annual schedules, both of which are likely to be poor assumptions.

In contrast, the IHS-Polk dataset contains at least two readings (and frequently several) for over 70 percent of the registered light duty vehicle population in 2016. Additionally, all the odometers reading in the newest National Household Transportation Survey (NHTS) are owner-reported, leading to questionable reliability of the individual data points (and conspicuously "round" numbers in many cases). Finally, the NHTS is intended to be a representative sample of households, but not a representative sample of vehicles. Research has found that creating a representative sample of households can represent a significant challenge, as past iterations of the NHTS have systematically oversampled high-income households.[631] The nature of the sample also explicitly excludes vehicles used for commercial purposes, which nonetheless represent meaningful shares of new vehicle sales, total vehicle use, and fuel consumption.

4.3.2.2 Methodology for Constructing the Schedules

The data used to construct the schedules initially included between two and fifty odometer readings from each of over 251 million unique vehicles within the dataset. While most of the readings had plausible reading dates, odometer counts, and implied usage rates, some of the readings appeared unrealistic and received additional scrutiny. We developed and applied criteria to identify and remove readings that were likely to reflect recording errors. For example, odometer readings predating the commercial release of the vehicle, showing negative VMT accumulation over time, or taken too closely together to provide meaningful insight into annual vehicle usage were removed from the analysis. Such "cleaning" of real datasets is typically necessary, and each step in the process was recorded and documented clearly. Table 4-13 shows the number of VINs, reading pairs, and average readings per VIN by body style.

[631] Lave, C. (1994). State and National VMT Estimates: It Ain't Necessarily So. UC Berkeley: University of California Transportation Center. Retrieved from https://escholarship.org/uc/item/5527j8dj. (Accessed: February 15, 2022).

Table 4-13 – Summary of IHS Polk VMT VIN and Reading Data by Body Style

Body Style	Number of VINs Included	Number of Reading Pairs	Mean Readings per VIN
Car	92,016,334	287,512,165	4.1
SUVs/vans	66,857,117	212,656,710	4.2
Pickups	29,926,984	83,208,986	3.8
MDHD pickups/vans*	10,515,168	27,418,353	3.6
Chassis*	486,471	1,186,653	3.4
Total	199,802,074	611,982,867	4.1

Once the dataset was cleaned, we created a random sample of one million reading pairs, where each pair represented an initial odometer/date reading and a subsequent odometer/date reading from the same vehicle. Analysis of the entire dataset was judged to be overly demanding computationally and unnecessary to provide the desired level of statistical precision in estimates of average vehicle use. Two conditions were created for sampling. The first controlled for IHS-Polk's censoring in the odometer readings recorded in the dataset (described below), while the second ensured the usage data were not biased by survival and represented usage rates over a relatively short period of time. Further analysis suggests that shorter periods between readings is correlated with higher usage rates, so further filtering of the data sample was considered in the regression analysis. Once these filters were applied, we considered several polynomial fits to the average odometer readings by age and body style, and used our preferred models to construct the mileage accumulation schedules used in this analysis. The details of this process are described below.

The reported odometer readings are limited to a maximum value of 250,000 miles. For this reason, we excluded readings recorded exactly as 250,000 miles. The censoring could bias estimates of usage rates if odometer readings and future usage rates are correlated, as seems likely to be the case. Vehicles with reported odometer readings of exactly 250,000 miles in the dataset almost certainly have higher true odometer readings. While we intend to reconcile this limitation of the dataset in future work, the benefits of observing actual usage through 30 years of a vehicle's life more than compensate for the limitation.

The IHS-Polk dataset is conditional on survival, so it represents the usage of vehicles remaining in use at the time of the sample (the end of the first quarter of 2017). In this way, it captures the actual observed usage rates of vehicles surviving to their current age son that date. This raises an important concern: if usage rates from earlier ages and survival are correlated, which they are likely to be, then including the readings for a 30-year-old vehicle when it was 10 years old will bias the estimated usage rates of 10-year-old vehicles downward because vehicles that survive to advanced ages tend to have been used less heavily than vehicles of the same vintage that were retired at earlier ages. To mitigate this issue, we applied a second filter when sampling the data set: we only included readings where the date of the second reading in the pair is January 2015 or later. This reduces any potential bias introduced by the joint probability distribution of usage and survival to only those vehicles scrapped between January 2015 and the first quarter of 2017. This decision balances the drawbacks of losing information on vehicles of older ages that are not well-represented in the sample by excluding too many of these vehicles against the potential for biasing the estimates of usage by age.

The distribution of vehicle use at a given age can initially be wide, but tends to narrow over time, as even the best-preserved old vehicles can only be driven so much. Figure 4-15 illustrates the distribution of observed VMT, by age, for SUVs (figures constructed for cars and pickup trucks showed similar patterns) across a 10 million-record random sample of the IHS-Polk odometer data. As the figure shows, the distribution of observed annual usage can be wide – particularly at early ages – but both the mean annual VMT and the range of observations decreases gradually with increasing age.

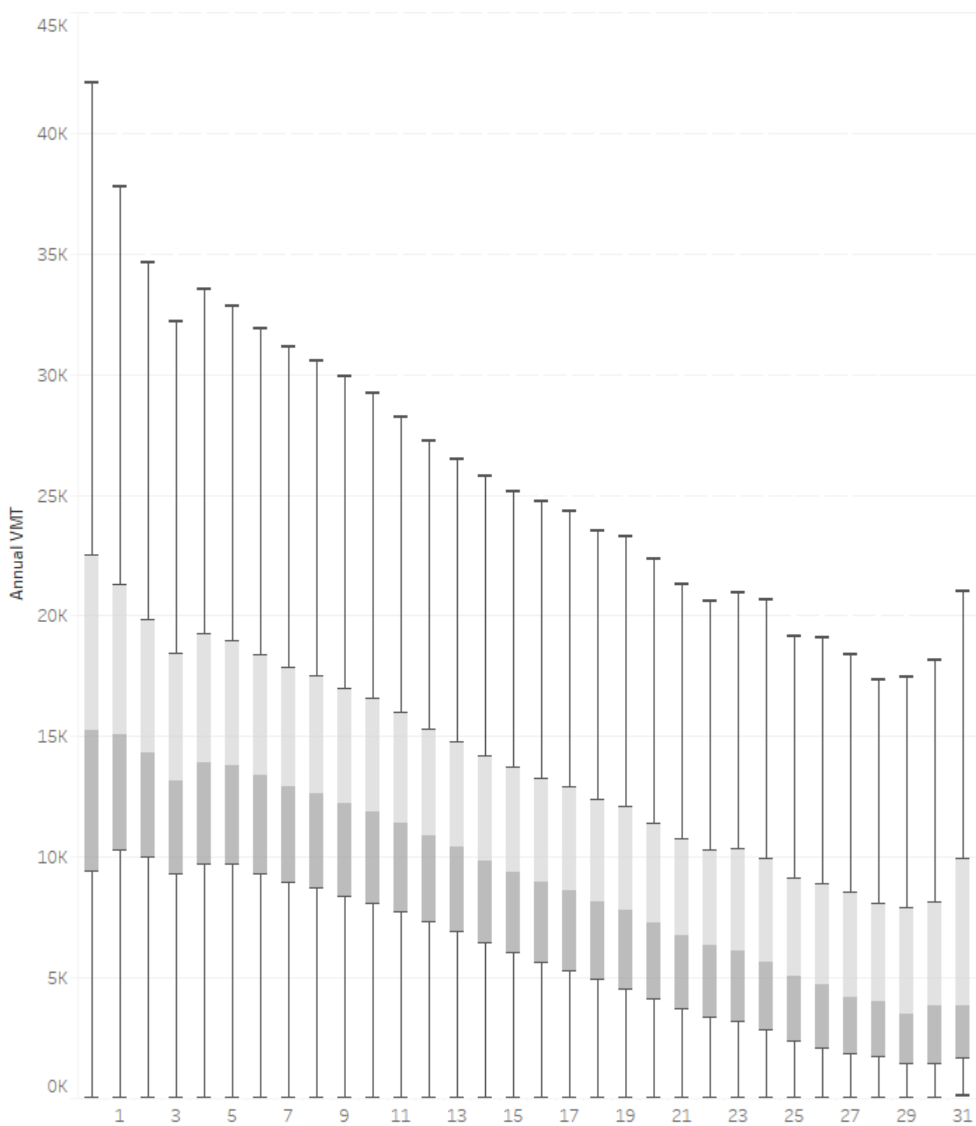

Figure 4-16 – Distribution of SUV Usage Rates by Age

Figure 4-15 also shows that average annual VMT occasionally fluctuates at certain ages, which is likely attributable to changes in ownership. For example, average annual use declines slightly at age 3 and then increases at age 4 before resuming its gradual decline, which is probably a consequence of vehicles coming off 3-year leases), with maximum permissible mileage and entering the resale market. The data are likely picking up the transfer of vehicles from their original owners to new households with higher demand for vehicles.

The agency tested several relationships to summarize the pattern of vehicle use with age. Because the CAFE Model carries no disaggregated representation of vehicle ownership or usage that would capture the variation in usage shown in Figure 4-15, using the average use at each age in the regression allows the CAFE Model to capture the total VMT attributable to a model year cohort, and to benchmark against other annual estimates of light-duty VMT. Figure 4-16 shows the average usage rates for cars by age (as black triangles) as well as linear, quadratic, and cubic polynomial fits of age on these points.[632] The average usage rates follow a relatively smooth pattern but appear to decline at an accelerating rate for the oldest ages. The linear equation captures this trend for older vehicles but underestimates average use at early ages. The quadratic fit shows a diminishing decrease in the usage of older vehicles and may overestimate their use. In contrast, the cubic model accurately captures both the usage patterns at early ages and the accelerating decrease in the usage of older ages. For this reason, NHTSA selected the cubic curve as the basis for the car VMT schedules by age. While the cubic fit performed the best for cars, SUVs were best fit by a quadratic polynomial, and pickup trucks by a cubic polynomial. The resulting annual VMT schedules based on these functions are shown in Table 4-14.

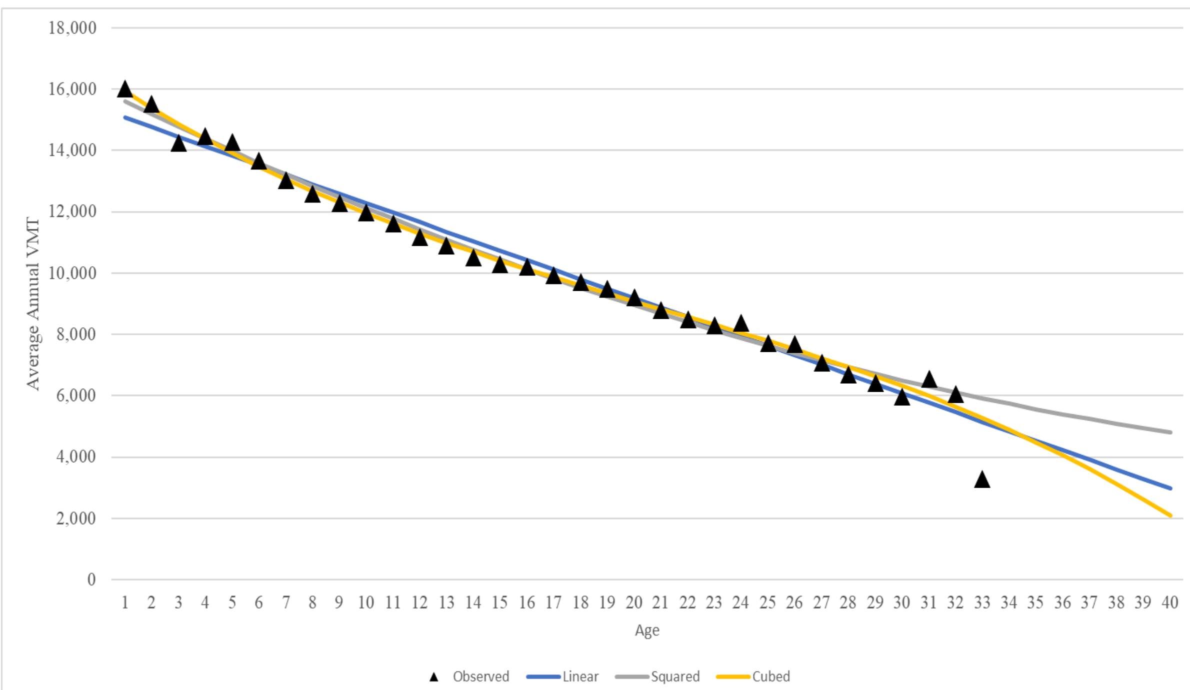

Figure 4-17 – Polynomial Fits for Average Car VMT

[632] In general, the objective of a polynomial regression is to capture the nonlinear relationship between two variables. While the fit produces a nonlinear curve, it is linear in the coefficients. Choosing the lowest degree of the polynomial function that captures the inflection points in the data preserves the degrees of freedom and ensures that applying the polynomial function to observations outside the range of data (as done here for ages beyond 30) is well behaved.

As Table 4-14 illustrates, passenger cars are driven on average slightly less than either SUVs or pickup trucks.[633] Importantly, these annual driving rates represent the estimated annual mileage accumulation of a vehicle, of a given body style, that survives to reach that age. While vehicle retirement rates are generally low across all body styles in the early years of ownership, rates accelerate with age and most of the vehicles originally produced during a model year cohort will have been retired by the time it reaches age 20. Using the average construction effectively shifts some accumulated miles within the cohort – vehicle owners who drive more than the average will benefit more than we estimate from improved fuel economy, while drivers who use their vehicles less intensively will benefit less.

However, because the benefit-cost analysis does not distinguish among individual vehicles or owners, it is sufficient to capture total benefits, and this can be accomplished by representing each model year cohort and age by its annual VMT. It is also generally true that the vehicles that survive to advanced ages are not the same vehicles that were used most intensively early in their lives. Future iterations of this work will continue to improve the CAFE Model's representation of the joint relationship between utilization and retirement beyond the cohort-specific representation in this analysis.

4.3.2.3 Mileage Accumulation Schedules for Base Year 2016

Table 4-14 presents the mileage accumulation schedules developed following the process described here. These show the relationship of average annual miles driven to age for vehicles of each body style during calendar year 2016, together with the model year corresponding to each average age during 2016.

Table 4-14 – VMT Schedule by Body Style and Age

Vehicle Age	Model Year Corresponding to Age During Calendar Year 2016	Mileage Accumulation		
		Cars	Vans/ SUVs	Pickups
0	2016	15,922	16,234	18,964
1	2014	15,379	15,805	17,986
2	2013	14,864	15,383	17,076
3	2012	14,378	14,966	16,231
4	2011	13,917	14,557	15,449
5	2010	13,481	14,153	14,726
6	2009	13,068	13,756	14,060
7	2008	12,677	13,366	13,448
8	2007	12,305	12,982	12,886
9	2006	11,952	12,605	12,372
10	2005	11,615	12,234	11,903

[633] These same mileage accumulation schedules can also be found in the CAFE Model input file "parameters," on the "Vehicle Age Data" tab.

Vehicle Age	Model Year Corresponding to Age During Calendar Year 2016	Mileage Accumulation		
		Cars	Vans/ SUVs	Pickups
11	2004	11,294	11,870	11,476
12	2003	10,986	11,512	11,088
13	2002	10,690	11,161	10,737
14	2001	10,405	10,816	10,418
15	2000	10,129	10,477	10,131
16	1999	9,860	10,146	9,871
17	1998	9,597	9,820	9,635
18	1997	9,338	9,501	9,421
19	1996	9,081	9,189	9,226
20	1995	8,826	8,883	9,047
21	1994	8,570	8,583	8,882
22	1993	8,313	8,290	8,726
23	1992	8,051	8,004	8,577
24	1991	7,785	7,724	8,433
25	1990	7,511	7,450	8,290
26	1989	7,229	7,183	8,146
27	1988	6,938	6,923	7,998
28	1987	6,635	6,669	7,842
29	1986	6,319	6,421	7,676
30	1985	5,988	6,180	7,497
31	1984	5,641	5,946	7,302
32	1983	5,277	5,718	7,089
33	1982	4,893	5,496	6,853
34	1981	4,488	5,281	6,593
35	1980	4,061	5,072	6,305
36	1979	3,610	4,870	5,987
37	1978	3,133	4,674	5,635
38	1977	2,629	4,485	5,248
39	1976	2,096	4,303	4,821

4.3.3 Using the Mileage Accumulation Schedules to Estimate Total VMT

There are several reasons that vehicles' use at different ages, or mileage accumulation rates, could differ from our most recent measurements of these rates based on odometer data for 2016. Fuel prices could change and affect the cost of operating cars and light trucks of all ages, economic growth could spur additional demand for travel and increase use of vehicles of various ages, or the fuel efficiency of cars and light trucks of each age can change over time as new model years featuring higher fuel economy are incorporated into the fleet and older models that originally met less stringent fuel economy standards are retired. To reflect these possibilities, the agency's CAFE Model adjusts the schedules of average annual vehicle use by age during 2016 described in the previous section it uses to calculate total VMT in future calendar years to reflect each of these potential developments.

It does so by calculating changes in the average cost of fuel per mile driven for cars and light trucks of each model year – and thus age – from the base year when the schedules of vehicle use were developed (2016) to each future calendar year. The CAFE Model then applies an elasticity of average annual vehicle use with respect to fuel cost per mile to these changes (expressed as percent changes) in per-mile fuel costs to estimate the percent change in the average use of vehicles of each age between the base year and each future year. Finally, these estimated percent changes are applied to the base year values of average annual driving by cars and light trucks of each age to produce revised estimates of their average use for future calendar years.

The change in the average cost of fuel per mile driven between the base year of 2016 when the mileage schedules were developed and a future calendar year CY for cars and light trucks produced during the current or an earlier model year MY (which are then of age = CY – MY) has two sources. The first is the difference in fuel prices between 2016 and the future year CY, which affects the per-mile cost for vehicles of all ages; they will be driven less in year CY than they were in 2016 if fuel prices have risen since 2016, and more if fuel process have declined. Its second component is the difference in the average on-road fuel economy of vehicles produced during the model year that has reached age = CY – MY during 2016 and that of the model year that was of that same age during 2016. Thus, the percent change in average fuel cost per mile driven (CPM) for vehicles of each age between the base year of 2016 and a future calendar year CY is:

$$\%\Delta CPM_{SN,MY,CY} = \frac{\left(\frac{FP_{CY}}{FE_{SN,MY}} - \frac{FP_{2016}}{FE_{REF}}\right)}{\frac{FP_{2016}}{FE_{REF}}}$$

Equation 4-10 – Full Change in Cost-Per-Mile of Travel

In Equation 4-10, FP_{2016} represents fuel price in dollars per gallon during 2016, FP_{CY} is fuel price during a future calendar CY, $FE_{SN,MY}$ is the average fuel economy of cars or light trucks produced during model year MY under the regulatory alternative or scenario SN, which will have reached age = CY – MY during CY. Finally, FE_{REF} is the fuel economy of the cars or light trucks that were of that same age during 2016.

Vehicle use responds to changes in fuel prices because as Equation 4-10 above suggests, these directly affect the cost of driving each mile, which in turn is a key determinant of vehicle use. Annual use of cars and light trucks of each model year or "vintage" (and thus age) that make up a future calendar year's light-duty vehicle fleet will decline from their base year averages if fuel prices and the cost of driving each mile are higher than they were during 2016, the base year when the original mileage accumulation schedules were developed. Conversely, if fuel prices are lower in a future calendar year than they were in 2016, per-mile driving costs will decline and the average annual use of cars and light trucks of each vintage and age comprising that year's fleet will increase from its original value tabulated during 2016. The magnitude of responses of average vehicle use to changes in fuel cost per mile driven is determined by the elasticity of annual vehicle use with respect to fuel price, which measures the percent change in average annual VMT resulting from a one percent change in the fuel cost of driving each mile.

Previous versions of NHTSA's CAFE Model, which did not incorporate the effect of overall economic conditions on future vehicle use, set the elasticity of average vehicle use with respect to fuel cost per mile equal to the value assumed for the fuel economy rebound effect that was used to estimate changes in the use of new vehicles as their fuel economy improved. As discussed in more detail below, the current version of the CAFE Model estimates total car and light truck during each future calendar year independently using a model developed to produce FHWA's official forecasts of vehicle travel, and this model includes fuel cost per mile as an explanatory variable. Thus, the coefficient attached to that variable, which is estimated econometrically using historical data on vehicle use, fuel prices, and fuel economy (as well as other variables), corresponds to the elasticity of total light-duty vehicle travel with respect to fuel cost per mile. Its estimated value implies an elasticity of -0.14 (which corresponds to a fuel economy rebound effect of about 14 percent), and the CAFE Model relies on this value to adjust the base year mileage accumulation schedules to account for changes in fuel prices from their level in 2016.[634]

As Equation 4-10 shows, changes in driving costs – and thus in vehicle use – since the base year when the original mileage accumulation schedules were developed (2016) are also affected by differences in the fuel economy of cars and trucks of different ages during future years and during the 2016 base year. Thus, the CAFE Model also accounts for future changes in the average use of cars and light trucks of different ages in response to their progressively higher fuel economy compared to those of corresponding ages during the 2016 base year. It seems intuitively clear that as the fuel economy of each new model year improves over time, vehicles of each age will be driven slightly more than their counterparts were during 2016 as long as fuel prices remain constant, since as Equation 4-10 illustrates, their higher fuel economy translates into lower operating costs.[635]

As an extreme example, even if there were no further improvements in fuel economy for new model years after 2020, the initial year of the agency's analysis, the fuel economy of cars and light trucks of all ages making up the future fleet would continue to increase throughout much or all of the analysis period. This is because the average fuel economy of new cars and light trucks has *already* increased consistently for many model years, so that for example, vehicles that were 10 years old at the beginning of the analysis period (cars and light trucks produced during model

[634] Although users of the CAFE Model can still define a different value for the fuel economy rebound effect used to estimate the increase in annual use of new cars and light trucks resulting from higher CAFE standards, doing so will not affect the VMT forecast generated internally by the CAFE Model or the forecast produced by FHWA's. Doing so creates an asymmetry between responses to fuel price and changes in fuel economy, the size of which depends on how much the user-specified rebound effect differs from 14 percent. This issue is present to some extent in NHTSA's analysis supporting this final rule, since as discussed in detail in FRIA Chapter 4, that analysis employs a fuel economy rebound effect of 10 percent.
[635] For estimates of the magnitude of this elasticity, see *e.g.,*Goodwin, P., J. Dargay, and M. Hanly. Elasticities of road traffic and fuel consumption with respect to price and income: a review. Transport Reviews, 24:275-292, 2004.

year 2011 are defined as being 10 years old during 2020) will have lower fuel economy than those produced in model year 2021, which will have reached age 10 in 2030.[636]

This gradual transition toward higher fuel economy levels for cars and light trucks of all ages occurs will proceed at exactly the same pace for cars and light trucks produced through model year 2020 in each regulatory alternative the agency analyzes, since these have *already* been manufactured by the time the analysis period begins in that year. The rate at which these historical or "legacy" model years will be retired and replaced by new, higher-MPG models will differ slightly among the alternatives considered; it will occur most rapidly under the No-Action Alternative and progressively more slowly under alternatives that require more rapid improvements in fuel economy, although these differences are likely to be very modest. At the same time, of course, more stringent regulatory alternatives will cause the fuel economy of the new cars and light trucks produced during future model years to increase more rapidly, so that on balance those alternatives will raise the overall average fuel economy of the car and light truck fleet faster.[637]

The agency's analysis ascribes the effects on vehicle use resulting from required improvements in the fuel economy of model years after 2020 entirely to the regulatory alternatives it considers, and attempts to isolate these from changes in vehicle use that occur in response to fluctuations in fuel prices and other economic conditions that are outside the realm of fuel economy regulations (i.e., "exogenous"). To do so the CAFE Model constructs a hypothetical measure of "non-rebound" VMT for future years that incorporates the response of driving costs and vehicle use to forecast changes in future fuel prices, and for improvements in the fuel economy of new cars and light trucks from the base year of 2016 only through model year 2020. Increases in vehicle use from this "non-rebound" level of VMT that are attributable to improvements in fuel economy required by each regulatory alternative the agency evaluates are then ascribed uniquely and fully to that alternative. This includes the No-Action Alternative, since even it reflects some minor improvements in fuel economy after 2020 in response to previously adopted standards and other factors.

The CAFE Model estimates non-rebound VMT by adjusting the 2016 base year mileage accumulation schedules using a slightly different measure of future changes in per-mile driving costs from that specified in Equation 4-10 above. Like that shown above, it includes the effects of changes in fuel prices since the base year of 2016, but it differs from Equation 4-10 by omitting the effects of fuel economy changes after from the changes in fuel cost per mile it calculates for future years. Equation 4-11 shows this revised measure of the change in fuel cost per mile for cars and light trucks of different ages during calendar year CY:

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[636] In practice, light-duty vehicles of the same regulatory class (cars and light trucks) or body style (cars, SUVs, vans, and pickups) produced during the same model year will be retired at different rates over time, and this process can change the average fuel economy of those remaining in use. Some specific vehicle models and manufacturers have reputations for longevity and individual vehicle models with different fuel economies may seem like better candidates for repairs under particular fuel price scenarios. In light of this, the fuel economy for a given body-style will likely differ from the sales-weighted average fuel economy when the cohort was new, even without accounting for degradation and changes to the on-road gap over time.

[637] Moreover, because newer vehicles are driven more each year than older ones, the fleet's usage-weighted average fuel economy will rise more rapidly than the average MPG of the vehicles making up the evolving fleet.

$$\%\Delta \boldsymbol{NonRbdCPM}_{\boldsymbol{MY,CY}} = \frac{\left(\frac{\boldsymbol{FP_{CY}}}{\boldsymbol{FE_{MIN(2016,MY)}}} - \frac{\boldsymbol{FP_{2016}}}{\boldsymbol{FE_{REF}}}\right)}{\frac{\boldsymbol{FP_{2016}}}{\boldsymbol{FE_{REF}}}}$$

Equation 4-11 – Fuel Price and Secular Improvement Component of Elasticity

In Equation 4-11, FP_{2016} again refers to fuel price per gallon during 2016, and FP_{CY} to fuel price per gallon during a future calendar year CY. As in the previous equation, FE_{REF} refers to the average FE of the model year cohort that was of age = 2016 – MY during calendar year 2016. In Equation 4-11, $FE_{MIN(2016,MY)}$ refers to the average fuel economy of cars or light trucks produced during any post-2016 model year MY, but this value differs from the corresponding factor in the previous equation. As its subscript *MIN(2016,MY)* indicates, it is the lower of the actual fuel economy of cars or light trucks that have reached age = CY – MY during CY and the fuel economy of those that were of the same age during 2016.

Thus, Equation 4-11 differs from the previous equation only in the respect that in Equation 4-10 the fuel economy in the denominator of the first term is the *actual* fuel economy of each (post-2016) model year being evaluated, while in Equation 4-11 it is the minimum of that value and the fuel economy cars or light trucks achieved during model year 2016. In effect, Equation 4-11 assumes that no improvements in fuel economy would have occurred after model year 2016, but that at the same time the fuel economy of cars and light trucks from newer model years would not be allowed to fall *below* their levels of model year 2016. This assumption implies that fuel economy improvements through model year 2016 *will* be accounted for when calculating non-rebound VMT for any later calendar year, but that further increases in fuel economy after model year 2016 *will not* be. Thus, increases in average annual non-rebound VMT per car or light truck during any post-2016 calendar year would reflect only changes in (inflation-adjusted) fuel prices occurring after 2016.

Conversely, changes in average annual VMT per car or light truck in response to the fuel economy rebound effect would reflect increases in the fuel economy of future model year cars and light trucks from the levels they achieved during model year 2016.[638] The agency's analysis ascribes the effects of post-model year 2016 improvements in fuel economy on fuel costs and vehicle use – and thus on fuel consumption, emissions, safety, and other consequences of vehicle use – to each of the regulatory alternatives it considers. Following this approach means that there will be some additional VMT attributable to the fuel economy rebound effect in future years even under the No-Action Alternative used in the analysis. This occurs because the actual fuel economy of new cars and light trucks will increase after MY 2016 under the No-Action Alternative due to previously-adopted increases in CAFE standards, efforts by manufacturers who under-complied with prevailing standards during earlier model years to "catch up" with standards for later years, and any voluntary overcompliance by manufacturers with standards prevailing after MY 2016.

[638] NHTSA intends to update this reference year the next time the agency acquires an update to the database of odometer readings.

Combining the adjustments to average annual VMT during the reference year of 2016 for different light-duty vehicle body styles (cars, SUVs/vans, and pickups) of each age from Equation 4-11 with the estimated populations of vehicles of different ages in use during a future calendar year produces an initial estimate of non-rebound VMT as described in $\mathrm{NonReboundVMT}\ \ CY = \sum_{S}^{\mathrm{Styles}} \mathrm{VMT}_{A,S} \cdot (1 + \%\Delta \mathrm{NonRbdCPM}_{MY,CY} \cdot \varepsilon) \cdot \mathrm{Population}_{CY.A,S}$

Equation 4-12 below:

$$NonReboundVMT_{CY} = \sum_{S}^{Styles} VMT_{A,S} \cdot (1 + \%\Delta NonRbdCPM_{MY,CY} \cdot \varepsilon) \cdot Population_{CY.A,S}$$

Equation 4-12 – Unadjusted Total Non-Rebound VMT in a Future Calendar Year

In $\mathrm{NonReboundVMT}\ \ CY = \sum_{S}^{\mathrm{Styles}} \mathrm{VMT}_{A,S} \cdot (1 + \%\Delta \mathrm{NonRbdCPM}_{MY,CY} \cdot \varepsilon) \cdot \mathrm{Population}_{CY.A,S}$

Equation 4-12, $VMT_{A,S}$ represents average annual mileage for light-duty vehicles of age A and body style *S*, $Population_{CY,A,S}$ is the number of vehicles of that age and body type estimated to remain in service during calendar year *CY*, and ε is the elasticity of annual vehicle use with respect to fuel cost per mile driven (derived from FHWA's VMT forecasting model, and equal to -0.14).

However, factors other than fuel costs can also affect households' and businesses' demands for travel using light-duty vehicles, even if fuel prices remain constant throughout the analysis period and fleetwide fuel economy improves only minimally as a consequence of continuing fleet turnover – as it does in the "non-rebound" case – total car and light truck VMT could still vary in response to changes in these other factors. Not only could the forecast of non-rebound VMT continue to grow under appropriate conditions, but it might actually do so at a faster rate than Equation 4-12 predicts, since that includes only the effect of fleet turnover on fuel economy, fuel costs, and vehicle use. Conversely, events such as recessions could depress actual VMT below levels estimated using Equation 4-12, as occurred for example during the Great Recession in 2008-2009.

To ensure that the CAFE Model's estimates of light-duty VMT for future years are also broadly consistent with demographic growth and economic conditions other than fuel prices, the agency constrains non-rebound VMT under each regulatory alternative – including the No-Action Alternative used to analyze future CAFE standards – to match an independent forecast based on demographic trends and aggregate economic growth. As described in more detail below, it uses a travel forecasting model developed and used by FHWA to produce a forecast of growth in car and light truck use that is consistent with the same forecasts of population growth, increases in household formation, growth in aggregate economic output and personal income, and consumer confidence used elsewhere throughout its analysis.

4.3.4 Constraining VMT in the CAFE Model

It is NHTSA's perspective that the total demand for VMT should not vary excessively among regulatory alternatives, because the basic travel demands and vehicle use patterns of a typical household are unlikely to be influenced by the stringency of CAFE standards. However, the method the CAFE Model uses to calculate total VMT (described previously and in more detail below) can cause the sales and scrappage responses it estimates for alternatives that require different levels of fuel economy can create modest differences in total VMT across the range of regulatory alternatives. Even these minor differences can have significant impacts on the analysis of incremental costs and benefits of different regulatory alternatives when those are measured against the baseline.

However, NHTSA prefers that the benefits and costs reported for the regulatory alternatives it analyzes reflect only differences in total vehicle use that are specifically attributable to each alternative's effects on fuel economy, and do not incorporate the slight differences in the number of cars and light trucks estimated to be sold and remain in use under each alternative. In addition, the agency believes it is useful to ensure that the estimates of total VMT the CAFE Model constructs using the schedules of average annual mileage by vehicle age and the numbers of vehicles of different ages making up the future light-duty fleet are consistent with levels of aggregate travel demand implied by the forecasts of overall economic activity it uses to project new vehicle sales and retirement rates for used vehicles, since these determine the size and composition of the future fleet.

To accomplish these two objectives, the CAFE Model constrains "pre-rebound" vehicle use (defined more explicitly below) under the baseline and each regulatory alternative during future years to match values projected using the Federal Highway Administration's VMT forecasting model, regardless of differences in the size or age distribution of the light-duty fleet among those alternatives. Thus, in future years where total VMT calculated internally by the CAFE Model differs from the FHWA forecast, each model year cohort's average VMT is adjusted up or down so that the two estimates match. This process ensures that any differences in total VMT among regulatory alternatives reflect only the different levels of fuel economy they require and their consequences for car and light truck use via the fuel economy rebound effect.

More specifically, the CAFE Model first uses the FHWA VMT forecasting model to produce independent estimates of total light-duty VMT for each year spanned by the analysis period, to which it constrains total VMT under each regulatory alternative before applying the fuel economy rebound effect, regardless of differences among alternatives in the overall size of each future year's light-duty fleet or the age distribution of vehicles making up the fleet. In calendar years where the CAFE Model's estimate of total VMT constructed from the schedules of average mileage by vehicle age and the numbers of vehicles of different ages making up the fleet is below the forecast of light-duty VMT produced by the FHWA model, the CAFE Model's estimates of annual VMT for cars and trucks of each age are each adjusted upward by the proportion necessary for its forecast to match that produced by the FHWA model. Conversely, if the initial estimate of total VMT for a calendar year the CAFE Model develops using the fleet size and age distribution in conjunction with the mileage accumulation schedules for cars and light trucks exceeds that forecast by the FHWA model, average use of vehicles of each age is scaled down proportionally until the two estimates match.

FHWA's VMT forecasting model uses a set of equations based on underlying theories of the determinants of travel demand, with their parameters estimated econometrically from annual time-series data on vehicle use, demographic variables, and measures of aggregate economic output and income. It employs an auto-regressive distributed lag specification including error correction terms in an effort to capture the long-run behavioral relationships between vehicle use and economic and demographic growth, as well as the year-to-year adjustments of vehicle use to short-term fluctuations in economic activity. Full documentation of its development, calibration, and use is available from FHWA, and the model is described only briefly here .[639] As FHWA has revised the model to improve its forecasting performance, updated versions have been fully integrated into NHTSA's CAFE Model. Table 4-15 reports the variables currently included in the light-duty VMT forecasting equation that forms part of FHWA's model and the most recently estimated values of their coefficients.

Table 4-15 – FHWA VMT Forecasting Model

Adjustment Variable	
LD VMT PC (-1)	-0.211 (0.048) ***
Long-Run Variables	
Personal Disposable Income PC	3.437 (1.124)**
Personal Disposable Income PC Sq.	-0.454 (0.168)**
Fuel Cost per Mile	-0.146 (0.041)***
Short-Run Variables (First Differenced)	
Personal Disposable Income PC	2.472 (1.025)*
Personal Disposable Income PC (-1)	-0.325 (0.094)***
Personal Disposable Income PC (-2)	-0.180 (0.086)*
Personal Disposable Income PC Sq.	-0.363 (0.157)*
Consumer Confidence	0.074 (0.017)***
Constant	0.163 (0.329)
Observations	47
Adj. R2	0.82
RMSE	0.01
Cumby-Huizinga Test for Autocorrelation (P-Value (One Lag))	0.455
Bounds F-Stat.	9.73***
Bounds T-Stat.	-4.43***
In-Sample MAPE (1970-2016)	0.67%
Out-of-Sample MAPE (2006-2016)	3.64%
Bounds T-Stat.	-4.43***
In-Sample MAPE (1970-2016)	0.67%
Out-of-Sample MAPE (2006-2016)	3.64%
Out-of-Sample MAPE (2011-2016)	0.79%
Out-of-Sample MAPE (2011-2016)	0.79%
Notes: Suffixes on the variable names indicate the values of a variable from the previous year (-1) period two years previous (-2). Critical values for the bounds test are taken from Pesaran et al. (2001) for case 3. Model lag lengths were based on best Bayesian Information Criterion statistic.	

[639] *See* "FHWA Travel Analysis Framework: Development of VMT Forecasting Models for Use by the Federal Highway Administration," Volpe, available at https://www.fhwa.dot.gov/policyinformation/tables/vmt/vmt_model_dev.pdf. (Accessed: February 15, 2022).

Adjustment Variable
Standard errors in parentheses: † $p<0.1$ * $p<0.05$ ** $p<0.01$ *** $p<0.001$

As indicated above, the CAFE Model uses the FHWA model to calculate total "non-rebound" VMT for each future calendar year and employs the result as a constraint on the level of VMT for all regulatory alternatives being analyzed. It does so by adding or subtracting VMT from the provisional forecast for each future year that was previously generated using Equation 4-13. The increment of VMT added or subtracted, denoted $\Delta Miles_{CY,S}$ in Equation 4-13 below, is simply the difference between each year's forecast of total VMT derived from the FHWA model and the estimate of total VMT obtained previously from Equation 4-12. That is:

$$\Delta Miles_{CY} = VMTConstraint_{CY} - NonReboundVMT_{CY}$$

Equation 4-13 – Difference between VMT Constraint and Unadjusted Non-Rebound VMT

Over time, each regulatory alternative results in a different size and composition of the on-road car and light truck fleet (the number of vehicles, their age distribution, and the average fuel economy of vehicles of each model year and age), and as a consequence the total unadjusted VMT in each calendar year given by Equation 4-12 will also differ among by regulatory scenarios. Because the constrained value of total VMT form the FHWA model will be identical among alternatives, Equation 4-13 shows that $\Delta Miles_{cy}$ will necessarily differ for each regulatory scenario as a result. By distributing $\Delta Miles_{cy}$ across the vehicle fleet in each calendar year, the CAFE Model scales unadjusted non-rebound VMT to equal the same level in each calendar year and under all each regulatory alternative.

While several different methods can be used to reallocate $\Delta Miles_{cy}$ across the on-road fleet in order to preserve the non-rebound VMT constraint, the CAFE Model applies one of the simplest. Lacking empirical evidence about how these additional miles should be distributed across the registered vehicle population (which would require data showing how the distribution of VMT has shifted among body styles and vehicles of different ages over time), a simple approach seemed most sensible. Under reasonable assumptions about model inputs, the magnitude of ΔMiles is relatively small for most vehicle types and ages – at most a few hundred miles per year for vehicles typically traveling 10,000 miles or more per year.[640]

The primary goal of reallocation is to adjust total non-rebound VMT so that it reflects the model-based forecast of total VMT in every calendar year and for each regulatory alternative. At the same time, it is important that any reallocation preserve the general pattern of declining average mileage with age apparent in the reference mileage accumulation schedule from 2016, since that represents the agency's best estimate of observed usage at the outset of the analysis. In particular, the reallocation approach preserves the basic ideas that annual mileage declines with vehicle age because newer (and more fuel-efficient) vehicles are used more intensively than their

640 A notable exception to this is the impact of the Covid pandemic on total light-duty VMT, which dropped precipitously during 2020 in response to both economic distress and mandated travel restrictions.

older counterparts, and that annual mileage accumulation rates vary among vehicles of different body styles.

To perform this reallocation, the CAFE Model computes a simple ratio that varies by calendar year and regulatory alternative. The resulting ratio is then used to scale the unadjusted miles from Equation 4-12, so that the new sum of annual (non-rebound) VMT across all vehicles comprising the on-road fleet equals the total forecast for that year using the FHWA model and the forecasts of economic variables used elsewhere in the analysis. For a future calendar year *CY* and body style *S*, the scaling ratio *R* is computed as:

$$R_{CY} = \frac{\Delta Miles_{CY}}{NonReboundVMT_{CY}}$$

Equation 4-14 – Scaling factor to reallocate non-rebound VMT

In Equation 4-14 $\Delta Miles_{CY}$ is calculated using Equation 4-13, while $NonReboundVMT_{CY}$ is obtained from Equation 4-12. Then total *adjusted* non-rebound VMT is calculated as:

$$AdjNonReboundVMT_{CY} = \sum_{A}^{Ages} \sum_{S}^{Styles} NonReboundVMT_{CY.A,S} * (\ 1 + R_{CY})$$

Equation 4-15 – Total Adjusted Non-Rebound VMT

While other schemes could be used to reallocate VMT across the on-road population (for example, a uniform approach that either adds or removes the same number of miles from each age cohort), the scaling approach described here has several advantages. Aside from its relative simplicity, the approach produces stable results. The newest model years (lowest ages) are affected the most by the constraint – mileage for all ages is scaled in proportion to unadjusted VMT, and the CAFE Model can neither add nor remove large amounts of VMT in age cohorts having either small numbers of vehicles or small quantities of VMT. Thus, by employing the scaling ratio as indicated here, we ensure that the model is robust to the widest possible array of input assumptions.

To make each alternative match the overall VMT constraint, Equation 4-15 first calculates the product of average mileage during the reference year for each body style and age, the value of *%ΔNonRbdCPM* calculated from Equation 4-11, and the elasticity of annual vehicle use with respect to fuel cost derived from the FHWA forecasting model. It then applies the appropriate scaling ratio from Equation 4-14. Unlike much of the CAFE Model's accounting, which focuses on the fuel consumption, emissions, and other impacts generated by a model year cohort over its entire lifetime, the rebound constraint and any mileage reallocation are inherently calendar year concepts. Conceptually, the constraint represents demand for motor vehicle travel in each future calendar year absent the contribution of increases in VMT resulting from fuel economy improvements beyond MY 2016. This reallocation occurs in every calendar year, so vehicles of each model year cohort are likely to experience many such reallocation events – most positive, but some potentially negative – over the course of their lifetime in the fleet.

As other elements of this analysis show, there are two primary reasons why raising CAFE standards cause travel demand to be redistributed across the on-road fleet. The first is that different alternatives create differently composed on-road fleets, while the constraint ensures that changing fleet size does not influence aggregate demand for travel, and this combination requires some redistribution of travel among vehicles of different ages. Each alternative also produces a fleet of a slightly different total size (number of vehicles), a specific age distribution, and a unique pattern of variation in fuel economy (and thus fuel costs) with the age and body-style of vehicles comprising it. All of these factors are a direct consequence of differences in CAFE stringency that influence the number of new vehicles sold each year, the fraction of them that are sold as different body styles, the likelihood that used vehicles of various ages will be retired in a given year, and the fuel efficiency of each model year cohort making up the on-road fleet. However, these factors do not influence aggregate demand for VMT in the model, except for the relatively minor differences caused by the response of driving to the fuel economy rebound effect.

To derive the average fuel economy under the constraint, we conduct a run that simply turns over the fleet, holding the fuel economy of new model years entering the fleet constant at the levels achieved during model year 2016. As the fleet turns over, its overall average fuel economy slowly improves, gradually approaching the fuel economy new vehicles achieved in MY 2016. In this way, fuel economy improvements in the new vehicle market that occur after MY 2016 are excluded from the projection of non-rebound VMT. This isolates the effects of fleet turnover and changes in fuel price on projected travel demand from those of requiring higher fuel economy, while assigning increases in vehicle use and its consequences resulting from improvements in fuel economy after model year 2016 to each regulatory alternative (again including the baseline, since it includes minor increases in fuel economy after model year 2016).

Although this distinction implies that some rebound-related increase in vehicle use occurs even in the No-Action Alternative – partly as a consequence of more stringent standards across multiple programs – those programs affect each of the action alternatives as well, so any rebound-effect travel attributable to fuel economy gains required under those other programs net out when comparing across alternatives. Aggregate travel demand is constant across scenarios until we account explicitly for the fuel economy rebound effect, and that demand must be met by the on-road fleet.

However, the CAFE Model simulates slightly different on-road fleets under each regulatory alternative, and these differences accumulate over time. Different alternatives' fleets may differ in both their total size and in the age distribution of vehicles comprising them, each of which has important consequences for the intensity with which vehicles of different ages are used to satisfy overall demand for travel. Vehicles of different ages making up each future year's on-road fleet are only imperfect substitutes for one another and thus the services they provide are not completely interchangeable. Thus, while in theory a modestly larger number of relatively new vehicles could compensate for a significantly reduces number of older vehicles (because those new vehicles would be driven more intensively than older ones), a fleet that is *both* older and smaller is likely to likely require higher annual driving rates for all age or model year cohorts to meet the same demand for travel.

The second reason why the model redistributes VMT across the on-road fleet is a discrepancy between unadjusted VMT (the product of average annual vehicle use and the on-road vehicle population) and forecasted non-rebound VMT. In most cases, this redistribution is small in scale and fluctuates between adding and removing miles in any given year. However, in this analysis, the constrained annual VMT is strongly affected by the COVID pandemic, especially in the early years of the simulation. Consequently, this redistribution more often *removes* miles from the unadjusted annual VMT than it adds to them to preserve the non-rebound VMT constraint, and this downward adjustment is particularly pronounced in the early years of the agency's analysis.

As Figure 4-18 shows, the unadjusted VMT – based on the simple product of the VMT schedule (by body style and age) and the on-road vehicle population – is consistently above the model forecast of aggregate VMT to which total travel is constrained through CY 2029.[641] Had growth continued normally from CY 2019 forward, it seems likely that the redistribution process would be *adding* rather than removing VMT throughout that period to preserve the constraint.

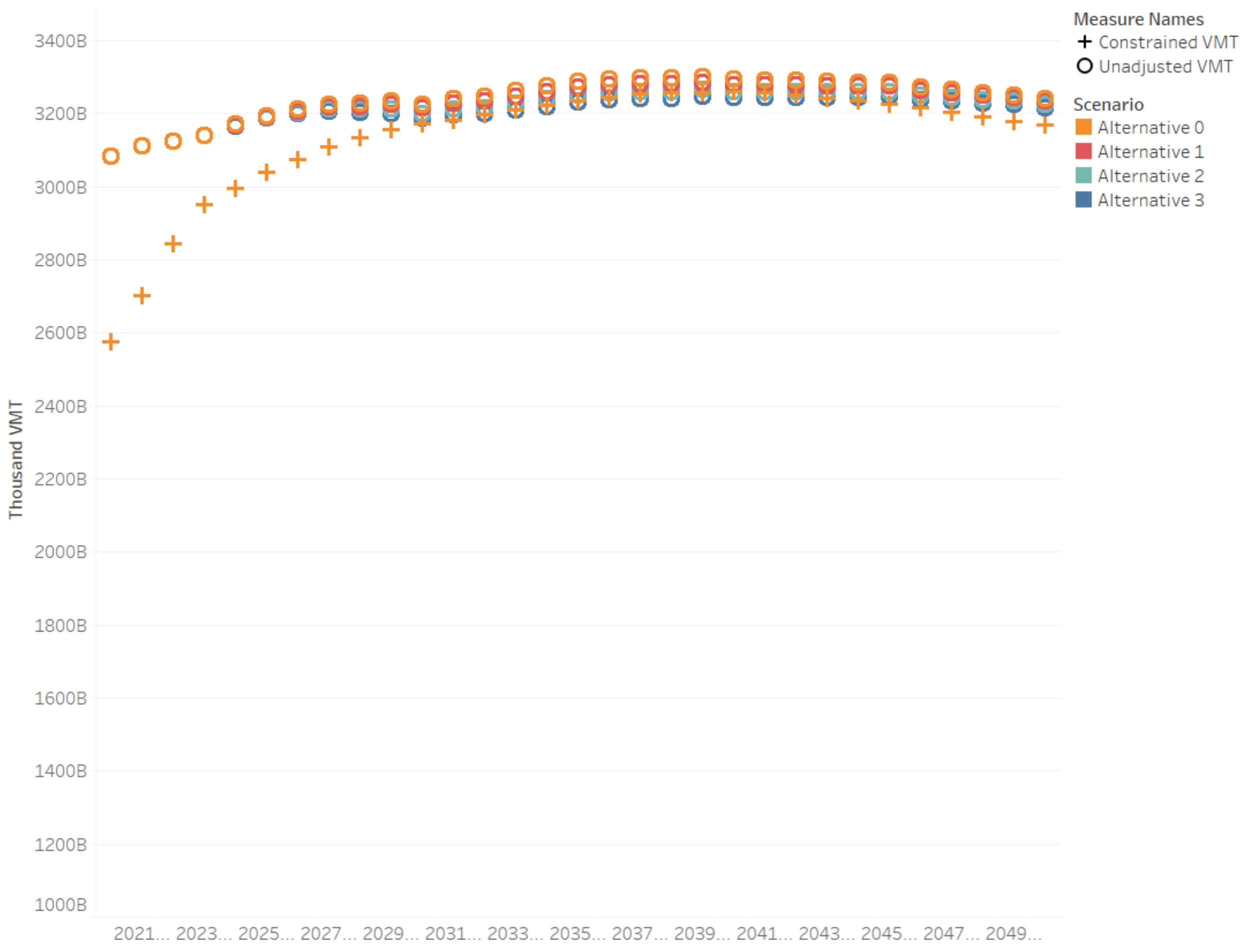

Figure 4-18 – Comparison of Unadjusted and Constrained VMT in the CAFE Model

[641] The figure has not been revised from that shown in the Draft TSD accompanying the agency's NPRM and includes a slightly different set of alternatives than considered for this final rule; it is included only to illustrate the effect of constraining VMT. Note that the scale on the y-axis has been truncated to exaggerate the magnitude of the discrepancies between the curves.

However, as a consequence of the calculated discrepancy between the VMT constraint and unadjusted VMT in the early years of the analysis, the redistribution process must aggressively remove miles from the unadjusted VMT estimate during the early years of the analysis period. While the earliest years (especially 2020) reflect the depth and recovery related to the pandemic, the two estimates converge by 2030, after which the adjustments to individual age cohorts' average use become insignificant. Figure 4-19 illustrates the adjustments that are necessary to enforce the VMT constraint in 2022 and 2029 for Alternative 0 and Alternative 3; adjustments for the other alternatives look similar, but those shown in the figure represent the bounding cases.[642]

The CAFE Model distinguishes between car body-styles, SUVs, and pickup trucks for the purposes of simulating usage, and the VMT adjustments occur at that level as well. As the top panel of Figure 4-19 shows, VMT adjustments are identical for both alternatives in 2022 but represent significant per-vehicle reductions in VMT; for each body style the reduction represents about 10 percent of VMT estimated in the schedule. However, this still represents an improvement from 2020 levels, where the per-vehicle reductions were closer to 15 percent. Consistent with the objective of the reallocation process, the largest absolute adjustments (in miles per year) are concentrated in age cohorts represented by larger numbers of vehicles and characterized by higher average usage, which thus make larger contributions to total VMT.

As the bottom panel of Figure 4-19 illustrates, by 2029 the unadjusted and constrained estimates of VMT have nearly converged. By the time they do, however, there are also large enough differences in the sizes and composition of the on-road fleets between Alternative 0 and Alternative 3 to create observable differences between the alternatives in the VMT adjustments required to preserve the VMT constraint. The model still reduces VMT under both alternatives, but by only about 1 percent of expected average VMT in Alternative 3, in contrast with almost 2 percent under Alternative 0. As Figure 4-18 suggested previously, there are also some years where the CAFE Model is forced to add miles to the unadjusted VMT in Alternative 3 to preserve the VMT constraint, although those additions are similarly small. As indicated previously, the model repeats this process in each calendar year to ensure identical "non-rebound" VMT across the alternatives.

[642] As with the previous figure, Figure 4-19 has not been revised from the corresponding figure shown in the Draft TSD and is included here only to illustrate the magnitude of the adjustments to vehicle use made using the process described above. Thus, it does not fully represent the alternatives considered in this analysis.

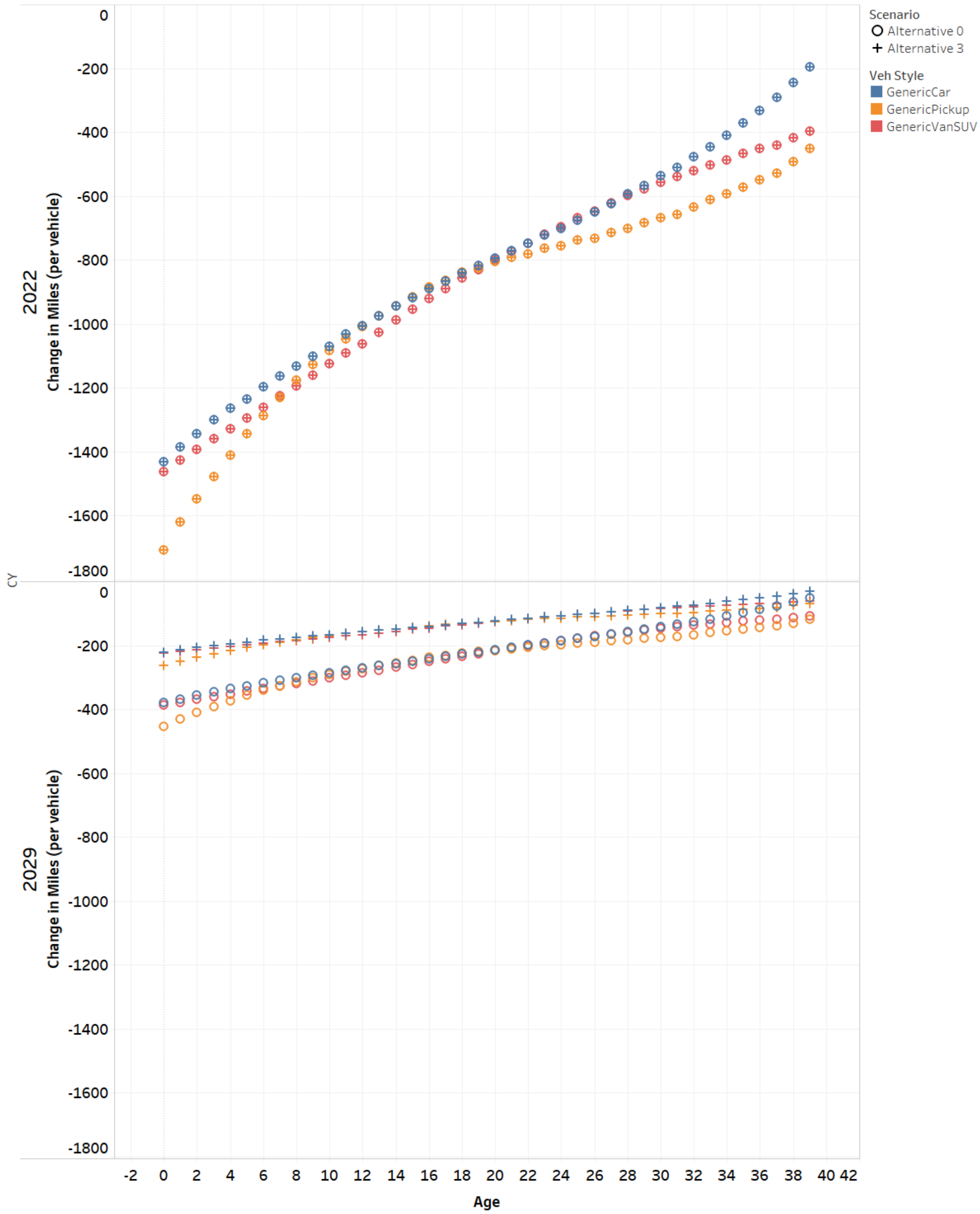

Figure 4-19 – Enforcing the VMT Constraint by Adjusting VMT

4.3.5 Accounting for the Fuel Economy Rebound Effect

The last step in the process of estimating the number of miles driven by cars and light trucks of different ages during each year spanned by the analysis period is to account for the effect of higher fuel economy on vehicle use. As indicated previously, the agency's evaluation views all impacts of requiring higher fuel economy as consequences of the regulatory alternatives that do so, including those on vehicle sales, retirement of used vehicles, and the lifetime use of vehicles produced during the model years subject to each alternative. The processes for constraining and reallocating mileage described above are intended to assign the consequences of resulting changes in the size and composition of the car and light truck fleets to the various regulatory alternatives, while the consequences of improved fuel economy for vehicle use – the rebound effect – are estimated directly.

The fuel economy rebound effect, one example of the well-documented energy efficiency rebound effect for energy-consuming capital goods, refers to the tendency of motor vehicles' use to increase when their fuel economy is improved and the cost per mile of driving declines as a result. Establishing more stringent CAFE standards than the baseline level will lead to higher fuel economy for new cars and light trucks, thus reducing the amount of fuel consumed in driving each mile. The resulting decline in the cost to drive each mile will prompt an increase in the number of miles new cars and light trucks are driven, and this increase in vehicle use represents the fuel economy rebound effect.

Because it governs the magnitude of this response, NHTSA recognizes that the value of the rebound effect influences the costs and benefits associated with establishing higher CAFE standards, and also the estimates of fatalities and injuries projected to occur under various regulatory alternatives. A larger rebound effect also reduces many of the environmental benefits associated with increased fuel efficiency. For these reasons, the estimated magnitude of the rebound effect must be considered carefully.

For the current analysis, NHTSA conducted an extensive review of recent estimates of the fuel economy rebound effect, covering the past two decades of research and spanning different geographic regions. In contrast to the agency's previous extensive reviews, which mainly compiled different authors' single "best" or most likely estimates of its magnitude, this most recent survey included all estimates of the rebound effect reported in each published study it reviewed, and also incorporated the often- wide uncertainty surrounding these estimates. The agency also reviewed previous surveys of published estimates of the rebound effect in order to compare their findings to its own most recent analysis.

Formally, the fuel economy rebound effect is defined as the elasticity of vehicle use with respect to vehicle fuel economy (distance traveled per unit of fuel consumed, such as miles per gallon) or fuel efficiency (fuel consumed per unit of distance traveled, such as liters per kilometer). Some research attempts to estimate this parameter directly by analyzing the relationship of vehicle use to variation in vehicles' fuel economy or fuel efficiency, while controlling separately for fuel prices. Because sources of exogenous or independent variation in fuel economy or efficiency are rare and their average values for an entire vehicle fleet change very slowly over time, however, many analysts instead estimate the elasticity of vehicle use with respect to fuel cost per unit of distance driven (dollars per mile, for example) and assume that this parameter is identical to the fuel economy rebound effect.

The agency's survey included examples of published studies that rely on each of these strategies. Within each category, the survey identified studies that estimate the rebound effect using national aggregate time-series data on vehicle use and fuel economy or fuel cost per unit of distance traveled, average values of these variables for geographic units (nations, provinces, or states) measured repeatedly over successive years, and estimated use and fuel economy or fuel cost for samples of vehicle-owning households or of individual vehicles themselves. Each of these data sources and measurement methods involves significant empirical and statistical challenges, but each also offers important advantages for obtaining reliable estimates of the rebound effect.

Table 4-16 – Summary of Recent Studies of the Rebound Effect for Light-Duty Vehicles

Study Details	Explanatory Variable	Nation		Vehicle Use Data:			
		U.S.	Other	National Time Series	Panel of Geographic Sub-Units	Household Sample	Vehicle Sample
Number of Studies	Fuel Economy or Efficiency	7	6	1	0	3	9
	Fuel Cost per Mile or km	14	5	4	5	2	8
Number of Estimates	Fuel Economy or Efficiency	27	35	2	0	31	29
	Fuel Cost per Mile or km	115	28	26	52	14	51
Mean Estimates	Fuel Economy or Efficiency	16%	22%	-15%	--	15%	26%
	Fuel Cost per Mile or km	18%	8%	19%	22%	15%	16%

Table 4-16 summarizes the details of studies of the rebound effect NHTSA included in its updated survey, and Table 4-17 identifies the individual studies and reports their locations, time periods they span, and type of data they utilize. As indicated previously, the agency's survey included all estimates of the rebound effect reported in each published study rather than a single best or most representative estimate. We weighted each published study equally, however, so that each individual value reported in a study that included a large number of alternative estimates received less weight than those from a study reporting a smaller number of differing estimates. Thus, for example, each value from a study that reported ten separate estimates was weighted only half as heavily as each value reported in a study that produced only five different estimates. To recognize the statistical uncertainty surrounding each study's findings, the agency combined econometric estimates of the magnitude of the rebound effect with the standard errors accompanying each estimate to simulate a probability distribution for each published estimate.[643] It then compiled these into summary probability distributions representing different definitions of the rebound effect and the various data sources and analytic approaches used toot estimate it.

Table 4-17 – Details of Recent Studies

Authors (Date)	Nation	Time Period	Data	Range of Estimates

[643] Some estimates of the rebound effect are mathematical combinations of two or more different parameters that are estimated econometrically; for example, the rebound effect calculated from time-series models that include a lagged value of vehicle use as an explanatory variable depends on the estimated coefficients of both fuel economy (or fuel cost per distance traveled) and the lagged value of vehicle use. In some of these cases, the standard error of the calculated rebound effect can be calculated directly using the reported standard errors of its separate parameters. In those where it could not be, the distribution of rebound effect values was simulated using repeated draws (1,000) from the probability distributions of its separate parameters, and its standard error was approximated using the standard deviation calculated from that resulting distribution.

Greene (2010)	U.S.	1966-2007	National aggregate VMT	0-13%
Wang *et al.* (2012)	Hong Kong	1993-2009	Year-to-year changes in nationwide driving	45%
Stapleton *et al.* (2016, 2017)	U.K.	1970-2012	National aggregate VMT	11-30%
FHWA (2018)	U.S.	1966-2016	National aggregate VMT	14%
Small and Van Dender (2007)	U.S.	1967-2004 2001-2004	Annual VMT for individual U.S. states	22-34% 11-32%
Barla (2009)	Canada	1990-2004	10 Canadian provinces over 15 years	17-19%
Hymel et al. (2010)	U.S.	1966-2009	Annual VMT for individual U.S. states	13-25%
Anjovic and Haas (2012)	6 EU nations	1970-2007	6 EU nations over 38 years	44%
Hymel and Small (2015)	U.S.	1966-2009 2000-2009	Annual VMT for individual U.S. states	16-25% 4-18%
Feng et al. (2013)	U.S.	1996-2000	U.S. households	2-12%
Liu (2014)	U.S.	2009	1,420 Washington, D.C. area households	39-40%
Wang and Chen (2014)	U.S.	2009	105,000 households	-20 to 70%
Dillon et al. (2017)	California	2009	3,500 households	1-18%
DeBorger (2016)	Denmark	2001-2011	23,000 households	5-12%
Andersson *et al.* (2019)	Sweden	2006-2012	29,000 households	2-34%
Waddud (2009)	U.S.	1984-2003	U.S income quintiles	1-25%
Su (2011)	U.S.	2009	45,000 household vehicles	3-20%
Su (2012)	U.S.	2009	45,000 household vehicles	11-19%
Frondel *et al.* (2012)	Germany	1997-2009	2,165 households	42-59%
Linn (2013)	U.S.	2001, 2009	230,000 household vehicles	23-66%
Weber and Farsi (2014)	Switzerland	2010	8,000 household vehicles	19-81%
Gillingham (2014)	California	2001-2009	5 million vehicles	22-23%

Su (2015)	U.S.	2009	45,000 household vehicles	9-17%
Gillingham et al. (2015)	Pennsylvania	2000-2010	7 million vehicles	8-15%
West *et al.* (2015)	U.S.	2009	166,000 new vehicles	0%
Langer *et al.* (2017)	Ohio	2009-2013	229,000 driver-months	11-15%
Wenzel and Fujita (2018)	Texas	2005-2020	32 million vehicles	0-40%
Knittel and Sandler (2018)	California	1996-2010	76 million vehicles	10-25%
Roth (2019)	Switzerland	1998-2010	72,000 vehicles	0-5%

Figure 4-19 displays the resulting probability distribution of estimates of the rebound effect derived from the elasticity of vehicle use with respect to fuel economy or fuel efficiency; it incorporates results from 12 separate published studies that report a total of 70 estimates. The figure shows the distribution of all estimates over the range from 0-30 percent, together with separate distributions for studies from the United States and other nations, as well as for those relying on households' combined use of the vehicles they own and on the use of individual vehicles. Multiple "peaks" in most of these distributions are evident, often reflecting the clustering of a single study's estimates, but also indicating the limited number of estimates they summarize. As it illustrates, the most likely estimate for the United States falls in the 15-20 percent range, while values from approximately 6-12 percent are most likely in studies from outside the United States. The most probable estimates from both household- and vehicle-based studies also appear to fall into the 6-12 percent range.

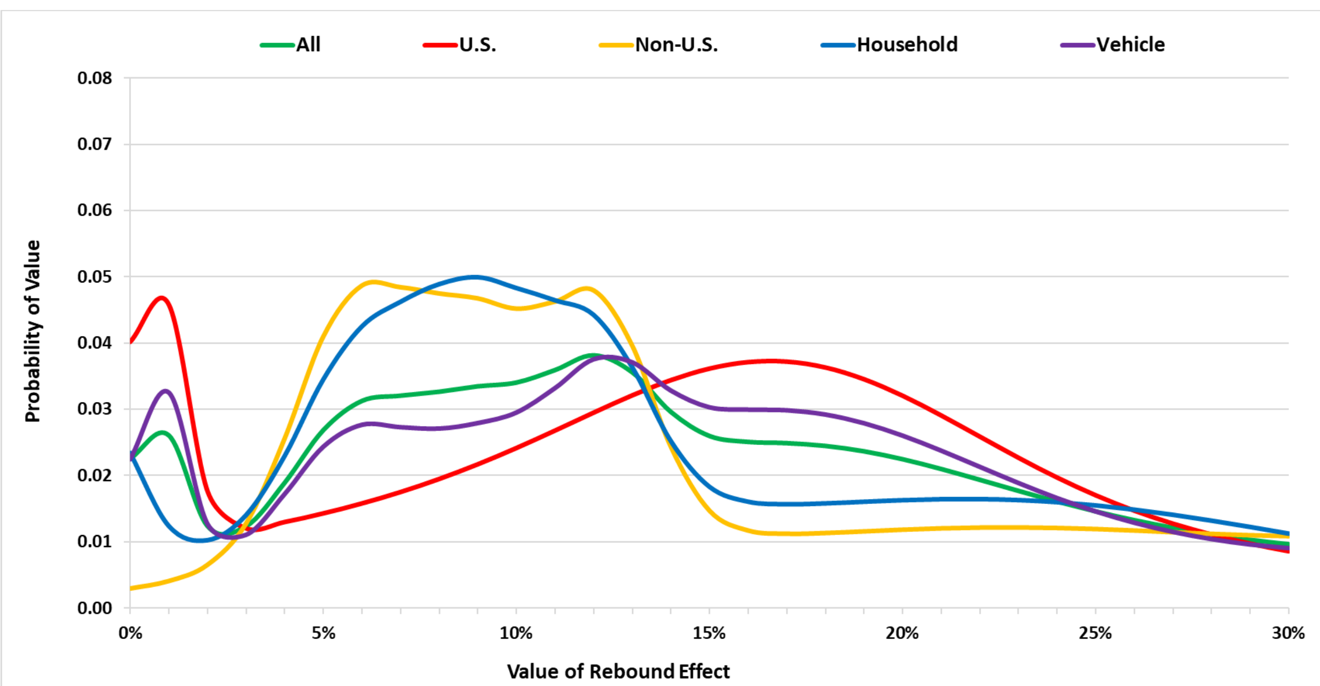

Figure 4-20 – Probability Distribution of Rebound Effect Estimates Based on Fuel Economy or Fuel Efficiency

Figure 4-21 displays the probability distribution of estimates of the rebound effect derived from the elasticity of vehicle use with respect to fuel cost per unit of distance traveled, which incorporates results from 19 published studies reporting a total of 143 estimates, more than twice the number included in the previous figure. As it shows, the two studies relying on household vehicle use suggest most likely values for the rebound effect of less than 5 percent, while studies using other types of data and measurement approaches consistently indicate most likely values in the 10-15 percent range. Estimates for the United States show a most likely value in this latter range as well, while the distribution of non-U.S. estimates suggests a central tendency of 15-20 percent but is so "flat" by comparison that values outside this range are only slightly less likely.

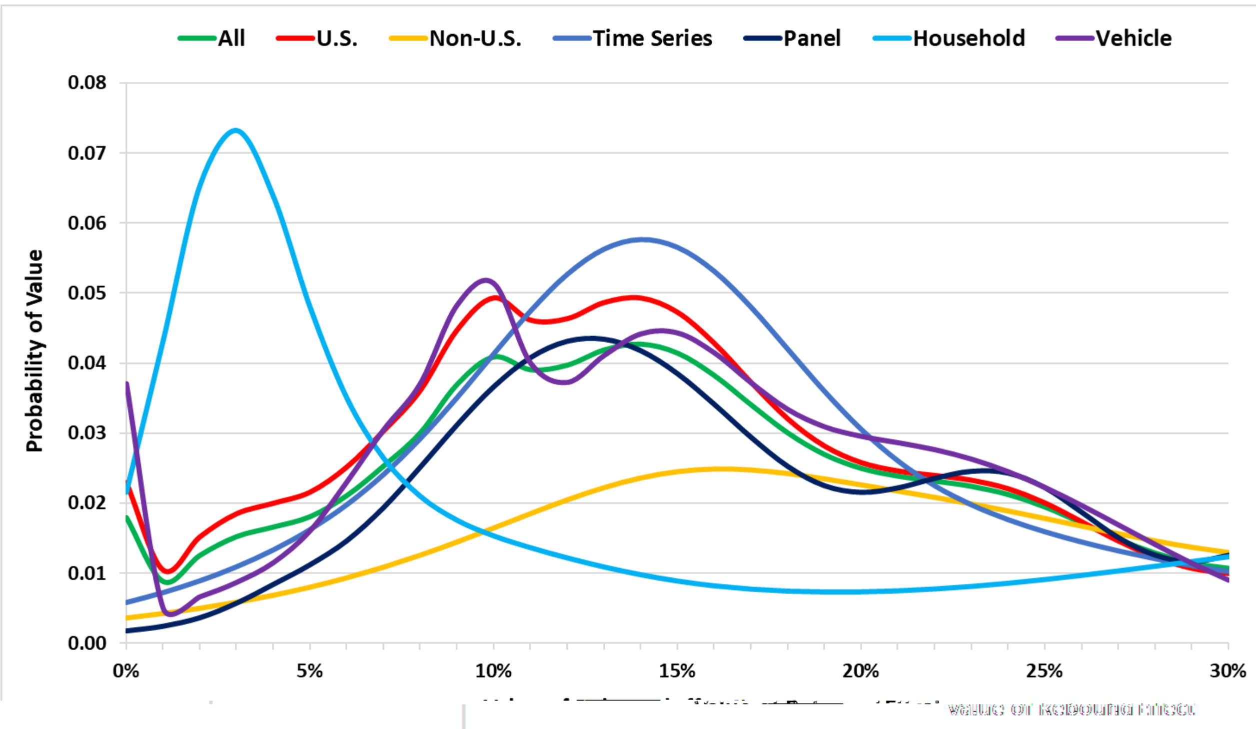

Figure 4-21 – Probability Distribution of Rebound Effect Estimates Based on Fuel Cost per Distance Traveled

NHTSA believes it is also important to benchmark the findings from its analysis against previous large-scale surveys of published research on the rebound effect, and Table 4-18 summarizes the findings from four such surveys. In the earliest, Greening, Greene, and Difiglio (2000) reviewed 7 studies that estimated the rebound effect for light-duty vehicles in the United States using the elasticity of vehicle use with respect to fuel cost per mile to measure it, and concluded that the U.S. rebound effect was likely to fall in the range of 10-30 percent.[644] Sorrell (2007) later reviewed 9 primarily European analyses and found considerably higher values; the studies based on fuel efficiency he reviewed suggested a figure of 40 percent, while the few based on fuel cost

[644] Greening, L.A., Greene, D.L. and Difiglio, C., "Energy efficiency and consumption—the rebound effect—a survey." *Energy Policy*, Vol. 28 (2000), at pp. 389-401.

per km indicated a range of 5-30 percent. Sorrell et al. (2009) later expanded that earlier survey to include 16 – again mostly European – studies and arrived at similar results, reporting a mean estimate of 44 percent for studies that measured the rebound effect as a response to variation in fuel efficiency but a mean value less than half that (21 percent) for those based on fuel cost per km traveled.[645] For various reasons, those authors speculated that the lower end of the range they identified might be most appropriate.

Table 4-18 – Findings from Previous Surveys of the Fuel Economy Rebound Effect

Author(s)	Publication Date	Number of Studies Reviewed	Estimates Based on Fuel Economy or Efficiency				EstimatesBased on Fuel Cost per Mile or KM				Recommended Values	
			Number	Mean	Low	High	Number	Mean	Low	High	U.S.	Global
Greening *et al.*	2000	7	--	--	--	--	13	20%	5%	31%	10-30%	--
Sorrel	2007	9	4	40%	0%	87%	5	--	5%	30%	--	10-30%
Sorrell *et al.*	2009	16	5	44%	0%	87%	12	21%	6%	32%	--	10-30%
Dimitropoulos	2018	69	203	27%	-64%	133%	445	20%	-28%	145%	~20%	26-29%

Most recently, a meta-analysis of 74 published studies of the rebound effect conducted by Dimitropoulos *et al.* (2018) found extremely wide variation in reported values, estimating that the long-run rebound effect averaged 27 percent when measured by the response of vehicle use to variation in fuel efficiency (the authors' preferred measure), and 20 percent when it is measured using variation in fuel cost per unit of distance traveled.[646] The authors concluded that "the magnitude of the rebound effect in road transport can be considered to be, on average, in the area of 20 [percent]," but noted that their most likely long-run estimate was about 32 percent.[647] A subsequent study by these same authors concluded that the most likely estimate of the long-run rebound effect is in the range of 26-29 percent.[648] Thus the finding from these surveys that the rebound effect offsets only a minor share of total potential fuel savings has remained surprisingly consistent over time, despite a rapidly expanding universe of empirical evidence drawn from increasingly diverse settings, continuing improvements in the data available to measure it, an expanding range of strategies for identifying the rebound effect and distinguishing it from other factors influencing vehicle use, and advances in the econometric procedures analysts use to estimate its magnitude.

On the basis of the evidence reviewed here, NHTSA has elected to use a rebound effect of 10 percent to analyze the effects of adopting higher CAFE standards. NHTSA's analysis of the probability distribution functions presented here suggest that the median value is between 10 and 15 percent. In weighing the available evidence, NHTSA considered factors similar to those cited by the EPA in its final rule and found by Dimitropoulos et al. (2018) to account for much of the wide variation among estimates reported in international studies. Thus the agency focused particularly on (1) estimates for the U.S. versus those for countries with differing transportation

[645] Sorrell, Steve, John Dimitropoulos, and Matt Sommerville, "Empirical Estimates of the Direct Rebound Effect: A Review," Energy Policy 37(2009), at pp. 1356–71.
[646] Dimitropoulos, Alexandros, Walid Oueslati, and Christina Sintek, "The rebound effect in road transport: a meta-analysis of empirical studies," Paris, OECD Environment Working Papers, No. 113; see esat Table 5, at p. 25 (and accompanying discussion).
[647] *Id.* at p. 28.
[648] Dimitropoulos, Alexandros, Walid Oueslati, and Christina Sintek, "The Rebound Effect in Road Transport: A Meta-Analysis of Empirical Studies," *Energy Economics* 75 (2018), at pp. 163–79; see esat Table 4, at p. 170, Table 5, at p. 172 (and accompanying discussion), and Appendix B, Table B.V., at p. 177.

systems, fuel prices, population densities and income levels, (2) those derived using more recent data or taking into account the potential for the rebound effect to change over time in response to factors such as rising income and increasing fuel economy (for example, Hymel and Small (2015) and Greene (2010)), (3) estimates based on multiple years of data versus those derived from a single year of survey data (which tend to produce the highest and most variable estimates), (4) values that are based on fuel efficiency or fuel cost per mile rather than the price of gasoline itself, and (5) estimates derived from more reliable data sources such as the U.S. Department of Transportation's historical statistics on aggregate vehicle use or odometer readings for individual vehicles (e.g., Gillingham et al. (2015), Knittel and Sandler (2018), Wenzel and Fujita (2018) and West et al. (2015)), rather than owners' self-reported estimates of driving. When these characteristics are taken into account, the totality of the evidence appears to support the use of a smaller rebound elasticity than that used in previous rules. Because there is a plausible range of values, we include a sensitivity analysis of 5 percent and 15 percent. As previously, the agency will continue to review new evidence on the magnitude of the fuel economy rebound effect and will update its summaries of that evidence and to adjust the value it employs in regulatory future analysis as appropriate.

4.3.6 VMT Resulting from Simulation

Lifetime mileage accumulation is now a function of new vehicle sales, annual rates of retirement for used vehicles, the base year mileage accumulation schedules (described in Table 4-14), the redistribution of VMT across the age distribution of registered vehicles in each calendar year to preserve the non-rebound VMT constraint, and any additional mile attributable to the rebound effect. As discussed in detail above, the definition of "non-rebound" VMT in this analysis determines the additional miles associated with secular fleet turnover and fuel price changes. Conversely, rebound miles measure the VMT difference due to fuel economy improvements relative to MY 2016 (independent of changes in fuel price, or secular fleetwide fuel economy improvement resulting from the continued retirement of older vehicles and their replacement with newer ones).

To calculate total VMT including the increase resulting from the rebound effect that occurs in response to required increases in fuel economy under the regulatory alternatives, the CAFE Model applies the price elasticity of VMT derived from the FHWA forecasting model to the full change in CPM and the initial VMT schedule. At the same time, however, it applies the (user defined) value of the rebound effect to the incremental percentage change in CPM between the non-rebound and full CPM calculations to the miles applied to each vehicle during the reallocation step that ensured adjusted non-rebound VMT matched the non-rebound VMT constraint. Equation 4-16 presents this calculation:

$$\sum_{A}^{Ages}\sum_{S}^{Styles}(VMT_{A,S}\cdot\left(1+\%\Delta CPM_{MY,CY}\cdot\varepsilon_{Rbd}\right)+\Delta Miles_{A,S,CY}\cdot(1+(\%\Delta CPM_{MY,CY}\cdot\varepsilon_{Rbd} - \%\Delta NonRbdCPM_{MY,CY}\cdot\varepsilon_{FHWA}))\cdot\ Population_{CY,A,S}$$

Equation 4-16 – Total Calendar Year VMT with Rebound Miles

In the equation, $VMT_{A,S}$ is the initial VMT schedule by age and body-style, %ΔNonReboundCPM and %ΔCPM are defined in Equation 4-11 and Equation 4-10, respectively, and $\Delta Miles_{A,S,CY}$ is the per-vehicle miles added by the reallocation described in Equation 4-15. However, the additional miles that are added to each vehicle in the reallocation step ($\Delta Miles_{A,S,CY}$) are multiplied by only the difference between the percentage changes in full CPM and non-rebound CPM, respectively. This is because the %ΔNonRbdCPM was used to derive the allocated miles, so using the full CPM change to scale the allocated miles would account for that change twice.

Taking this difference avoids overestimating the total mileage in the presence of the rebound effect. And the presence of both the elasticity from the FHWA model that was applied to the non-rebound VMT constraint, $\boldsymbol{\varepsilon_{FHWA}}$, and the user-defined elasticity of travel, $\boldsymbol{\varepsilon_{Rbd}}$, ensure consistency with the constraint even if the user defines a value of rebound that does not equal the value in the FHWA model. The "rebound miles" will be the difference between Equation 4-16 and Equation 4-15 for each alternative. To the extent that regulatory scenarios produce comparable numbers of rebound miles in early calendar years, the impacts associated with those miles net out across the alternatives in the benefit cost analysis.

5 Simulating Emissions Impacts of Regulatory Alternatives

This analysis includes the adoption of electric vehicles and other fuel-saving technologies, which produce additional co-benefits. These co-benefits include reduced vehicle tailpipe emissions during operation as well as reduced upstream emissions during petroleum extraction, transportation, refining, and finally fuel transportation, storage, and distribution (TS&D). This chapter has a detailed discussion on the development and evolution of input parameters for criteria pollutants, greenhouse gases, and air toxics emitted, in particular for the reference case.

The rule implements an emissions inventory methodology for estimating impacts. Vehicle emissions inventories are often described as three-legged stools, comprised of activity (*i.e.*, miles traveled, hours operated, or gallons of fuel burned), population (or number of vehicles), and emission factors. An emissions factor is a representative rate that attempts to relate the quantity of a pollutant released to the atmosphere per unit of activity.[649]

In this rulemaking, upstream emission factors are on a fuel volume basis and tailpipe emission factors are on a distance basis. Simply stated, the rule's upstream emission inventory is the product of the per-gallon emission factor and the corresponding number of gallons of gasoline or diesel consumed. Similarly, the tailpipe emission inventory is the product of the per-mile emission factor and the appropriate miles traveled estimate. The only exceptions are that tailpipe sulfur oxides (SO_X) and carbon dioxide (CO_2) also use a per-gallon emission factor in the CAFE Model. The activity levels—both miles traveled and fuel consumption—are generated by the CAFE Model while the emission factors have been incorporated from other federal models.

For this rule, vehicle tailpipe (downstream) and upstream emission factors and subsequent inventories were developed independently from separate data sources. Upstream emission factors are estimated from a lifecycle emissions model developed by the U.S. Department of Energy's (DOE) Argonne National Laboratory. Tailpipe emission factors are estimated from the

[649] U.S. Environmental Protection Agency, Basics Information of Air Emissions Factors and Quantification, https://www.epa.gov/air-emissions-factors-and-quantification/basic-information-air-emissions-factors-and-quantification. (Accessed: February 15, 2022).

regulatory highway emissions inventory model developed by the U.S. Environmental Protection Agency's (EPA) National Vehicle and Fuel Emissions Laboratory. Data from the latest EPA and DOE models have been utilized to update the CAFE Model for this rulemaking.

This chapter also details how these emissions will adversely affect human health, particularly from criteria pollutants known to cause poor air quality and damage human health, particularly when inhaled. Further description on how the health impacts of upstream and tailpipe criteria pollutant emissions can vary and how these emission damages have been monetized and incorporated into the rule can be found in Chapter 6.2.2 and the Final SEIS accompanying this analysis.

5.1 Activity Levels Used to Calculate Emissions Impacts

Emission inventories in this rule vary by several key activity parameters, especially relating to the vehicle's model year and relative age. Most importantly, the CAFE Model accounts for vehicle sales, turnover, and scrappage as well as travel demands over its lifetime. Like other models, the CAFE Model includes procedures to estimate annual rates at which new vehicles are purchased, driven, and subsequently scrapped. Together, these procedures result in, for each vehicle model in each model year, estimates of the number remaining in service in each calendar year, as well as the annual mileage accumulation (*i.e.*, VMT) at each age. Inventories by model year are derived from the annual mileage accumulation rates and corresponding emission factors.

As discussed in Chapter 2.1, for each vehicle model/configuration in each model year from 2020 to 2050 for upstream estimates and 2060 for tailpipe estimates, the CAFE Model estimates and records the fuel type (*e.g.*, gasoline, diesel, electricity), fuel economy, and number of units sold in the United States. The model also makes use of an aggregated representation of vehicles sold in the United States during 1975-2019. The model estimates the numbers of each cohort of vehicles remaining in service in each calendar year, and the amount of driving accumulated by each such cohort in each calendar year.

The CAFE Model estimates annual vehicle-miles of travel (VMT) for each individual car and light truck model produced in each model year at each age of their lifetimes, which extend for a maximum of 40 years.[650] Since a vehicle's age is equal to the current calendar year minus the model year in which it was originally produced, the age span of each vehicle model's lifetime corresponds to a sequence of 40 calendar years beginning in the calendar year corresponding to the model year it was produced.[651] These estimates reflect the gradual decline in the fraction of each car and light truck model's original model year production volume that is expected to remain in service during each year of its lifetime, as well as the well-documented decline in their

[650] Registration data indicate that survival rates for 39-year-old vehicles have tended to fall between 1 and 2.5 percent, and odometer reading data indicate that 39-year-old vehicles have tended to be driven far less intensively than newer vehicles. Uncertainties tend to increase for the oldest vehicles, and accounting for vehicle survival and mileage accumulation over a 40-year span has also proven analytically practicable.

[651] In practice, many vehicle models bearing a given model year designation become available for sale in the preceding calendar year, and their sales can extend through the following calendar year as well. However, the CAFE Model does not attempt to distinguish between model years and calendar years; vehicles bearing a model year designation are assumed to be produced and sold in that same calendar year.

typical use as they age. Using this relationship, the CAFE Model calculates fleet-wide VMT for cars and light trucks in service during each calendar year spanned by this analysis.

Based on these estimates, the model also calculates quantities of each type of fuel or energy, including gasoline, diesel, and electricity, consumed in each calendar year. By combining these with estimates of each model's fuel or energy efficiency, the model also estimates the quantity and energy content of each type of fuel consumed by cars and light trucks at each age, or viewed another way, during each calendar year of their lifetimes. As with the accounting of VMT, these estimates of annual fuel or energy consumption for each vehicle model and model year combination are combined to calculate the total volume of each type of fuel or energy consumed during each calendar year, as well as its aggregate energy content.

The procedures the CAFE Model uses to estimate annual VMT for individual car and light truck models produced during each model year over their lifetimes and to combine these into estimates of annual fleet-wide travel during each future calendar year, together with the sources of its estimates of their survival rates and average use at each age, are described in detail in Chapters 4.2 and 4.1. The data and procedures it employs to convert these estimates of VMT to fuel and energy consumption by individual model, and to aggregate the results to calculate total consumption and energy content of each fuel type during future calendar years, are also described in detail in that same section.

The model documentation accompanying today's notice describes these procedures in detail.[652] The quantities of travel and fuel consumption estimated for the cross section of model years and calendar years constitutes a set of "activity levels" based on which the model calculates emissions. The model does so by multiplying activity levels by emission factors. As indicated in the previous section, the resulting estimates of vehicle use (VMT), fuel consumption, and fuel energy content are combined with emission factors drawn from various sources to estimate emissions of GHGs, criteria air pollutants, and airborne toxic compounds that occur throughout the fuel supply and distribution process, as well as during vehicle operation, storage, and refueling. Emission factors measure the mass of each GHG or criteria pollutant emitted per vehicle-mile of travel, gallon of fuel consumed, or unit of fuel energy content. The following sections identifies the sources of these emission factors and explains in detail how the CAFE Model applies them to its estimates of vehicle travel, fuel use, and fuel energy consumption to estimate total annual emissions of each GHG, criteria pollutant, and airborne toxic.

5.2 Simulating Upstream Emissions Impacts

The effect of reductions in U.S. fuel consumption that result from adopting more stringent CAFE standards on upstream emissions of criteria air pollutants, GHGs, and air toxics depends partly on the responses of domestic petroleum production and refining, together with changes in U.S. imports of crude petroleum and refined fuel. To illustrate why, there are three major supply "pathways" for fuel consumed by the U.S. light-duty vehicle fleet:

[652] CAFE Model documentation is available at https://www.nhtsa.gov/corporate-average-fuel-economy/compliance-and-effects-modeling-system. (Accessed: February 15, 2022).

1. Refining fuel in the United States from crude petroleum produced within the United States.
2. Refining fuel in the United States from crude petroleum produced overseas and imported into the United States.
3. Importing fuel that has been refined overseas into the United States.[653]

Each of these supply pathways produces emissions at different facilities and locations – oil fields, pipelines, refineries, and fuel storage facilities. Thus, while total upstream emissions from supplying fuel are identical regardless of how it is supplied, *domestic* emissions will differ depending on its source of supply. For example, pathway 1 involves domestic emissions that occur during crude petroleum extraction, transportation of crude oil from production or temporary storage facilities to domestic refineries, refining of crude petroleum to produce transportation fuels, and storage and distribution of refined fuels.[654] In contrast, pathway 2 generates domestic emissions during transportation of crude petroleum from U.S. coastal ports to domestic refineries, as well as from fuel refining, storage, and distribution, while pathway 3 produces domestic emissions only from fuel storage and distribution.

Thus, reductions in the volume of fuel supplied via each of these pathways will have different consequences for domestic emissions occurring throughout the fuel supply and distribution process. In addition, because the United States is now a net exporter of refined gasoline (and is likely to remain so for at least the next two decades), some of the anticipated reduction in domestic gasoline consumption may result in refiners simply redirecting fuel that is currently supplied for domestic consumption via pathways 1 and 2 to the export market, resulting in no change in upstream emissions. NHTSA considers only the consequences of changes in upstream emissions of criteria air pollutants and air toxics within the United States that result from reduced fuel consumption. The agency's analysis estimates these by applying emission factors for each stage of the fuel supply chain (petroleum extraction, petroleum transportation to refineries, fuel refining, and fuel storage and distribution) to the estimated changes in the total energy content of fuel assumed to be supplied via each of the pathways identified above. In contrast, the agency's analysis considers changes in global emissions of GHGs, and estimates these by including the effects of lower domestic fuel consumption on emissions that occur during all stages of the fuel supply chain, regardless of whether those activities take place within the United States or outside its borders.

The agency considers both the physical quantities and societal cost of both tailpipe and upstream emissions when setting CAFE standards. Early CAFE rulemakings utilized upstream emission factors from the U.S. Department of Energy's previous releases of the Greenhouse gases, Regulated Emissions, and Energy use in Transportation (GREET) Model.[655] This rule includes

[653] We assume that all fuel refined outside the United States and then imported into the United States is refined from petroleum that was also produced outside the United States. Although some of it could be refined from crude petroleum produced in the United States and exported, we assume the fraction supplied via this pathway is negligible.
[654] By longstanding EPA convention, emissions that occur when vehicles are being refueled at retail stations or vehicle storage depots (such as buses) are ascribed to vehicle use, rather than to fuel supply.
[655] U.S. Department of Energy, Argonne National Laboratory, Greenhouse gases, Regulated Emissions, and Energy use in Transportation (GREET) Model, Last Update: 11 Oct. 2021, https://greet.es.anl.gov/. (Accessed: February 15, 2022).

data from GREET 2021 and additionally uses a Python script to manipulate data formats, allowing for quicker, easier replication. Rulemaking updates to upstream emissions were made for certain fuel types:

- Gasoline,
- Diesel, and
- Electricity.

This chapter provides the calculation methodology of these updated upstream emission factors (in g/mmBTU) for the following regulated criteria pollutants as well as greenhouse gases derived from GREET 2021:

- Regulated criteria pollutants
  - carbon monoxide (CO),
  - volatile organic compounds (VOCs),
  - nitrogen oxides (NO_X),
  - sulfur oxides (SO_X), and
  - particulate matter with 2.5-micron (µm) diameters or less ($PM_{2.5}$);
- Greenhouse gases
  - carbon dioxide (CO_2),
  - methane (CH_4), and
  - nitrous oxide (N_2O).

Emission factors for air toxics and diesel particulate matter of 10 µm or less (PM_{10}) were unchanged from the 2018 NPRM and 2020 final rule.

Each analysis year has emission factors of the four upstream emission processes for gasoline and diesel:

- Petroleum Extraction,
- Petroleum Transportation,
- Petroleum Refining, and
- Fuel Transportation, Storage, and Distribution (TS&D).

By contrast, electricity only has a single value per analysis year. In the sections below, the specific emission calculations for each upstream process are described. For this rulemaking, analysis years of 2015 and earlier were removed. The upstream CAFE parameters for this rule include 2020 through 2050 in five-year intervals:

- 2020, 2025, 2030, 2035, 2040, 2045, 2050

5.2.1 Petroleum Extraction

The first step in the process for calculating upstream emissions includes any emissions related to the extraction, recovery, and production of petroleum-based feedstocks, namely conventional crude oil, oil sands, and shale oils. This methodology was initially implemented by Volpe with example guidance from the Department of Energy's Argonne National Laboratory. The

Petroleum Extraction calculation began by summing all of the emission factors by extraction subprocess from the GREET 2021 Petroleum tab. For example, the emission factor EF of oil sands surface mining for diluted bitumen (dilbit) production is the sum of each extraction subprocess EF: bitumen extraction and separation, on-site H_2 production, co-produced electricity credit, flaring emissions, and bitumen extraction and separation non-combustion emissions.

Each extraction EF is then multiplied by the associated loss factors—or process inefficiencies—and energy share for the following combinations of feedstock and primary extraction process:

- Crude Oil
    - Recovery
- Oil Sands
    - Surface Mining + Dilbit
        - Bitumen Extraction and Separation,
        - On-site H_2 Production,
        - Co-produced Electricity Credit,
        - Flaring Emissions, and
        - Bitumen Extraction and Separation Non-Combustion Emissions;
    - Surface Mining + Synthetic Crude Oil (SCO)
        - Bitumen Extraction and Separation,
        - On-site H_2 Production,
        - Co-produced Electricity Credit,
        - Flaring Emissions, and
        - Bitumen Extraction and Separation Non-Combustion Emissions;
    - In-Situ Production + Dilbit
        - Bitumen Extraction and Separation,
        - On-site H_2 Production,
        - Co-produced Electricity Credit,
        - Flaring Emissions, and
        - Bitumen Extraction and Separation Non-Combustion Emissions;
    - In-Situ Production + SCO
        - Bitumen Extraction and Separation,
        - On-site H_2 Production,
        - Co-produced Electricity Credit,
        - Flaring Emissions, and
        - Bitumen Extraction and Separation Non-Combustion Emissions;
- Shale Oil (Bakken)
    - Recovery
- Shale Oil (Eagle Ford)
    - Recovery

These seven upstream feedstock/extraction process combinations produce identical estimates for both gasoline and diesel; differences by fuel type only occur during and after the refining process. The extraction calculation includes the two associated loss factors, which are constant across all analysis years and both fuel types, and energy share (rather than the volumetric share) for each combination above:

- Loss Factors
    - Transportation to U.S. Refineries
    - Storage
- Energy Share of Crude Feedstocks to U.S. Refinery

In mathematical terms, the Petroleum Extraction calculation for the emission factor EF dependent on the energy share es (from the GREET Petroleum tab), fuel type f (either gasoline or diesel), analysis year y, and pollutant p can be expressed as shown in Equation 5-1.

$$
\begin{aligned}
EF_{petrol\ extract_{f,y,p}} &= \left(EF_{crude\ oil_{f,y,p}} \cdot loss_{trans} \cdot loss_{storage} \cdot es_{crude\ oil_y}\right) \\
&+ \left(EF_{surface\ mining,dilbit_{f,y,p}} \cdot loss_{trans} \cdot loss_{storage} \cdot es_{surface\ mining,dilbit_y}\right) \\
&+ \left(EF_{surface\ mining,SCO_{f,y,p}} \cdot loss_{trans} \cdot loss_{storage} \cdot es_{surface\ mining,SCO_y}\right) \\
&+ \left(EF_{in\text{-}situ,dilbit_{f,y,p}} \cdot loss_{trans} \cdot loss_{storage} \cdot es_{in\text{-}situ,dilbit_y}\right) \\
&+ \left(EF_{in\text{-}situ,SCO_{f,y,p}} \cdot loss_{trans} \cdot loss_{storage} \cdot es_{in\text{-}situ,SCO_y}\right) \\
&+ \left(EF_{Bakken\ shale_{f,y,p}} \cdot loss_{trans} \cdot loss_{storage} \cdot es_{Bakken\ shale_y}\right) \\
&+ \left(EF_{Eagle\ Ford\ shale_{f,y,p}} \cdot loss_{trans} \cdot loss_{storage} \cdot es_{Eagle\ Ford\ shale_y}\right)
\end{aligned}
$$

Equation 5-1 – Yearly Gasoline Petroleum Extraction Emission Factor

For every year in the series of analysis years $y \in Y$ (note that the year evaluated must be changed in the GREET Inputs tab) and every pollutant in the full set of pollutants $p \in P$ mentioned above, the final gasoline Petroleum Extraction EF is multiplied by the percent non-ethanol remainder of the standard E10 blend currently distributed at fuel pumps across the United States (also found in the GREET Petroleum tab), simply 1 – pure ethanol energy content ($EC_{EtOH}\ \%$) while the final diesel EF is assumed to have no ethanol content, such that:

$$EF'_{petrol\ extract_{gas,y \in Y,p \in P}} = EF_{petrol\ extract_{gas,y \in Y,p \in P}} \cdot (1 - EC_{EtOH}\ \%)$$

and

$$EF'_{petrol\ extract_{diesel,y \in Y,p \in P}} = EF_{petrol\ extract_{diesel,y \in Y,p \in P}}.$$

Equation 5-2 – Total Gasoline Petroleum Extraction Emission Factor

There are a few notable pollutant exceptions that have been originally separated out in GREET by their sources and were later combined in the extraction calculation:

- $Total\ VOC = VOC + VOC\ from\ bulk\ terminal$, and
- $Total\ CH_4 = CH_4{:}\ combustion + CH_4{:}\ non\text{-}combustion.$

Many extraction processes do not include VOC from bulk terminal and CH_4: non-combustion but are added to primary VOC and CH_4 estimates respectively for crude oil and shale oil recovery. The Petroleum Transportation and Fuel TS&D processes also consider combined VOC and CH_4 emission factors.

5.2.2 Petroleum Transportation

The Petroleum Transportation process is quite similar to the Petroleum Extraction process described above, but instead only includes the transport processes of crude feedstocks sent for domestic refining:

- Crude Oil
    - Transportation to U.S. Refineries
- Oil Sands
    - Surface Mining + Dilbit: Transportation to U.S. Refineries,
    - Surface Mining + Synthetic Crude Oil (SCO): Transportation to U.S. Refineries,
    - In-Situ Production + Dilbit: Transportation to U.S. Refineries, and
    - In-Situ Production + SCO: Transportation to U.S. Refineries;
- Shale Oil (Bakken)
    - Transportation to U.S. Refineries
- Shale Oil (Eagle Ford)
    - Transportation to U.S. Refineries

While the Petroleum Transportation calculation does still use energy share es by crude feedstock, it omits the loss factors. As with Petroleum Extraction, the Petroleum Transportation emission factor EF, shown in Equation 5-3, is aggregated by feedstock/process combinations also located in the GREET 2021 Petroleum tab.

$$
\begin{aligned}
EF_{petrol\ transport_{f,y,p}} \\
&= \left(EF_{crude\ oil_{f,y,p}} \cdot es_{crude\ oil_y}\right) \\
&+ \left(EF_{surf\ mining,dilbit_{f,y,p}} \cdot es_{surf\ mining,dilbit_y}\right) \\
&+ \left(EF_{surf\ mining,SCO_{f,y,p}} \cdot es_{surf\ mining,SCO_y}\right) \\
&+ \left(EF_{in\text{-}situ,dilbit_{f,y,p}} \cdot es_{in\text{-}situ,dilbit_y}\right) + \left(EF_{in\text{-}situ,SCO_{f,y,p}} \cdot es_{in\text{-}situ,SCO_y}\right) \\
&+ \left(EF_{Bakken\ shale_{f,y,p}} \cdot es_{Bakken\ shale_y}\right) \\
&+ \left(EF_{Eagle\ Ford\ shale_{f,y,p}} \cdot es_{Eagle\ Ford\ shale_y}\right)
\end{aligned}
$$

Equation 5-3 – Yearly Gasoline Petroleum Transportation Emission Factor

As in the extraction process calculation, the crude feedstock transportation EFs are generated for each fuel type f, year in the series of analysis years $y \in Y$, and each pollutant is the full set of pollutants $p \in P$. The final Petroleum Transportation EF for gasoline is multiplied by the national default non-ethanol remainder ($1 - EC_{EtOH}$ %), whereas the final transport EF for diesel will not contain any ethanol, shown in Equation 5-4.

$$EF'_{petrol\ transport_{gas,y\in Y,p\in P}} = EF_{petrol\ transport_{gas,y\in Y,p\in P}} \cdot (1 - EC_{EtOH}\ \%)$$

and

$$EF'_{petrol\ transport_{diesel,y\in Y,p\in P}} = EF_{petrol\ transport_{diesel,y\in Y,p\in P}}.$$

Equation 5-4 – Total Gasoline Petroleum Transportation Emission Factor

Lastly, the total VOC for Petroleum Transportation is the sum of the primary VOC and the VOC from bulk terminal as shown above for Petroleum Extraction while the total CH_4 is comprised of the combustion component alone.

5.2.3 Petroleum Refining

Unlike the Petroleum Extraction and Petroleum Transportation calculations, the Petroleum Refining calculation is based on the aggregation of fuel blendstock processes rather than the crude feedstock processes. In GREET 2021, the refining processes are found in the finished gasoline and low-sulfur diesel sections of the Petroleum tab, as listed below:

- Gasoline
  - Gasoline Blendstock Refining: Feed Inputs
  - Gasoline Blendstock Refining: Intermediate Product Combustion
  - Gasoline Blendstock Refining: Non-Combustion Emissions
- Low-Sulfur Diesel
  - LS Diesel Refining: Feed Inputs
  - LS Diesel Refining: Intermediate Product Combustion
  - LS Diesel Refining: Non-Combustion Emissions

Since the distribution of crude feedstocks is not considered directly in the refining process, the finished fuel transportation loss adjustment (Gasoline Blendstock Transportation and LS Diesel Transportation Distribution respectively) is factored into the refining emission factor EF calculation while the energy share es is not. This leads to Equation 5-5 for the Petroleum Refining process.

$$EF_{petrol\ refine_{f,y,p}} = \left(EF_{feed\ inputs_{f,y,p}} + EF_{intermediate\ combust_{f,y,p}} + EF_{non\text{-}combust_{f,y,p}}\right) \cdot loss_{blend\ transportation_{y}}$$

Equation 5-5 – Yearly Gasoline Petroleum Refinery Emission Factor

In a similar fashion to the extraction and transportation processes of crude feedstocks, the final Petroleum Refining EF for gasoline applies the non-ethanol energy content adjustment $(1 - EC_{EtOH}\ \%)$ for E10. The final Petroleum Refining EF for diesel does not apply any such non-ethanol adjustment because the fuel is purely based on petroleum. The final refining EFs can be written as shown in Equation 5-6.

$$EF'_{petrol\ refine_{gas,y\in Y,p\in P}} = EF_{petrol\ refine_{gas,y\in Y,p\in P}} \cdot (1 - EC_{EtOH}\,\%)$$

and

$$EF'_{petrol\ refine_{diesel,y\in Y,p\in P}} = EF_{petrol\ refine_{diesel,y\in Y,p\in P}}.$$

Equation 5-6 – Total Gasoline Petroleum Refinery Emission Factor

In the refining calculations, there are no exceptions for VOC or CH_4. Both primary VOC and CH_4 combustion account for the total VOC and total CH_4, respectively.

5.2.4 Fuel TS&D

The final upstream process after refining is the TS&D of the finished fuel product. For gasoline, the blendstock transportation and distribution subprocesses were previously combined in a single GREET value on the Petroleum tab, but now these emission factors (EFs) are reported separately to avoid double-counting of pre-blended E0 transportation in the Fuel TS&D process. This issue does not exist for low-sulfur diesel, which does not require blending like E10. The Fuel TS&D subprocesses for gasoline and diesel in GREET 2021 are summarized:

- Gasoline
  - Gasoline Blendstock Transportation
  - Gasoline Blendstock Distribution
  - Gasoline Distribution
  - Gasoline Storage
- Low-Sulfur Diesel
  - LS Diesel Transportation Distribution
  - LS Diesel Storage

In the default settings, GREET does not report any emissions associated with fuel storage. Given that all storage EFs are zero, the initial Fuel TS&D calculation with GREET 2021 is just the reported EFs for E0 blendstock transportation and distribution.

$$EF_{fuel\ TS\&D_{f,y,p}} = EF_{E0\ blend\ trans_{f,y,p}} + EF_{E0\ blend\ dist_{f,y,p}}$$

Equation 5-7 – Yearly E0 Blendstock Transportation and Distribution Emission Factor

The final Fuel TS&D EF for gasoline accounts for emissions before and after E10 blending. This final gasoline EF utilizes the percent energy content of the non-ethanol remainder—the same as earlier petroleum processes. It also incorporates ethanol energy content with upstream ethanol for gasoline blending EFs on the GREET EtOH tab, where the total ethanol EF is the sum of its fuel and feedstock subprocesses.

$$EF_{EtOH\ \rightarrow gas\ blend_{y,p}} = EF_{EtOH\ \rightarrow gas\ blend,fuel_{y,p}} + EF_{EtOH\ \rightarrow gas\ blend,feedstock_{y,p}}$$

Equation 5-8 – Fuel Transportation and Distribution Emission Factor with E10 Blending

The final Fuel TS&D EFs for gasoline and for diesel can be broken into three terms, E0 distribution, ethanol TS&D, and E10 distribution, such that in GREET 2021:

$$EF'_{fuel\ TS\&D_{gas,y\in Y,p\in P}} = \left(EF_{E0\ blend\ dist_{gas,y\in Y,p\in P}} \cdot (1 - EC_{EtOH}\ \%)\right) + \left(EF_{EtOH \rightarrow gas\ blend_{y\in Y,p\in P}} \cdot EC_{EtOH}\ \%\right) + EF_{E10\ dist_{gas,y\in Y,p\in P}}$$

and

$$EF'_{fuel\ TS\&D_{diesel,y\in Y,p\in P}} = EF_{T\&D_{diesel,y\in Y,p\in P}}$$

Equation 5-9 – Total Fuel Transportation and Distribution Emission Factor

These Fuel TS&D equations have omitted the non-existent storage terms for simplicity. The E0 distribution cannot be directly pulled from GREET 2021 and must be inferred from reported E0 EFs for T&D and transportation alone.

$$EF_{E0\ blend\ dist_{gas,y\in Y,p\in P}} = EF_{E0\ blend\ T\&D_{gas,y\in Y,p\in P}} - EF_{E0\ blend\ trans_{gas,y\in Y,p\in P}}$$

Equation 5-10 – E0 Blend Distribution Emission Factor

Total CH_4 for Fuel TS&D is based solely on the CH_4: combustion component and total VOC is the sum of the primary VOC and other components from the T&D process.

$$Total\ VOC = VOC + VOC\ from\ bulk\ terminal + VOC\ from\ ref.\ station.$$

Equation 5-11 – Total Volatile Organic Compounds from the Transportation and Distribution Process

However, for the gasoline TS&D calculation in GREET 2021 the primary VOC comes from the blendstock distribution while the other VOC components come from the blendstock transportation.

5.2.5 Aggregated Gasoline and Diesel Emission Factors

The upstream gasoline and diesel emission factors EFs for this analysis continue to be aggregated using the same method as previous CAFE analyses. While the particular gasoline and diesel EFs vary by analysis year and pollutant, the aggregation of the four upstream processes—Petroleum Extraction, Petroleum Transportation, Petroleum Refining, and Fuel TS&D—follows the same calculation for both fuel types. The CAFE aggregation method differs from the GREET method and considers the following two upstream adjustments for CAFE:

- Share of Fuel Savings Leading to Reduced Domestic Fuel Refining, and
- Share of Reduced Domestic Refining from Domestic Crude.

In this case, the final CAFE aggregation applies a fuel savings adjustment to the Petroleum Refining process and a combined fuel savings and reduced domestic refining adjustment to the pair of Petroleum Extraction and Petroleum Transportation processes for each fuel type in the gasoline-diesel pair $f \in F$, each year in the series of analysis years $y \in Y$, and each pollutant in the full set of pollutants $p \in P$.

$$EF''_{agg\;y\in Y,p\in P} = EF'_{fuel\;TS\&D_{f\in F,y\in Y,p\in P}} + \left(EF'_{petrol\;refine_{f\in F,y\in Y,p\in P}} \cdot share_{fuel\;savings}\right) + \left(\left(EF'_{petrol\;extract_{f\in F,y\in Y,p\in P}} + EF'_{petrol\;transport_{f\in F,y\in Y,p\in P}}\right) \cdot share_{fuel\;savings} \cdot share_{reduced\;refine}\right)$$

Equation 5-12 – Aggregated Fuel Emissions Factor

For consistency, these aggregated gasoline and diesel EF calculations occur in the CAFE Model rather than the Python script or elsewhere. Note that the upstream adjustments in the CAFE Model are constant across fuel types, analysis years, and pollutants and are unchanged since the 2020 final rule.

5.2.6 Electricity Emission Factors

As part of this rulemaking upstream emissions updates, the electricity emission factors EFs were also transitioned to GREET 2021. The electricity EF calculations were similar to the calculations for ethanol. They project a national default electricity generation mix for transportation use from the latest AEO data available, in this case from 2021 The final electricity EF simply sums the feedstock and fuel subprocesses for every unique analysis year and pollutant.

$$EF_{electric,transport\;use_{y\in Y,p\in P}} = EF_{electric,transport\;use_{feedstock,y\in Y,p\in P}} + EF_{electric,transport\;use_{fuel,y\in Y,p\in P}}$$

Equation 5-13 – Electricity Transportation Emissions Factor

Unlike for the upstream gasoline and diesel EFs, the CAFE Model utilizes the single upstream electricity EF for transportation use highlighted above and does not differentiate by process.

5.3 Simulating Tailpipe Emissions Impacts

Tailpipe emission factors are generated using the latest regulatory model for on-road emission inventories from the U.S. Environmental Protection Agency, the Motor Vehicle Emission Simulator (MOVES3). This section has two primary components of discussion: 1) preparing model runs to estimate tailpipe emission inventories and vehicle activity, referred to below as pre-processing, and 2) calculating tailpipe emission factors on a per-mile basis, referred to below as post-processing. In addition, this section discusses the separate process for generating tailpipe CO_2 emissions levels in the CAFE Model.

5.3.1 Pre-Processing of MOVES Data

For this rulemaking, the CAFE Model's tailpipe input parameters for criteria pollutants, non-CO_2 greenhouse gases, and mobile-source air toxics have been updated with the latest available emission factors. The most recent version of the Motor Vehicle Emission Simulator (MOVES3), first released in November 2020, is a state-of-the-science, mobile-source emissions inventory model for regulatory applications.[656] New MOVES3 tailpipe emission factors have been incorporated into the CAFE parameters, and these updates supersede tailpipe data previously provided by EPA from MOVES2014 for past CAFE analyses.

5.3.1.1 Overview of MOVES Modeling

To maintain continuity in the historical inventories, only emission factors for model years 2020 and after were updated; all emission factors prior to MY 2020 were unchanged from previous CAFE rulemakings. In addition, this updated tailpipe data in the current CAFE reference case no longer accounts for any fuel economy improvements or changes in VMT from the 2020 rule. In order to avoid double-counting effects from the previous rulemaking in the current rulemaking, the new tailpipe baseline backs out:

1) 1.5 percent year-over-year stringency increases in fuel economy, and
2) 0.3 percent VMT increases assumed each year (20 percent rebound on the 1.5 percent improvements in stringency).

The baseline was reverted in the MOVES3 default database prior to executing the new runs for the tailpipe data updates. Detailed MOVES3 run specifications have been listed in Table 5-1. Tailpipe parameters in the CAFE Model have otherwise maintained their format, besides now extending to MY 2060. The most relevant factors from these tailpipe parameters have been summarized as follows:

- MOVES Release: 3.0.1 (March 2021)[657]
- MOVES Default Database: 20210209
- Fuel Types:
  - gasoline
  - diesel
- Vehicle Classes:
  - light-duty vehicles (MOVES regulatory class 21)
  - light-duty trucks, Classes 1 and 2a (MOVES regulatory class 30)
  - light-duty trucks, Classes 2b and 3 (MOVES regulatory class 41)
- Model Years: 2020 – 2060
- Vehicle Ages: 0 – 39 years old
- Criteria Pollutants:
  - carbon monoxide (CO)
  - volatile organic compounds (VOCs)
  - nitrogen oxides (NO_X)
  - particulate matter with 2.5-micron (μm) diameters or less ($PM_{2.5}$)[658]
- Greenhouse gases

[656] U.S. Environmental Protection Agency, Office of Transportation and Air Quality, Motor Vehicle Emission Simulator (MOVES), Last Updated: September 2021, https://www.epa.gov/moves/latest-version-motor-vehicle-emission-simulator-moves. (Accessed: February 15, 2022).

[657] As of the date of this document, the latest version of MOVES is 3.0.2. Because the difference between MOVES 3.0.1 and 3.0.2 are very minor for light duty vehicle emissions, the decision was made not to update the emission factors for tailpipe emissions.

[658] For CAFE modeling, $PM_{2.5}$ emission factors include exhaust processes and excludes brake and tire wear.

    - methane (CH_4)
    - nitrous oxide (N_2O)
- Air Toxics
    - acetaldehyde
    - acrolein
    - benzene
    - butadiene
    - formaldehyde
    - diesel particulate matter with 10-micron (μm) diameters or less (PM_{10})

Table 5-1 – National-Scale Run Specifications

Categories	Variable	Input
Description	-----	<blank>
Scale	Model	Onroad
	Domain/Scale	National
	Calculation Type	Inventory
Time Spans	Time Aggregation Level	Year
	Years	2020, 2021, 2022, 2023… 2057, 2058, 2059, 2060 [each year was run separately]
	Months	All Selected
	Days	All Selected
	Hours	All Selected
Geographic Bounds	-----	Nation
Vehicles/ Equipment	On-Road Vehicle Equipment	All Fuel/Type Combinations Selected
Road Type	Road Type	All Road Types
Pollutants and Processes	Total Gaseous Hydrocarbons	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust, Evap Permeation, Evap Fuel Vapor Venting, Evap Fuel Leaks, Refueling Displacement Vapor Loss, Refueling Spillage Loss
	Non-methane Hydrocarbons	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust, Evap Permeation, Evap Fuel Vapor Venting, Evap Fuel Leaks, Refueling Displacement Vapor Loss, Refueling Spillage Loss
	Volatile Organic Compounds	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust, Evap Permeation, Evap Fuel Vapor Venting, Evap Fuel Leaks, Refueling Displacement Vapor Loss, Refueling Spillage Loss
	Methane (CH_4)	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust
	Carbon Monoxide (CO)	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust
	Oxides of Nitrogen (NO_X)	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust
	Nitrous Oxide (N_2O)	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust

Categories	Variable	Input
	Primary Exhaust $PM_{2.5}$ – Total	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust
	Primary Exhaust $PM_{2.5}$ – Species	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust
	Primary $PM_{2.5}$ – Brakewear Particulate	Brakewear[659]
	Primary $PM_{2.5}$ – Tirewear Particulate	Tirewear
	Primary Exhaust PM_{10} – Total	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust
Pollutants and Processes	Primary Exhaust PM_{10} – Species	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust
	Primary PM_{10} – Brakewear Particulate	Brakewear
	Primary PM_{10} – Tirewear Particulate	Tirewear
	Sulfur Dioxide (SO_2)	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust
	Carbon Dioxide Equivalent (CO_2e)	Running Exhaust, Start Exhaust
	Total Energy Consumption (TEC)	Running Exhaust, Start Exhaust
	Benzene	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust, Evap Permeation, Evap Fuel Vapor Venting, Evap Fuel Leaks, Refueling Displacement Vapor Loss, Refueling Spillage Loss
	1,3-Butadiene	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust
	Formaldehyde	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust
	Acetaldehyde	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust
	Acrolein	Running Exhaust, Start Exhaust, Crankcase Running Exhaust, Crankcase Start Exhaust
Manage Input Data Series	-----	<blank>
Strategies	Rate of Progress	<blank>
General Output	Units	Mass: kilograms, Energy: million BTU, Distance: miles
	Activity	Distance Traveled, Population
Output Emissions Detail	Always	Year, Nation
	On Road/Off Road	Road Type, Source Use Type, Regulatory Class
	For All Vehicle/Equipment Combinations	Model Year, Fuel Type, Emission Process

659 For CAFE modeling, the post-processing of emission factors for $PM_{2.5}$ included exhaust processes (running, start, crankcase running, and crankcase start) and excluded brake and tire wear.

Categories	Variable	Input
Advanced Performance Features	-----	<blank>

5.3.1.2 Implementation of MOVES Runs

To begin, a MOVES3 run specification (runspec) for calendar year 2020 was built as a template and then replicated for all other years out to 2060, creating a total of 41 runs. The 2020 template run uses the national-scale specifications denoted in Table 5-1. In addition, the MOVES3 default database has been updated with the light-duty vehicle changes noted earlier, namely higher energy consumption rates and lower annual VMT estimates compared to the 2020 final rule. Beyond designating one year per run, all runs were executed with the same runspecs and modified default database. The 41 runs were then batched together and executed continuously. Performance ranged from roughly 5-8 hours of time to complete each run depending on the machine on which it was executed and its available resources.

Post-processing the MOVES3 data into an appropriate format for the CAFE Model is described below. This post-processing discussion details how the tailpipe emission factors were calculated from the MOVES3 output databases and then translated into the CAFE input parameters file.

5.3.2 Post-Processing of MOVES Data

The Motor Vehicle Emission Simulator (MOVES3) data were post-processed into input parameters for the CAFE Model using a Python script. Tailpipe emission parameters for this rulemaking were updated for gasoline and diesel light-duty vehicles and trucks, including the criteria pollutants, greenhouse gases, and air toxics across model years 2020 to 2060, as mentioned in the run specifications in the MOVES pre-processing discussion above.

5.3.2.1 Overview of Tailpipe Data Development from MOVES

As noted earlier, each MOVES3 run created an output database for a single evaluation year, meaning there were 41 total runs and subsequent output databases. Output databases contain a number of tables with model emissions inventories and vehicle activities, such as VMT.

The next section describes the specific steps taken to alter the output database from MOVES3. The data for years before 2020 were removed and previous data were used. This should not affect the outcome of the model because emission rates for previous models cannot be changed.

5.3.2.2 Description of MOVES Output Tables

The MOVES output database contains many tables; however, the post-processing script pulls from only two of these tables. The post-processing script uses the following tables:

- movesoutput
- movesactivityoutput

Each table contains many columns, including calendar year, vehicle model year, regulatory class based on vehicle weight and build, fuel type, specific pollutant, and emission inventory, and the vehicle activity. The following columns from each table were used in the post-processing script:

- movesoutput: yearID, modelYearID, regClassID, fuelTypeID, pollutantID, emissionQuant
- movesactivityoutput: yearID, modelYearID, regClassID, fuelTypeID, activity

5.3.2.3 Connecting to and Querying the MOVES Database

After establishing a MariaDB connection, the code queries the database and returns a dataframe with the following columns:

- yearID, modelYearID, age, regClassID, fuelTypeID, pollutantID, VMT, emissionRate

The age, VMT, and emissionRate columns are calculated from the other columns, which are generated in the default outputs. Age is simply calculated by subtracting the modelYearID from the yearID, while the VMT is taken as the sum of the distance traveled activity and then grouped by yearID, modelYearID, pollutantID, and regClassID for gasoline and diesel separately. Lastly, emissionRate was calculated as the aggregated emissions inventories divided by the aggregated VMT at a corresponding level of resolution.[660]

5.3.2.4 MOVES Data Manipulation

After querying and calculating the columns in the correct units, the next step is simply arranging the data into the appropriate format and copying them to the appropriate parameters file. To do so, we first separated the data into two dataframes by fuel type. We then sorted the data by ascending model year, meaning the data began with model year 1990. Within the model year, the data were again sorted by descending age, ascending pollutant, and ascending regulatory class. The resulting dataframe had the structure shown in Table 5-2.

Table 5-2 – Example of General MOVES Output

Model Year	Age	Pollutant	Regulatory Class
2020	0		
2020	1		
2020	2		
2020	3		
2020	4		
…	…	…	…
2060	34		
2060	35		
2060	36		
2060	37		
2060	38		

[660] Note, although the emissions rate is distance based (VMT), the emissions include both on-network and off-network emissions. Therefore, the resulting emissions include all emissions from the vehicle.

2060	39		

Next, the script pivots this dataframe such that the pollutant and regulatory class values become column headers in the format shown in Table 5-3.

Table 5-3 – Example of MOVES Output Prepared in CAFE Parameters Format

	Pollutant	2	2	2	3	3	3	…
Model Year	Regulatory Class Age	20	30	41	20	30	41	…
2020	0							
2020	1							
2020	2							
2020	3							
2020	4							
….	…	…	…	…	…	…	…	…
2060	34							
2060	35							
2060	36							
2060	37							
2060	38							
2060	39							

The MOVES3 output does not cover all the model years and ages required by the CAFE Model, MOVES only generates emissions data for vehicles made in the last 30 model years for each calendar year being run. This means emissions data for some calendar year and vehicle age combinations are missing. To remedy this, the script takes the last vehicle age that has emissions data and forward fills those data for the following vehicle ages. Due to incomplete available data for years prior to MY 2020, tailpipe emission factors for MY 2019 and earlier have not been modified and continue to utilize MOVES2014 data.

5.3.2.5 Exporting MOVES Data to Excel

The Python code connects to an Excel spreadsheet and requires a reference Excel spreadsheet that contains the CAFE parameters. This file is copied, and the new data are added to the copied file. Copying the reference file builds in redundancy and ensures that all original data remains intact.

5.3.2.6 Validation Testing of MOVES Updates

To ensure the parameters file was modified correctly, we conducted quality assurance tests. These consisted of checking the data from previous parameters files with the new file. The data are the same in model years before 2020 and have changed in MY 2020 and later. As an example, Figure 5-1 shows light-duty gasoline CO emission factors over time, and illustrates how the updated MOVES3 data ("2021 update" indicates current CAFE analysis) diverge from the previous MOVES2014 data ("Ref" indicates previous CAFE analyses) in MY 2020.

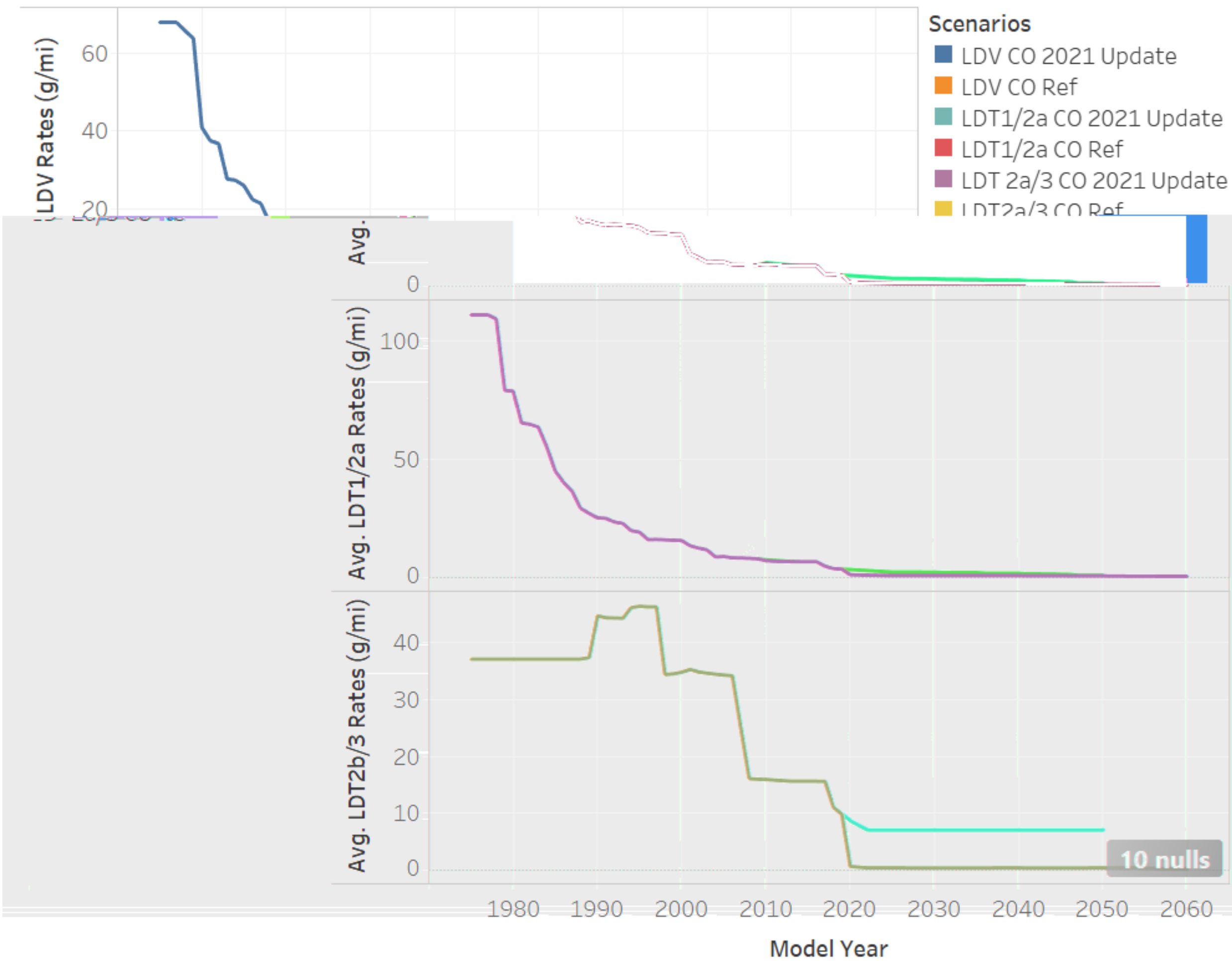

Figure 5-1 – Illustration of Newly Updated CO Emission Rate Projections for Gasoline Cars and Light Trucks Over the Next 40 Years

5.3.3 Simulating Tailpipe CO_2 Emissions

Much like the impacts from criteria pollutant emissions, the CAFE input parameters for greenhouse gases are generally taken from other models. As discussed at length above, upstream GHG emission factors come from GREET 2021 and tailpipe non-CO_2 GHG emission factors come from MOVES3. This section briefly describes the methodology for the development and use of the tailpipe CO_2 emission factors.

For tailpipe CO_2 emissions, these factors are defined based on the fraction of each fuel type's mass that represents carbon (the carbon content) along with the mass density per unit of the specific type of fuel. To obtain the emission factors associated with each fuel, the carbon content is then multiplied by the mass density of a particular fuel as well as by the ratio of the molecular weight of carbon dioxide to that of elemental carbon. This ratio, a constant value of 44/12, measures the mass of carbon dioxide that is produced by complete combustion of mass of carbon contained in each unit of fuel. The resulting value defines the emission factor attributed to CO_2 as the amount of grams of CO_2 emitted during vehicle operation from each type of fuel. This calculation is repeated for gasoline, E85, diesel, and compressed natural gas (CNG) fuel types. In the case of CNG, the mass density and the calculated CO_2 emission factor are denoted as grams per standard cubic feet (scf), while for the remainder of fuels, these are defined as grams per gallon of the given fuel source. Since electricity and hydrogen fuel types do not cause CO_2 emissions to be emitted during vehicle operation, the carbon content and the CO_2 emission factors for these two fuel types are assumed to be zero. For the other fuel types, the table below summarizes the mass density, carbon content, and CO_2 emission factors for each.

Table 5-4 – CO_2 Emission Factors by Fuel Type

Fuel Type	Mass Density (grams/unit)	Carbon Content (% by weight)	CO_2 Emission Factor (grams/unit)
Gasoline (gallons)	2,823	85.9%	8,887
Ethanol-85 (gallons)	2,963	57.3%	6,226
Low Sulfur Diesel (gallons)	3,206	86.6%	10,180
CNG (scf)	19.09	76%	53.20

The CAFE Model calculates CO_2 tailpipe emissions associated with vehicle operation of the surviving on-road fleet by multiplying the number of gallons (or scf for CNG) of a specific fuel consumed by the CO_2 emissions factor for the associated fuel type. More specifically, the amount of gallons or scf of a particular fuel are multiplied by the carbon content and the mass density per unit of that fuel type, and then applying the ratio of carbon dioxide emissions generated per unit of carbon consumed during the combustion process.[661]

The next section describes and helps to quantify the adverse human health impacts from both upstream and vehicle tailpipe emissions.

5.4 Estimating Health Impacts from Changes in Criteria Pollutant Emissions

The CAFE Model computes select health impacts resulting from three criteria pollutants: NO_X, SO_X,[662] and $PM_{2.5}$. Out of the six criteria pollutants currently regulated, NO_X, SO_X, and $PM_{2.5}$ are known to be emitted regularly from mobile sources and have the most adverse effects to human health. These health impacts include several different morbidity measures, as well as a mortality estimate, and are measured by the number of instances predicted to occur per ton of emitted pollutant.[663] The model reports total health impacts by multiplying the estimated tons of each criteria pollutant by the corresponding health incidence per ton value. The inputs that inform the calculation of the total tons of emissions resulting from criteria pollutants are

[661] Chapter 3, Section 4 of the CAFE Model Documentation provides additional description for calculation of CO_2 tailpipe emissions with the model.

[662] Any reference to SO_X in this section refers to the sum of sulfur dioxide (SO_2) and sulfate particulate matter (pSO_4) emissions, following the methodology of the EPA papers cited.

[663] The complete list of morbidity impacts estimated in the CAFE Model is as follows: acute bronchitis, asthma exacerbation, cardiovascular hospital admissions, lower respiratory symptoms, minor restricted activity days, non-fatal heart attacks, respiratory emergency hospital admissions, respiratory emergency room visits, upper respiratory symptoms, and work loss days.

described in Chapter 5.2. See Chapter 6.2.4.3 for discussion of domestic petroleum production and fuel import share assumptions. This section discusses how the health incidence per ton values were obtained. See Chapter 6.2.2 for information regarding the monetized damages arising from these health impacts. For a discussion of public comments received regarding the modeling of health impacts of criteria pollutants in the NPRM, see Section III.F of the preamble.

NHTSA's Final SEIS for MYs 2024-2026 that accompanies this analysis includes a detailed discussion of the criteria pollutants and air toxics analyzed in the effects analysis. Both the Final SEIS and the preamble also contain information regarding environmental justice impacts that arise from the CO_2 and criteria pollutants emitted from motor vehicles and the associated upstream sectors. See Chapter 6 of the FRIA for discussion of overall changes in health impacts associated with criteria pollutant changes across the different rulemaking scenarios. In addition, consistent with past analyses, NHTSA has performed full-scale photochemical air quality modeling and presented those results in the Final SEIS. That analysis provides additional assessment of the human health impacts from changes in ambient $PM_{2.5}$ and ozone associated with this rule.

5.4.1 Health Impacts per Ton from Upstream Emissions

This chapter describes the health incidence per ton values that are used to calculate the total health impacts from upstream criteria pollutant emissions. The health incidence per ton values in this analysis reflect the differences in health impacts arising from five upstream emission source sectors (Petroleum Extraction, Petroleum Transportation, Refineries, Fuel Transportation, Storage and Distribution, and Electricity Generation), based on publicly available EPA reports that appropriately correspond to these sectors.[664] As the health incidences for the different source sectors are all based on the emission of one ton of the same pollutants, NO_X, SO_X, and $PM_{2.5}$, the differences in the incidence per ton values arise from differences in the geographic distribution of the pollutants, a factor which affects the number of people impacted by the pollutants.[665]

The CAFE Model health impacts inputs are based partially on the structure of EPA's 2018 technical support document, Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors (referred to here as the 2018 EPA source apportionment TSD).[666] The 2018 EPA source apportionment TSD describes a reduced-form benefit-per-ton (BPT) approach to inform the assessment of health impacts. In this approach, the $PM_{2.5}$-related BPT values are the total monetized human health benefits (the sum of the economic value of the reduced risk of premature death and illness) that are expected from reducing one ton of directly-emitted $PM_{2.5}$ or $PM_{2.5}$ precursor such as NO_X or SO_2. We note, however, that the complex, non-linear photochemical processes that govern ozone formation prevent us from developing reduced-form

[664] For further discussion of the EPA reports used for each upstream emissions source sector, see preamble Section III.F.
[665] *See* Environmental Protection Agency (EPA). 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. https://www.epa.gov/sites/production/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf. (Accessed: February 15, 2022).
[666] Environmental Protection Agency (EPA). 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. https://www.epa.gov/sites/production/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf. (Accessed: February 15, 2022).

ozone, ambient NO_X, or other air toxic BPT values. This is an important limitation to recognize when using the BPT approach. We include additional discussion of uncertainties in the BPT approach in Chapter 5.4.3.

The 2018 EPA source apportionment TSD reports benefit per ton values for the years 2016, 2020, 2025, and 2030. As the year 2016 is not included in this analysis, the 2016 values are not used. For the years in between the source years used in the input structure, the CAFE Model applies values from the closest source year. For instance, 2020 values are applied for 2020-2022, and 2025 values are applied for 2023-2027. For further details, see the CAFE Model documentation, which contains a description of the model's computation of monetized health impacts.

The following subsections detail the calculations involved in mapping each CAFE Model upstream component to the appropriate sector or combination of sectors from EPA reports. Despite efforts to be as consistent as possible with the EPA sources already used in the mapping, the need to use up-to-date sources based on newer air quality modeling updates led to the use of multiple papers. Table 5-3 provides specific details of the EPA to CAFE Model upstream sector mapping.

The CAFE Model divides upstream emissions into the five varying components based on the GREET Model from Argonne National Laboratory.[667] DOT staff examined how each component was defined in GREET 2021 in order to appropriately map EPA source sectors to the ones used in the CAFE Model.

Table 5-5 – CAFE/GREET Source Sectors to EPA Source Mapping

CAFE Model Upstream Component (per GREET)	Corresponding EPA Source Categories
Petroleum Extraction	Assigned to the "Oil and natural gas" sector from a 2018 EPA paper (Fann et al.).[668] Health incidents per ton were calculated using BenMAP files received from EPA staff.

[667] U.S. Department of Energy, Argonne National Laboratory, Greenhouse gases, Regulated Emissions, and Energy use in Transportation (GREET) Model, Last Update: 11 Oct. 2021, https://greet.es.anl.gov/. (Accessed: February 15, 2022).

[668] Fann et al. 2018. Assessing Human Health $PM_{2.5}$ and Ozone Impacts from U.S. Oil and Natural Gas Sector Emissions in 2025. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6718951/. (Accessed: February 15, 2022).

CAFE Model Upstream Component (per GREET)	Corresponding EPA Source Categories
Petroleum Transportation	Assigned to several mobile source sectors from a 2019 EPA paper (Wolfe et al.)[669] and one source sector from the 2018 EPA source apportionment TSD.[670] The specific mode mappings are as follows: From Wolfe et al.: Rail sector (for GREET's rail mode) C1&C2 marine vessels sector (for GREET's barge mode) C3 marine vessels sector (for GREET's ocean tanker mode) On-road heavy-duty diesel sector (for GREET's truck mode) From the 2018 EPA source apportionment TSD: Electricity generating units (for GREET's pipeline mode) A weighted average of these different sectors was used to determine the overall health impact values for the sector as a whole.
Refineries	Assigned to the refineries sector in the 2018 EPA source apportionment TSD.
Fuel TS&D	Assigned to several mobile source sectors from a 2019 EPA paper (Wolfe et al.)[669] and one source sector from the 2018 EPA source apportionment TSD.[671] The specific mode mappings are as follows: From Wolfe et al: Rail sector (for GREET's rail mode) C1&C2 marine vessels sector (for GREET's barge mode) C3 marine vessels sector (for GREET's ocean tanker mode) On-road heavy-duty diesel sector (for GREET's truck mode) From the 2018 EPA source apportionment TSD: Electricity generating units (for GREET's pipeline mode) A weighted average of these different sectors was used to determine the overall health impact values for the sector as a whole.
Electricity Generation	Assigned to the electricity-generating units sector from the 2018 EPA source apportionment TSD.[672]

[669] Wolfe, P., Davidson, K., Fulcher, C., Fann, N., Zawacki, M., & Baker, K. R. (2019). Monetized health benefits attributable to mobile source emission reductions across the United States in 2025. The Science of the total environment, 650(Pt 2), 2490–2498 (*hereinafter* Wolfe et al.). Health incidence per ton values corresponding to this paper were sent by EPA staff.

[670] Environmental Protection Agency (EPA). 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. https://www.epa.gov/sites/production/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf. (Accessed: February 15, 2022).

[671] Environmental Protection Agency (EPA). 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. https://www.epa.gov/sites/production/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf. (Accessed: February 15, 2022).

[672] Environmental Protection Agency (EPA). 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. https://www.epa.gov/sites/production/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf. (Accessed: February 15, 2022).

5.4.1.1 Health Incidence per Ton Values Associated with the Petroleum Extraction Sector

The basis for the health impacts from the petroleum extraction sector was a 2018 oil and natural gas sector paper written by EPA staff (Fann et al.), which estimates health impacts for this sector in the year 2025.[673] This paper defines the oil and gas sector's emissions not only as arising from petroleum extraction but also from transportation to refineries, while the CAFE/GREET component is composed of only petroleum extraction. After consultation with the authors, it was determined that these were the best available estimates for the petroleum extraction sector, notwithstanding this difference.

Specific health incidences per pollutant were not reported in the paper, so EPA staff sent BenMAP health incidence files for the oil and natural gas sector upon request. DOT staff then calculated per ton values based on these files and the tons reported in the Fann et al. paper.[674]

The only available health impacts corresponded to the year 2025. Rather than trying to extrapolate, these 2025 values were used for all the years in the CAFE Model structure: 2020, 2025, and 2030.[675] This simplification implies an overestimate of damages in 2020 and an underestimate in 2030.[676]

We understand that uncertainty exists around the contribution of VOCs to $PM_{2.5}$ formation in the modeled health impacts from the petroleum extraction sector; however, based on feedback to the 2020 final rule, we believe that the updated health incidence values specific to petroleum extraction sector emissions may provide a more appropriate estimate of potential health impacts from that sector's emissions than the previous approach of applying refinery sector emissions impacts to the petroleum extraction sector.

5.4.1.2 Health Incidence per Ton Values Associated with the Petroleum Transportation Sector

The petroleum transportation sector did not correspond to any one EPA source sector, so a weighted average of multiple different EPA sectors was used to determine the health impact per ton values for the petroleum transportation sector as a whole. In calculating the weighted average, DOT staff mapped the petroleum transportation sector as described in GREET to a

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[673] Fann, N., Baker, K. R., Chan, E., Eyth, A., Macpherson, A., Miller, E., & Snyder, J. (2018). Assessing Human Health $PM_{2.5}$ and Ozone Impacts from U.S. Oil and Natural Gas Sector Emissions in 2025. *Environmental science & technology*, *52*(15), 8095–8103 (*hereinafter* Fann et al.).

[674] Nitrate-related health incidents were divided by the total tons of NO_X projected to be emitted in 2025, sulfate-related health incidents were divided by the total tons of projected SO_X, and EC/OC (elemental carbon and organic carbon) related health incidents were divided by the total tons of projected EC/OC. Both Fann et al. and the 2018 EPA source apportionment TSD define primary $PM_{2.5}$ as being composed of elemental carbon, organic carbon, and small amounts of crustal material. Thus, the EC/OC BenMAP file was used for the calculation of the incidents per ton attributable to $PM_{2.5}$.

[675] These three years are used in the CAFE Model structure because it was originally based on the estimate provided in the 2018 EPA source apportionment TSD.

[676] *See* EPA. 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. https://www.epa.gov/sites/production/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf p.9. (Accessed: February 15, 2022).

combination of different EPA mobile source sectors from two different papers, the 2018 EPA source apportionment TSD,[677] and a 2019 mobile source sectors paper (Wolfe et al.).[678]

Wolfe et al. include more sectors than the 2018 EPA source apportionment TSD; for instance, where 'Aircraft, Locomotive, and Marine Vessels' is a single category in the 2018 source apportionment TSD, Wolfe et al. specify four: 'Aircraft', 'Rail', 'C1&C2 Marine Vessels', and 'C3 Marine Vessels'. Therefore, sectors from Wolfe et al. are used wherever possible, and the 2018 EPA source apportionment TSD is used for the transportation mode mapping only when there are no appropriate sectors reported in the 2019 Wolfe et al. paper. Wolfe et al. only report impacts for the year 2025, but DOT staff determined that these values could be applied to the other years in the input structure, after communication with one of the authors at EPA. Therefore, this implies a slight overestimation of health incidence per ton in 2020 and a slight underestimation of health incidence per ton in 2030.

A weighted average of these different sectors was used to calculate the total health incidences per ton by pollutant, based on the percent of upstream emissions attributable to each transportation mode.

In GREET, the model that informs the CAFE upstream component categories, there are five types of petroleum products relevant to upstream emissions for gasoline:

- Conventional crude oil
- Synthetic crude oil (SCO)
- Dilbit
- Shale oil (Bakken)
- Shale oil (Eagle Ford)

Table 5-6 – Petroleum Transportation Mode Shares in 2020[679]

Fuel Type[680]	Ocean Tanker	Barge	Pipeline	Rail	Truck
Conventional Crude Oil	10.3%	23.2%	79.9%	2.9%	0
Synthetic Crude Oil (SCO)	0	0	100%	0	0
Dilbit	0	0	100%	0	0
Shale Oil (Bakken)	0	0	50.0%	50.0%	100%
Shale Oil (Eagle Ford)	0	20.0%	65.0%	15.0%	100%

677 Environmental Protection Agency (EPA). 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. https://www.epa.gov/sites/production/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf. (Accessed: February 15, 2022).
678 Wolfe et al. 2019. Monetized health benefits attributable to mobile source emissions reductions across the United States in 2025. https://pubmed.ncbi.nlm.nih.gov/30296769/. (Accessed: February 15, 2022).
679 These values are from the GREET 2021 model, using baseline year 2020. In the Excel version, this information can be found in the T&D Flowcharts worksheet. *See* https://greet.es.anl.gov/ to download the model.
680 Conventional crude oil is both extracted domestically and imported. SCO and Dilbit are oil sand products and are imported exclusively from Canada. Shale oil is exclusively domestic. *See* the 'T&D Flowcharts' worksheet in the GREET model.

GREET provides the percentage of these five petroleum products transported by each mode, as shown in Table 5-4. Transportation both within the United States and outside of U.S. borders is included, provided that the destination of the transported products is the continental United States. The percentages add up to more than 100 percent because there are multiple stages of the transportation journey. For example, 50 percent of shale oil (Bakken) is transported by pipeline and the other 50 percent by rail during the first part of the journey to the refinery, but 100 percent of it is transported by truck on the second part of the journey.

GREET also provides emissions in grams/mmBTU of fuel transported attributable to each transportation mode. These emissions values are multiplied by the percentage of petroleum product transported by each mode, as seen in Table 5-4, to obtain a weighted value. Total emissions from each mode are used for all modes except ocean tanker. Health effects from ocean transport are concentrated in populated areas, rather than while the tankers are at sea. To address this, the ocean tanker mode includes only urban emissions. Additionally, using urban emissions for ocean tankers ensures that the emissions attributable to this mode are not underestimated, because the percentage of related health impacts decreases when using the high total emissions figure.

This process of multiplying emissions by transportation mode share is done five times, once for each of the five petroleum types. Since the transportation mode shares are projected to change over time, different weights are used for years 2020, 2025, and 2030, based on the mode percentages GREET reports for those years.[681]

Table 5-7 – Energy Share by Petroleum Type[682]

Conventional Crude Oil	SCO	Dilbit	Shale (Bakken)	Shale (Eagle Ford)
76.8%	3.4%	4.6%	8.2%	7.0%

The energy share of each petroleum type is multiplied by its corresponding emissions value to reflect how much of each emissions value should go into the weighted average. For example, using the energy share information in

Table 5-5, the conventional crude emissions are multiplied by 76.8 percent, SCO emissions are multiplied by 3.4 percent, Dilbit emissions are multiplied by 4.6 percent, shale (Bakken) emissions are multiplied by 8.2 percent, and shale (Eagle Ford) emissions are multiplied by 7 percent.

Next, the resulting weighted emissions values are summed by pollutant to represent the total upstream emissions in grams/mmBTU of petroleum product transported. With that information, the percentages of each pollutant attributable to each mode for petroleum transportation overall

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681 These are the three years used in the CAFE Model inputs for health impacts, based on the structure of the 2018 EPA source apportionment TSD that originally informed the analysis. Baseline years may be changed in the 'Inputs' worksheet in the GREET model.

682 Taken from the Petroleum tab of the GREET Excel model, using 2020 as a base year.

can be calculated. These calculations are completed three times, for each different base year (2020, 2025, 2030). Table 5-6 shows these percentages, using base year 2020 as an example.

Table 5-8 – Percent of Emissions Attributable to each Mode for the Petroleum Transportation Category[683]

Mode	EPA source category	NO_X	SO_X	$PM_{2.5}$
Ocean Tanker	C3 marine vessels	5.04%	13.87%	9.10%
Barge	C1 & C2 marine vessels	56.47%	1.70%	39.83%
Pipeline	Electricity-generating units	24.82%	83.62%	45.79%
Rail	Rail	12.31%	0.59%	4.79%
Truck	On-road heavy duty diesel	1.36%	0.22%	0.48%

Finally, a weighted average of health incidence is created when the percentages of emissions by mode are multiplied by the health incidence per ton from the relevant EPA sector that matches each mode. Equation 5-14 illustrates this process. The variables beginning with "%" represent the percent of SO_X emissions attributable to each specified mode. The other variables indicate the incidents per ton resulting from SO_X emissions coming from each sector: *C3marine* corresponds to C3 marine vessels, *C1&C2* marine to C1&C2 marine vessels, *EGU* corresponds to electricity-generating units, *Rail* to railroad, and *Truck* corresponds to on-road heavy duty diesel.

$$Asthma\ Exacerbation\ incidents\ per\ ton\ from\ SOx\ in\ Petroleum\ Transportation =$$

$$(\%\ SOx\ ocean\ tanker * C3marine) \quad + (\%\ SOx\ barge * C1\&C2\ marine) + (\%SOx\ pipeline * EGU\ ) + (\%\ SOx\ rail * Rail) + (\%\ SOx\ truck * Truck)$$

Equation 5-14 – Weighted Average of Health Incidences from the Petroleum Transportation Sector

Following guidance from the 2018 EPA source apportionment TSD, the incidence per ton are rounded to two significant digits.[684]

5.4.1.3 Health Incidence per Ton Values Associated with the Fuel TS&D Sector

The Fuel TS&D sector, similarly to the Petroleum Transportation sector, corresponded to several different EPA source sectors, so DOT staff used the same weighted average approach as described in Chapter 5.3.1.2. Gasoline blendstocks and finished gasoline are the two components of the Fuel TS&D category described in GREET. DOT staff mapped these components to five different transportation source sectors from two EPA papers, the 2018 EPA source apportionment TSD and the 2019 mobile sources paper.[685]

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683 These percentages are calculated using the 2020 base year in GREET.
684 Environmental Protection Agency (EPA). 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. https://www.epa.gov/sites/production/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf. (Accessed: February 15, 2022).
685 Environmental Protection Agency (EPA). 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. https://www.epa.gov/sites/production/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf (Accessed: March 26, 2022); Wolfe et al. 2019. Monetized health benefits attributable to mobile source emissions reductions across the United States in 2025. https://pubmed.ncbi.nlm.nih.gov/30296769/. (Accessed: February 15, 2022).

GREET provides the percentage of each fuel type transported by each mode, and as in the case of the petroleum transportation calculations, the percentages change based on the year. In the case of the gasoline blendstocks fuel type, the mode shares add up to more than 100 percent because there are distinct parts of the trip and multiple modes are taken. As an example, Table 5-7 shows the estimated mode shares in 2020.

Table 5-9 – Transportation Mode Shares for the Fuel TS&D Sector[686]

Mode Share	Gasoline Blendstocks	Finished Gasoline
Ocean Tanker	3.0%	0
Barge	31.2%	0
Pipeline	67.6%	0
Rail	2.2%	0
Truck	100%	100%

The emissions by pollutant attributed to each mode, measured in grams/mmBTU, are multiplied by these mode share percentages to create weighted emissions values.

Next, the weighted emissions from trucks transporting gasoline blendstocks are added to the emissions arising from finished gasoline transportation. Using that information, the total emissions per pollutant may be calculated in order to find the percentage of emissions attributable to each mode for Fuel TS&D overall. Table 5-8 provides an example of these percentages.

Table 5-10 – Percent of Emissions Attributable to each Mode for the Fuel TS&D Sector[687]

Mode	EPA category	NO_X	SO_X	$PM_{2.5}$
Ocean Tanker	C3 marine vessels	2.83%	22.07%	6.90%
Barge	C1 & C2 marine vessels	68.33%	5.81%	65.75%
Pipeline	Electricity-generating units	6.56%	62.33%	16.50%
Rail	Rail	0.81%	0.11%	0.43%
Truck	On-road heavy duty diesel	21.47%	9.67%	10.42%

The fuel TS&D calculations follow the same process as the petroleum transportation category, matching the modes to EPA sectors and using the calculated percentages to create a weighted average of health incidence associated with emissions of each pollutant. DOT staff completed these calculations three times, for years 2020, 2025, and 2030. As stated previously, the sectors in the 2019 mobile sources paper only showed health incidence per ton estimated for the year 2025, but analysts determined that this information was the most up-to-date available, after communications with EPA staff. The use of 2025 health incidence for all three years implies a slight overestimation of incidences in 2020 and a slight underestimation in 2030.

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686 Using baseline year 2020 in GREET. These values can be found in the 'T&D Flowcharts' tab of the GREET model.

687 Calculated using baseline year 2020 in GREET.

5.4.1.4 Health Incidence per Ton Values Associated with the Refineries Sector

DOT staff matched the health incidence per ton values associated with the refineries sector in the 2018 EPA source apportionment TSD to the petroleum refining emission category in the CAFE Model. Table 5-9 shows the various types of health effects per ton corresponding to each pollutant emitted from the refineries sector.

Table 5-11 – Health Incidences per Ton from the Refineries Sector

Health Effects	2020			2025			2030		
	NO_X	SO_X	$PM_{2.5}$	NO_X	SO_X	$PM_{2.5}$	NO_X	SO_X	$PM_{2.5}$
Premature Deaths - (Krewski)	0.00082	0.0082	0.039	0.00087	0.0088	0.041	0.00094	0.0095	0.044
Respiratory emergency room visits	0.00044	0.0045	0.022	0.00045	0.0047	0.023	0.00047	0.0049	0.024
Acute bronchitis	0.0012	0.012	0.059	0.0013	0.013	0.061	0.0014	0.014	0.066
Lower respiratory symptoms	0.016	0.16	0.75	0.016	0.16	0.78	0.018	0.18	0.84
Upper respiratory symptoms	0.023	0.22	1.1	0.023	0.23	1.1	0.025	0.25	1.2
Minor Restricted Activity Days	0.66	6.7	31	0.67	6.8	32	0.68	7.0	33
Work loss days	0.11	1.1	5.3	0.11	1.2	5.4	0.12	1.2	5.6
Asthma exacerbation	0.026	0.26	1.2	0.027	0.28	1.3	0.029	0.29	1.4
Cardiovascular hospital admissions	0.00019	0.0021	0.0095	0.00022	0.0023	0.010	0.00024	0.0026	0.012
Respiratory hospital admissions	0.00019	0.0020	0.0089	0.00021	0.0022	0.010	0.00024	0.0025	0.011
Non-fatal heart attacks (Peters)	0.00080	0.0082	0.038	0.00088	0.0091	0.041	0.00097	0.010	0.045
Non-fatal heart attacks (All others)	0.000087	0.00089	0.0041	0.000095	0.00099	0.0045	0.00010	0.0011	0.0049

5.4.1.5 Health Incidence per Ton Values Associated with the Electricity Generation Sector

The 2018 EPA source apportionment TSD contains health incidence per ton values associated with emissions of NO_X, SO_X, and $PM_{2.5}$ arising from electricity-generating units. DOT staff mapped these to the electricity generation sector in the CAFE Model. The health effects per ton associated with the emissions of criteria pollutants from this sector are shown in Table 5-10.

Table 5-12 – Health Effects per Ton from the Electricity Generation Sector

Health Effects	2020			2025			2030		
	NO_X	SO_X	$PM_{2.5}$	NO_X	SO_X	$PM_{2.5}$	NO_X	SO_X	$PM_{2.5}$
Premature Deaths - (Krewski)	0.00066	0.0045	0.016	0.00070	0.0048	0.017	0.00074	0.0051	0.018
Respiratory emergency room visits	0.00032	0.0022	0.0091	0.00033	0.0023	0.0094	0.00034	0.0024	0.0098
Acute bronchitis	0.00085	0.0055	0.021	0.00089	0.0057	0.022	0.00096	0.0062	0.024
Lower respiratory symptoms	0.011	0.070	0.27	0.011	0.073	0.29	0.012	0.079	0.31
Upper respiratory symptoms	0.016	0.10	0.39	0.016	0.10	0.41	0.017	0.11	0.44
Minor Restricted Activity Days	0.46	3.0	12	0.46	3.0	12	0.46	3.1	12
Work loss days	0.077	0.51	2.0	0.077	0.52	2.0	0.078	0.53	2.1
Asthma exacerbation	0.018	0.12	0.46	0.019	0.12	0.48	0.020	0.13	0.51
Cardiovascular hospital admissions	0.00016	0.0011	0.0040	0.00017	0.0012	0.0044	0.00018	0.0014	0.0048
Respiratory hospital admissions	0.00015	0.0011	0.0038	0.00017	0.0012	0.0043	0.00018	0.0013	0.0047
Non-fatal heart attacks (Peters)	0.00063	0.0045	0.016	0.00068	0.0049	0.018	0.00074	0.0053	0.019
Non-fatal heart attacks (All others)	0.000068	0.00049	0.0017	0.000074	0.00054	0.0019	0.000079	0.00058	0.0021

5.4.2 Health Impacts per Ton from Tailpipe Emissions

The CAFE Model follows a similar process for computing health impacts resulting from tailpipe emissions as it does for calculating health impacts from upstream emissions. The analysis relies on a 2019 paper from EPA (Wolfe et al.) that computes monetized per ton damage costs for mobile sources in several categories, based on vehicle type and fuel type. Wolfe et al. did not report incidences per ton, but that information was obtained through communications with EPA staff.

Three source categories from the Wolfe et al. paper were matched to the CAFE Model tailpipe emissions inventory: “on-road light duty gas cars and motorcycles,” “on-road light duty gas trucks," and "on-road light duty diesel."[688] Table 5-11 shows the health incidence per ton associated with these sectors in 2025.

Table 5-13 – Health Incidents per Ton from On-Road Source Sectors in 2025

Health Effects	On-road Light Duty Gas Cars & Motorcycles Sector			On-road Light Duty Gas Trucks			On-road Light Duty Diesel		
2025	NO_X	SO_X	$PM_{2.5}$	NO_X	SO_X	$PM_{2.5}$	NO_X	SO_X	$PM_{2.5}$
Premature Deaths - (Krewski)	0.00075	0.013	0.073	0.00068	0.011	0.061	0.00060	0.031	0.050
Respiratory emergency room visits	0.00039	0.0076	0.041	0.00035	0.0061	0.035	0.00032	0.019	0.029
Acute bronchitis	0.0010	0.020	0.11	0.00096	0.016	0.091	0.00085	0.047	0.075
Lower respiratory symptoms	0.013	0.25	1.4	0.012	0.20	1.2	0.011	0.59	0.95
Upper respiratory symptoms	0.018	0.35	2.0	0.017	0.28	1.7	0.015	0.84	1.35
Minor Restricted Activity Days	0.53	11	60	0.49	8.5	49	0.44	25	40
Work loss days	0.090	1.8	10	0.084	1.4	8.4	0.075	4.3	6.9
Asthma exacerbation	0.022	0.42	2.3	0.020	0.33	1.9	0.018	1.0	1.6
Cardiovascular hospital admissions	0.00019	0.0036	0.020	0.00017	0.0028	0.016	0.00015	0.0085	0.013
Respiratory hospital admissions	0.00018	0.0034	0.018	0.00016	0.0027	0.015	0.00015	0.0081	0.013
Non-fatal heart attacks (Peters)	0.00075	0.014	0.076	0.00068	0.011	0.064	0.00060	0.033	0.053
Non-fatal heart attacks (All others)	0.000080	0.0015	0.0082	0.000073	0.0012	0.0069	0.000065	0.0035	0.0057

[688] Wolfe et al. 2019. Monetized health benefits attributable to mobile source emissions reductions across the United States in 2025. https://pubmed.ncbi.nlm.nih.gov/30296769/. (Accessed: February 15, 2022).

5.4.3 Uncertainty

Uncertainties and limitations exist at each stage of the emissions-to-health benefit analysis pathway (e.g., projected emissions inventories, air quality modeling, health impact assessment, economic valuation). As discussed above, we used a BPT approach to estimate health impacts from changes in criteria pollutant emissions and the resulting monetized benefits, which are discussed further in Chapter 6.2.2, Monetized Health Impacts from Changes in Criteria Pollutant Emissions. The following discussion applies to that section as well.

The BPT approach to monetizing benefits relies on many assumptions; when uncertainties associated with these assumptions are compounded, even small uncertainties can greatly influence the size of the total quantified benefits. Some key assumptions associated with $PM_{2.5}$-related health benefits and uncertainties associated with the BPT approach are described below.

We assume that all fine particles, regardless of their chemical composition, are equally potent in causing premature mortality. Support for this assumption comes from the 2019 PM ISA, which concluded that "many $PM_{2.5}$ components and sources are associated with many health effects and that the evidence does not indicate that any one source or component is consistently more strongly related with health effects than $PM_{2.5}$ mass."[689]

We assume that the health impact function for fine particles is log-linear without a threshold. Thus, the estimates include health benefits from reducing fine particles in areas with different concentrations of $PM_{2.5}$, including both areas with projected annual mean concentrations that are above the level of the fine particle standard and areas with projected concentrations below the level of the standard.

We also assume that there is a "cessation" lag between the change in PM exposures and the total realization of changes in mortality effects. Specifically, we assume that some of the incidences of premature mortality related to $PM_{2.5}$ exposures occur in a distributed fashion over the 20 years following exposure based on the advice of the Science Advisory Board Health Effect Subcommittee,[690] which affects the valuation of mortality benefits at different discount rates. The above assumptions are subject to uncertainty.

In general, we are more confident in the magnitude of the risks we estimate from simulated $PM_{2.5}$ concentrations that coincide with the bulk of the observed PM concentrations in the epidemiological studies that are used to estimate the benefits. Likewise, we are less confident in the risk we estimate from simulated $PM_{2.5}$ concentrations that fall below the bulk of the observed data in these studies. There are uncertainties inherent in identifying any particular point at which our confidence in reported associations decreases appreciably, and the scientific evidence provides no clear dividing line. Applying BPT values to estimates of changes in policy-related

[689] U.S. Environmental Protection Agency (U.S. EPA). 2019. Integrated Science Assessment (ISA) for Particulate Matter (Final Report, 2019). U.S. Environmental Protection Agency, Washington, DC, EPA/600/R-19/188, 2019.
[690] U.S. Environmental Protection Agency—Science Advisory Board (U.S. EPA-SAB). 2004. Advisory Council on Clean Air Compliance Analysis Response to Agency Request on Cessation Lag. EPA-COUNCIL-LTR-05-001. December. Located in Docket ID NHTSA-2021-0053.

emissions precludes us from assessing the distribution of risk as it relates to the associated distribution of baseline concentrations of $PM_{2.5}$.

Another limitation of using the BPT approach is an inability to provide estimates of the health benefits associated with exposure to ozone, ambient NO_X, and air toxics. Furthermore, the air quality modeling that underlies the $PM_{2.5}$ BPT value did not provide estimates of the $PM_{2.5}$-related benefits associated with reducing VOC emissions, but these unquantified benefits are generally small compared to benefits associated with other $PM_{2.5}$ precursors.[691]

National-average BPT values reflect the geographic distribution of the underlying modeled emissions used in their calculation, which may not exactly match the geographic distribution of the emission reductions that would occur due to a specific rulemaking. Similarly, BPT estimates may not reflect local variability in population density, meteorology, exposure, baseline health incidence rates, or other local factors for any specific location. For instance, even though we assume that all fine particles have equivalent health effects, the BPT estimates vary across precursors depending on the location and magnitude of their impact on $PM_{2.5}$ levels, which drives population exposure. The emissions and photochemically-modeled $PM_{2.5}$ concentrations used to derive the BPT values may not match the changes in air quality that would result from this rule.

6 Simulating Economic Effects of Regulatory Alternatives

6.1 Costs and Benefits Accrued to Consumers

Many, if not most, of the benefits and costs resulting from changes to CAFE standards are private benefits that accrue to the buyers of new cars and trucks, produced in the model years under consideration. These benefits and costs largely flow from the changes to vehicle ownership and operating costs that result from improved fuel economy, and the cost of the technology required to achieve those improvements. In general, increasing CAFE standards cause manufacturers to apply additional technology to new vehicles offered for sale. These technologies increase the cost of vehicle production, and manufacturers pass along those cost increases to consumers in the form of higher purchase prices. In turn, the higher purchase prices that buyers of new cars and light trucks pay also mean that their expenses for sales taxes, vehicle registration fees, financing their purchases, and insuring their new vehicles will rise. At the same time, consumers reap substantial benefits from reduced fuel costs over the lifetimes of new vehicles, and also save time because they require less frequent refueling.

6.1.1 Additional Consumer Purchasing Costs

Some costs of purchasing and owning new vehicles scale with the value of the vehicle. When fuel economy standards increase the price of new vehicles, both taxes and registration fees increase, too, because they are calculated as a percentage of vehicle price. Increasing the price of new vehicles also affects the average amount paid on interest for financed vehicles and the insurance premiums for similar reasons. NHTSA computes these additional costs as scalar

[691] U.S. EPA. 2012. Regulatory Impact Analysis for the Proposed Revisions to the National Ambient Air Quality Standards for Particulate Matter.

multipliers on the MSRP of new vehicles. These costs are included in the consumer per-vehicle cost-benefit analysis but, for the reasons described below, are not included in the societal cost-benefit analysis.

6.1.1.1 Sales Tax and Vehicle Registration Costs

In the analysis, sales taxes and registration fees are considered transfer payments between consumers and the government and are therefore not considered a cost from the societal perspective. However, these costs do represent an additional cost to consumers and are accounted for in the private consumer perspective. To estimate the sales tax for the analysis, NHTSA weighted the auto sales tax of each state by its population—using Census population data—to calculate a national weighted-average sales tax of 5.46 percent.[692]

We recognize that weighting state sales tax by new vehicle purchases within a state would likely produce a better estimate since new vehicle purchasers represent a small subset of the population and may differ between states. NHTSA explored using Polk registration data to approximate new vehicle sales by state by examining the change in new vehicle registrations across several recent years. The results derived from this examination resulted in a national weighted-average sales tax rate slightly above 5.5 percent, which is almost identical to the rate calculated using population instead. NHTSA opted to utilize the population estimate, rather than the registration-based proxy of new vehicle sales, because the results were negligibly different, and the analytical approach was more straightforward.

6.1.1.2 Financing Costs

Between the NPRM and final rule, NHTSA discovered that it had inappropriately accounted for costs associated with financing new vehicles that are more expensive due to more stringent fuel economy standards. Specifically, NHTSA treated the discounted stream of increased interest payments as a cost to consumers of more stringent fuel economy standards without considering the benefits of financing. When a consumer elects to finance a vehicle, the consumer is demonstrating a revealed preference for purchasing a vehicle using smaller and smoother payments over time, rather than a large one-time payment at the point of sale, and that they are willing to pay the interest payments in exchange for that payment pattern. In other words, the consumer is revealing that their discount rate is higher than the real interest of the loan.

However, at the NPRM stage, NHTSA's per-vehicle analysis included the interest payments as a cost, without taking account of the benefits of financing by discounting the stream of principal and interest payments over time. Instead, NHTSA treated the financial costs as additive with the upfront price increase of the vehicle owing to more stringent fuel economy standards. As such, NHTSA's NPRM implied that the flexibility offered to consumers by the availability of

[692] *See* Car Tax by State, FactoryWarrantyList.com, http://www.factorywarrantylist.com/car-tax-by-state.html. (Accessed: February 15, 2022). Note: County, city, and other municipality-specific taxes were excluded from weighted averages, as the variation in locality taxes within states, lack of accessible documentation of locality rates, and lack of availability of weights to apply to locality taxes complicate the ability to reliably analyze the subject at this level of detail. Localities with relatively high automobile sales taxes may have relatively fewer auto dealerships, as consumers would endeavor to purchase vehicles in areas with lower locality taxes, therefore reducing the effect of the exclusion of municipality-specific taxes from this analysis.

financing reduced consumer welfare. Whereas, if anything, NHTSA expects that the availability of financing options should reduce the cost of fuel economy standards to consumers by permitting them to spread the costs out over time.

To address this issue, NHTSA considered two alternative solutions. The first alternative is to assume that the availability of financing does not make consumers worse off than if that financing were not available. With this assumption, we can exclude financing costs as a conservative position, given that it is more likely than not that financing availability actually reduces the cost of more stringent standards. The second approach considered was to include the discounted stream of principal and interest payments in lieu of the upfront price increase for those consumers that elect to finance. The benefit of the second alternative is that it would produce quantifiable estimates and may give a better sense of the true cost of higher fuel economy standards. However, the downside of this approach is that, if NHTSA were to use discount rates prescribed by OMB Circular A-4, it is plausible that our estimates would still indicate that financing availability harms consumers. For this reason, NHTSA has elected the first alternative of excluding financing costs from the per-vehicle consumer cost and benefit accounting.

6.1.1.3 Insurance Cost

More expensive vehicles will require more expensive collision and comprehensive (e.g., fire and theft) car insurance. Actuarially fair insurance premiums for these components of value-based insurance will be the amount an insurance company will pay out in the case of an incident weighted by the risk of that type of incident occurring. For simplicity, we assume that the vehicle has the same exposure to harm throughout its lifetime in this calculation. However, the value of vehicles will decline at some depreciation rate so that the absolute amount paid in value-related insurance will decline as the vehicle depreciates. This is represented in the CAFE Model as the Equation 6-1 stream of expected collision and comprehensive insurance payments. In this final rule analysis, we are reducing insurance costs by 20 percent to avoid double counting the costs associated with replacing totaled and stolen vehicles (more on this below).

$$(Comprehensive \,\&\, Collision)_{age} = \frac{MSRP * (share\ MSRP)}{(1 + depreciation\ )^{age}} * \ .8$$

Equation 6-1 – Estimating Insurance Costs

To utilize the framework described by Equation 6-1, estimates of the share of MSRP paid on collision and comprehensive insurance and of annual vehicle depreciations are needed. Wards Automotive has data on the average annual amount paid by model year for new light trucks and passenger cars on collision, comprehensive and damage and liability insurance for model years 1992-2003; for model years 2004-2016, they only offer the total amount paid for insurance premiums. The share of total insurance premiums paid for collision and comprehensive coverage throughout the lifetime of a vehicle was computed for 1979-2003. For cars, the share ranges from 49 to 55 percent, with the share tending to be largest towards the end of the series. For trucks, the share ranges from 43 to 61 percent, again, with the share increasing towards the end of the series. We assume that for model years 2004-2016, 60 percent of insurance premiums for trucks, and 55 percent for cars, is paid for collision and comprehensive. Using these shares, we computed the aggregate amount paid for collision and comprehensive coverage for cars and trucks. Then each regulatory class in the fleet is weighted by share to estimate the overall average amount paid for collision and comprehensive insurance by model year as shown in Table 6-1. The ratio of annual collision and comprehensive costs to average MSRP results in a range from 1.74 to 2.03 percent over the series. The average annual share paid for model years 2010-2016 is 1.83 percent of the initial MSRP. This is used as the share of the value of a new vehicle paid for collision and comprehensive in the future.

Table 6-1 – Average Share of MSRP Paid for Collision and Comprehensive Insurance

Model Year	Collision and Comprehensive	Average MSRP	Percent MSRP
2016	$681	$33,590	2.03%
2015	$601	$32,750	1.84%
2014	$567	$31,882	1.78%
2013	$548	$31,056	1.76%
2012	$530	$30,062	1.76%
2011	$517	$29,751	1.74%
2010	$548	$29,076	1.88%

To estimate depreciation rates, we used recent data from Black Book and Fitch,[693] which showed that the average annual depreciation rate of two- to six-year-old vehicles fluctuated over the last decade from a high of 17.3 percent to a low of 8.3 percent [694] prior to the pandemic. The pandemic rates are unlikely to be representative of future depreciation rates, so we averaged the annual rates from 2016 – 2019 to construct a more representative average depreciation rate (14.9 percent). We assume that future depreciation rates will resemble pre-pandemic trends as the pandemic continues to recede, and the analysis assumes the same depreciation rate for all future years.

Table 6-2 shows the cumulative share of the initial MSRP of a vehicle estimated to be paid in collision and comprehensive insurance in five-year age increments under this depreciation assumption, conditional on a vehicle surviving to that age—that is, the expected insurance payments at the time of purchase will be weighted by the probability of surviving to that age. If a vehicle lives to 10 years, 10.6 percent of the initial MSRP is expected to be paid in collision and comprehensive payments; by 20 years 13.2 percent of the initial MSRP; finally, if a vehicle lives to age 40, 14.1 percent of the initial MSRP.

Table 6-2 – Cumulative Percentage of MSRP Paid in Collision/Comprehensive Premiums by Age

AGE	PERCENTAGE OF VALUE REMAINING	CUMULATIVE PERCENTAGE OF MSRP PAID

[693] *Vehicle Depreciation Report 2021,* Black Book and Fitch Ratings, https://2j6hf2q7wf819gchr14pr7l1-wpengine.netdna-ssl.com/wp-content/uploads/2021/04/FitchFINAL.pdf. (Accessed: February 15, 2022).
[694] During the pandemic depreciation largely halted, with two- to six-year old vehicles depreciating at only 2 percent in 2020 and projected at only 5 percent in 2021.

5	64%	7.0%
10	32%	10.6%
15	16%	12.4%
20	8.0%	13.2%
25	4.0%	13.7%
30	2.0%	13.9%
35	1.0%	14.0%
40	0.5%	14.1%

The increase in insurance premiums resulting from an increase in the average value of a vehicle is a result of an increase in the expected amount insurance companies will have to pay out in the case of damage occurring to the driver's vehicle. In this way, it is a cost to the private consumer, attributable to the CAFE standard, that caused the insurance price increase.

Between the NPRM and final rule, NHTSA staff identified a mistake in the per-vehicle accounting of technology costs and insurance costs. In the NPRM analysis, NHTSA included collision and comprehensive insurance premiums without adjusting these premiums to exclude the portion of premiums that cover the costs to replace totaled or stolen vehicles. When a consumer uses insurance payouts to purchase a new vehicle, the consumer will incur all of the costs and benefits of the standards at the time of purchase. Therefore, in this case, including the costs of the standards and the insurance costs associated with replacing totaled and stolen vehicles is duplicative.

In the case where a consumer uses insurance payouts to purchase a used vehicle, the consumer will likely replace the totaled or stolen vehicle with a used vehicle that was subject to the revised fuel economy standards. For example, consider a consumer that purchases a new vehicle in 2025. If that consumer experiences an event that leads to an insurance payout to replace the MY 2025 vehicle, that event is likely to take place in some year after 2025 when the used vehicle fleet is comprised of a greater share of vehicles subject to the updated standards. In this scenario, in order for this consumer to replace the 2025 vehicle with a vehicle not subject to the updated standards the consumer would have to use to the insurance payout to purchase a vehicle at least two years older than the model they are replacing. NHTSA believes it is more likely that the consumer will replace their totaled or stolen vehicle with newer vehicle than the one they are replacing, and in those instances, insurance costs associated replacing vehicles subject to the standards with other used vehicles subject to the standards are duplicative.

For this final rule, NHTSA is taking a conservative approach to reducing insurance costs to avoid double counting the costs of the standards by multiplying them by the percentage of insurance claims for vehicle repairs, excluding claims for totaled and stolen vehicles. This approach is conservative because the cost to replace a vehicle is higher than the cost to repair a vehicle, so the share of insurance outlays that cover replacements will be higher than the percentage of claims for totaled or stolen vehicles. Based on NHTSA's research, the percentage of claims for replacing totaled or stolen vehicles is 20 percent.[695]

6.1.2 Consumer Sales Surplus

Buyers who would have purchased a new vehicle with the baseline standards in effect but decide not to do so in response to the increase in new vehicles' prices due to more stringent standards experience a decrease in welfare. The collective welfare loss to potential buyers who are deterred by higher prices is measured by the foregone consumer surplus they would have received from their purchase of a new vehicle in the baseline. However, because the fuel economy of vehicles they would otherwise have purchased also increases, and higher fuel economy would have provided some value to them, measuring their loss in consumer surplus is more complicated than in the conventional case where the price of a product changes but its other attributes do not.[696]

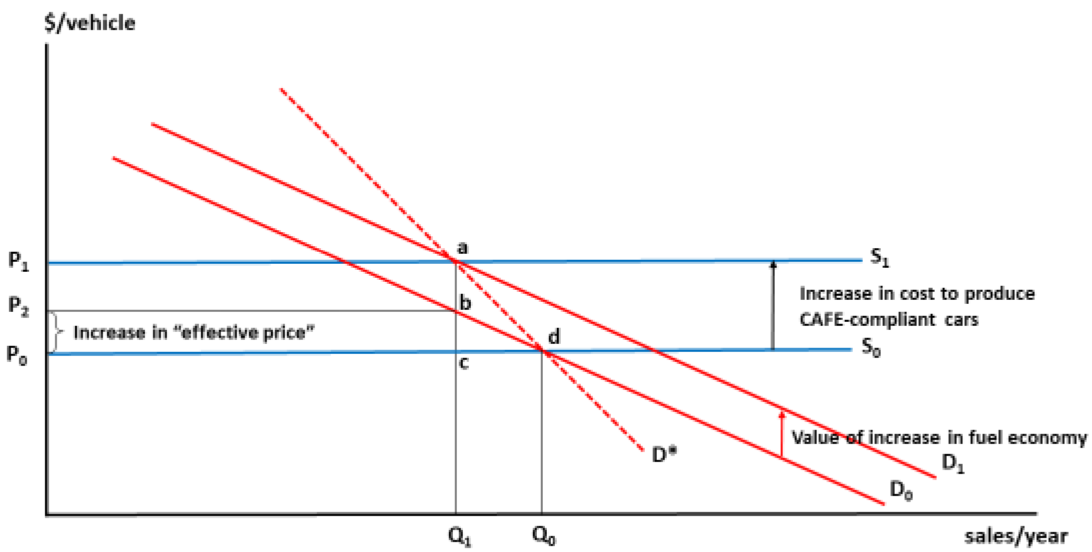

Figure 6-1 – New Vehicle Consumer Surplus

The triangle bcd in Figure 6-1 reflects the loss of consumer surplus to new vehicle buyers, calculated based on changes to new vehicle sales. Line P_0 reflects the baseline vehicle cost. More stringent regulatory alternatives are expected to increase the cost of light duty vehicles, as represented by line P_1. Consistent with other sections of the analysis, we assume that consumers

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[695] Industry reports indicate 19.1 percent of all car insurance claims are for totaled or stolen vehicles, *see* https://www.repairerdrivennews.com/2019/06/18/ccc-q1-data-claim-counts-down-nearly-1-severity-total-loss-value-up. (Accessed: February 15, 2022).

[696] Consumer surplus is a fundamental economic concept and represents the net value (or net benefit) a good or service provides to consumers. It is measured as the difference between what a consumer is willing to pay for a good or service and the market price. OMB circular A-4 explicitly identifies consumer surplus as a benefit that should be accounted for in cost-benefit analysis. For instance, OMB Circular A-4 states the "net reduction in total surplus (consumer plus producer) is a real cost to society," and elsewhere elaborates that consumer surplus values be monetized "when they are significant." OMB Circular A-4, at pp. 37–8.

value 30 months of fuel savings at the time of purchase and offset the price increase accordingly, thus shifting price from line P_1 to line P_2. This shift leads the quantity demanded to move from Q_0 to Q_1, Dotted line D* is a linear representation of the change in quantity of vehicles purchased.[697] The consumer surplus is equal to the area of triangle bcd.[698]

6.1.3 Value of Fuel Savings

Fuel savings are calculated by multiplying avoided fuel consumption by fuel prices. Each vehicle of a given body style is assumed to be driven the same as all the others of a comparable age and body style in each calendar year. The ratio of that cohort's VMT to its fuel efficiency produces an estimate of fuel consumption. The difference between fuel consumption in the baseline, and in each alternative, represents the gallons (or energy) saved. Under this assumption, our estimates of fuel consumption from increasing the fuel economy of each individual model depend only on how much its fuel economy is increased, and do not reflect whether its actual use differs from other models of the same body type. Neither do our estimates of fuel consumption account for variation in how much vehicles of the same body type and age are driven each year, which appears to be significant (see Chapter 4.3.1). Consumers save money on fuel expenditures at the average retail fuel price (fuel price assumptions are discussed in detail in Chapter 4.1.2), which includes all taxes and represents an average across octane blends. For gasoline and diesel, the included taxes reflect both the federal tax and a calculated average state fuel tax. Expenditures on alternative fuels (E85 and electricity, primarily) are also included in the calculation of fuel expenditures, on which fuel savings are based. And while the included taxes net out of the social benefit cost analysis (as they are a transfer), consumers value each gallon saved at retail fuel prices including any additional fees such as taxes.

This assumption that each vehicle is driven the average miles for its cohort may cause our estimates of fuel consumption under more stringent CAFE standards to be too large. Because the distribution of annual driving is wide, using its mean value to estimate fuel savings for individual car or light truck models may overstate the fuel consumption likely to result under tighter standards, even when the fuel economy of different models are correctly averaged.[699] This will be the case even when increases in fuel economy can be estimated reliably for individual models, which this analysis does, because the reduction in a specific model's fuel consumption depends on how much it is actually driven as well as on the change in fuel economy under alternative fuel economy standards.

To illustrate, we estimate that new automobiles are driven about 17,000 miles on average during their first year.[700] If the 17,000 mile figure represents the average of two different models that are driven 14,000 and 20,000 miles annually, and the two initially achieve, respectively, 30 and

[697] D* is not a demand curve. It is included in Figure 6-1 to help visualize the change in consumer welfare.
[698] The exact calculation is half the increase in sales multiplied by the reduction in the cost of light duty vehicles net of the increased fuel cost.
[699] The correct average fuel economy of vehicles whose individual fuel economy differs is the harmonic average of their individual values, weighted by their respective use; for two vehicles with fuel economy levels MPG_1 and MPG_2 that are assumed to be driven identical amounts (as in the agencies' analysis), their harmonic average fuel economy is equal to $2/(1/MPG_1 + 1/MPG_2)$.
[700] While the mileage accumulation schedule reflects this estimate, the actual VMT during 2020 (and the next few subsequent years) is lower, as U.S. light-duty VMT declined significantly during the pandemic.

40 miles per gallon—thus averaging 35 miles per gallon—they will consume a total of 967 gallons annually.[701] Improving the fuel economy of each model by 5 miles per gallon will reduce their total fuel use to 844 gallons, thus saving 123 gallons annually.[702] In contrast, using the 17,000 mile average figure for both two vehicles yields estimated fuel savings of 128 gallons per year, about 5 percent above the correct value.[703]

The magnitude of this potential overestimation of fuel savings increases with any association between annual driving and fuel economy. Car and light truck buyers who anticipate driving more should be more likely to choose models offering higher fuel economy because the number of miles driven directly affects their fuel costs, and thus the savings from driving a model that features higher fuel economy.[704] Conversely, buyers who anticipate driving less are likely to purchase models with lower fuel economy. Such behavior— whereby buyers who expect to drive more extensively are likely to select models offering higher fuel economy—cannot be fully accounted for in today's analysis, which is necessarily based on empirical estimates of average vehicle use. To the extent it occurs, we are likely to consistently overstate actual fuel savings from requiring higher fuel economy. Thus, NHTSA's central analysis is likely to overestimate the impact on consumer benefits such as reduced fuel consumption and increased refueling time, as well as on the resulting environmental impacts of fuel production and use.

A similar phenomenon may cause the analysis to overstate the *value* of fuel savings resulting from requiring higher fuel economy as well. As with miles driven, our analysis assumes all vehicle owners pay the national average fuel price at any time. However, fuel prices vary substantially among different regions of the United States, and one would expect buyers in regions with consistently higher fuel prices to purchase vehicles with higher fuel economy, on average. To the extent they actually do so, evaluating the savings from requiring higher fuel economy identically in all regions using nationwide average fuel prices is likely to overstate their actual dollar value.

As an illustration, suppose gasoline averages $3.00 per gallon nationwide, but a buyer who expects to drive a new car 17,000 miles during its first year (the same value used in the example above) faces a local price of $4.00 per gallon, and chooses a model that achieves 40 mpg. That driver's cost of fuel during the vehicle's first year will total $1,700 (calculated at 17,000 miles / 40 miles per gallon x $4.00 per gallon). A buyer who plans to drive the same number of miles but faces a lower price of $2.00 per gallon and thus chooses a vehicle that offers only 30 mpg

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701 Calculated as 14,000 miles / 30 miles per gallon + 20,000 miles / 40 miles per gallon = 467 gallons + 500 gallons = 967 gallons (all figures in this calculation are rounded to whole gallons).

702 Calculated as 14,000 miles / 35 miles per gallon + 20,000 miles / 45 miles per gallon = 400 gallons + 444 gallons = 844 gallons (again, all figures in this calculation are rounded to whole gallons).

703 Our estimate of their combined initial fuel consumption would be 17,000 miles / 30 miles per gallon + 17,000 miles / 40 miles per gallon, or 567 gallons + 425 gallons = 992 gallons. After the 5 mile per gallon improvement in fuel economy for each vehicle, our estimate would decline to 17,000 miles / 35 miles per gallon + 17,000 miles / 45 miles per gallon = 486 + 378 = 863 gallons, yielding an estimated fuel savings of 992 gallons - 863 gallons = 128 gallons (as previously, all figures in this calculation are rounded to whole gallons).

704 For example, some businesses, rental car firms, taxi operators, and ride sharing drivers are likely to anticipate using their vehicles significantly more than the average new car or light truck buyer. Furthermore, their choices among competing models are likely to be more heavily influenced by economics than by the preferences for other attributes that motivate many other buyers, making them more likely to select vehicles with higher fuel economy in order to improve their economic returns.

will have first-year fuel costs of $1,133 (calculated as 17,000 miles / 30 miles per gallon x $2.00 per gallon), so total annual fuel costs for these two vehicles will be $1,700 + $1,133 = $2,633. If the fuel economy of both vehicles increases by 5 mpg, their actual fuel savings will be $189 and $162, or a total savings of $351. However, evaluating total fuel savings using a price of $3.00 per gallon yields savings of $382, thus overstating actual savings by about 10 percent.

6.1.4 Benefits of Less Frequent Refueling

Increasing CAFE standards, all else being equal, affects the amount of time drivers spend refueling their vehicles in several ways. First, they increase the fuel economy of ICE vehicles produced in the future, which increases vehicle range and decreases the number of refueling events for those vehicles. Second, to the extent that more stringent standards increase the purchase price of new vehicles, they may reduce sales of new vehicles and scrappage of existing ones, causing more VMT to be driven by older and less efficient vehicles which require more refueling events for the same amount of VMT driven. Finally, sufficiently stringent standards may also change the number of electric vehicles that are produced, and shift refueling to occur at a charging station, rather than at the pump—changing per-vehicle lifetime expected refueling costs. The basic calculation for all three effects is the same: we multiply the additional amount of time spent refueling by the value of time of passengers, which is assumed to be the same for all three effects.

6.1.4.1 Value of Travel Time Savings

The calculation of the value of time follows the guidance from DOT's 2016 *Value of Travel Time Savings* memorandum ("VTTS Memo").[705] The economic value of refueling time savings is calculated by applying valuations for travel time savings from the VTTS Memo to estimates of how much time is saved across alternatives.[706] The value of travel time depends on average hourly valuations of personal and business time, which are functions of annual household income and total hourly compensation costs to employers, respectively. As designated by the 2016 VTTS Memo, the nationwide median annual household income, $56,516 in 2015, is divided by 2,080 hours to yield an income of $27.20 per hour. Total hourly compensation cost to employers, inclusive of benefits, in 2015$ was $25.40.[707] Table 6-3 demonstrates NHTSA's approach to estimating the value of travel time ($/hour) for urban and rural driving; we make the simplifying assumption that urban travel consists entirely of local trips, while travel in rural areas is exclusively longer-distance intercity travel. This approach relies on the use of DOT-recommended weights that assign a lesser valuation to personal travel time than to business travel time, as well as weights that adjust for the distribution between personal and business travel.[708] In accordance with DOT guidance, wage valuations are estimated with base year 2015 dollars and end results are adjusted to 2018 dollars.

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[705] U.S. Department of Transportation, The Value of Travel Time Savings: Departmental Guidance for Conducting Economic Evaluations, (2016), available at https://www7.transportation.gov/office-policy/transportation-policy/revised-departmental-guidance-valuation-travel-time-economic. (Accessed: February 15, 2022).
[706] VTTS Memo Tables 1, 3, and 4.
[707] *Ibid* at p. 11.
[708] Business travel is higher than personal travel because an employer has additional expenses, *e.g.* taxes and benefits costs, above and beyond an employee's hourly wage.

Table 6-3 – Estimating the Value of Travel Time for Urban and Rural (Intercity) Travel ($/hour, 2015 Dollars)

	Personal Travel	Business Travel	Total
Urban Travel			
Wage Rate ($/hour)	$27.20	$25.40	-
DOT - Recommended Value of Travel Time Savings, as % of Wage Rate	50%	100%	-
Hourly Valuation (=Wage Rate * DOT-Recommended Value)	$13.60	$25.40	-
% of Total Urban Travel	95.4%	4.6%	100%
Hourly Valuation (Adjusted for % of Total Urban Travel)	$12.97	$1.17	$14.14
Rural (Intercity) Travel			
Wage Rate ($/hour)	$27.20	$25.40	
DOT - Recommended Value of Travel Time Savings, as % of Wage Rate	70%	100%	
Hourly Valuation (=Wage Rate * DOT-Recommended Value)	$19.04	$25.40	
% of Total Rural Travel	78.6%	21.4%	100%
Hourly Valuation (Adjusted for % of Total Rural Travel)	$14.97	$5.44	$20.40

Estimates of the hourly value of urban and rural travel time ($14.14 and $20.40, respectively), shown in Table 6-4, must be adjusted to account for the nationwide ratio of urban to rural driving.[709] This adjustment, which gives an overall estimate of the hourly value of travel time—independent of urban or rural status—is shown in Table 6-5.

Table 6-4 – Estimating Weighted Urban/Rural Value of Travel Time ($/hour, 2015 Dollars)

	Unweighted Value of Travel Time ($/hour)	Weight (% of Total Miles Driven)	Weighted Value of Travel Time ($/hour)
Urban Travel	$14.14	71.6%	$10.12
Rural Travel	$20.40	28.4%	$5.80
Total	-	100.0%	$15.92

[709] Estimate of Urban vs. Rural travel weights from FHWA Highway Statistics 2019, Table VM-1 (light-duty vehicles only), https://www.fhwa.dot.gov/policyinformation/statistics/2019/pdf/vm1.pdf. (Accessed: February 15, 2022).

Table 6-5 – Estimating the Value of Travel Time for Light-Duty Vehicles ($/hour, 2015 Dollars)

	Passenger Cars	Light Trucks
Average Vehicle Occupancy During Refueling Trips (persons)	1.52	1.83
Weighted Value of Travel Time ($/hour)	$15.92	$15.92
Occupancy-Adjusted Value of Vehicle Travel Time During Refueling Trips ($/hour)	$24.23	$29.16

Note that the calculations in Table 6-5 represent the hourly value of travel time for each individual vehicle occupant, and many vehicles have multiple occupants. To estimate the average value of travel time per *vehicle*-hour, Table 6-6 accounts for all passengers in vehicles making refueling stops. We estimated average vehicle occupancy using data from the 2017 National Household Travel Survey, and our estimate of average vehicle occupancy includes the driver and all passengers who are age five and above.[710] The average occupancy assumption used in the refueling benefit is consistent with occupancy assumptions used to estimate the social cost of additional traffic congestion. Lastly, the occupancy-adjusted value of travel time per vehicle-hour is converted to 2018 dollars using the GDP deflator as shown in Table 6-6.[711]

Table 6-6 – Value of Vehicle Travel Time in 2018 Dollars ($/hour, 2018 Dollars)

	Passenger Cars	Light Trucks
Occupancy-Adjusted Value of Vehicle Travel Time During Refueling Trips ($/hour)	$25.55	$30.75

6.1.4.2 Accounting for Improved Fuel Economy of ICE Vehicles

The CAFE Model calculates the number of refueling events for each ICE vehicle in a calendar year. This is calculated as the number of miles driven by each vehicle in that calendar year divided by the product of that vehicle's on-road fuel economy (rather than fuel economy as measured for compliance), tank size, and an assumption about the average share of the tank refueled at each event, as shown in Equation 6-2.

$$Refuel\ Events_{CY,Veh} = \frac{Miles_{CY,Veh}}{FE_{Veh} * Tank_{Veh} * Share_{Veh}}$$

Equation 6-2 – Calculating the Number of Refueling Events

The model then computes the cost of refueling as the product of the number of refueling events, total time of each event and the value of the time spent on each event (computed as average salary), as shown in Equation 6-3.

[710] The National Household Travel Survey excludes trips by children under age five.
[711] Bureau of Economic Analysis, NIPA Table 1.1.9 Implicit Price Deflators for Gross Domestic Product, available at https://apps.bea.gov/iTable/index_nipa.cfm. (Accessed: February 15, 2022).

$$Cost_{CY,Veh} = Refuel\ Events_{CY,Veh} * (Event\ Time_{Veh}) * Time\ Value$$

Equation 6-3 – Calculating the Cost of Refueling Events

The refueling event time of each vehicle is calculated by summing a fixed and variable component. The fixed component is the number of minutes required for each refueling event, regardless of the tank size or share refueled at each event (i.e., the time it takes to get to and from the pump). The variable component is the ratio of the average number of gallons refueled for each event (the product of the tank size and share refueled) and the rate at which gallons flow from the pump. This is shown in Equation 6-4.

$$Event\ Time_{Veh} = Fixed_{Veh} + \frac{Tank_{Veh} * Share_{Veh}}{Rate}$$

Equation 6-4 – Calculating the Time of Refueling Events

The value of time is taken from DOT guidance on travel time savings, as described in Chapter 6.1.4.1. The fixed time component, share refueled, and rate of flow are calculated from survey data gathered as part of our 2010-2011 National Automotive Sampling System's Tire Pressure Monitoring System (TPMS) study.[712] Finally, the vehicle fuel tank sizes are taken from manufacturer specs for the reference fleet and historical averages are calculated from popular models for the existing vehicle fleet, as described later in this section and in Table 6-8 through Table 6-10.

We estimated the amount of saved refueling time using survey data gathered as part of the aforementioned TPMS study. In this nationwide study, researchers gathered information on the total amount of time spent pumping and paying for fuel. From a separate sample (also part of the TPMS study), researchers conducted interviews at the pump to gauge the distances that drivers travel in transit to and from fueling stations, how long that transit takes, and how many gallons of fuel are purchased.

We focused on the interview-based responses in which respondents indicated the primary reason for the refueling trip was due to a low reading on the gas gauge. Such drivers experience a cost due to added mileage driven to detour to a filling station, as well as added time to refuel and complete the transaction at the filling station. Drivers who refuel on a regular schedule or incidental to stops they make primarily for other reasons (e.g., using restrooms or buying snacks) do not experience the cost associated with detouring in order to locate a station or paying for the transaction, because the frequency of refueling for these reasons is unlikely to be affected by fuel economy improvements. This restriction was imposed to exclude distortionary effects of those who refuel on a fixed (*e.g.*, weekly) schedule and may be unlikely to alter refueling patterns as a result of increased driving range. The relevant TPMS survey data on average refueling trip characteristics are presented below in Table 6-7.

[712] Docket for Peer Review of NHTSA/NASS Tire Pressure Monitoring System, *available at* https://www.regulations.gov/docket?D=NHTSA-2012-0001. (Accessed: February 15, 2022).

Table 6-7 – Average Refueling Trip Characteristics for Passenger Cars and Light Trucks

	Gallons of Fuel Purchased	Round-Trip Distance to/from Fueling Station (miles)	Round-Trip Time to/from Fueling Station (minutes)	Time to Fill and Pay (minutes)	Total Time (minutes)
Passenger Cars	10	0.97	2.28	4.1	6.38
Light Trucks	13	1.08	2.53	4.3	6.83

From the data, we assume that all of the round-trip time necessary to travel to and from the fueling station is a part of the fixed time component of each refueling event. Some portion of the time to fill and pay is also a part of the fixed time component. Given the information in Table 6-7, we assume that each refueling event has a fixed time component of 3.5 minutes. For example, the sum for passenger cars of 2.28 minutes round trip time to/from fueling station and roughly 1.2 minutes to select and pay for fuel, remove/recap fuel tank, remove/replace fuel nozzle, etc. The time to fill the fuel tank is the variable time component; about 2.9 minutes for passenger cars (2.28 + 1.2 + 2.9 = 6.38 total minutes).

To calculate the variable time component, the agency estimates how much time is spent during a refueling event just pumping gas. Cars have an average tank size of about 15 gallons, SUVs/vans of about 18 gallons, and pickups of about 27 gallons (see Table 6-8 through Table 6-10). For simplicity of this calculation, the agency assumes that the average passenger car has a tank of 15 gallons and the average light truck—which includes SUVs for this calculation—has a tank of 20 gallons (there are more SUVs/vans than pickups in the light truck fleet). From these assumptions, we calculate that the average refueling event fills approximately 65 percent of the fuel tank—as derived from the TPMS study— for both passenger cars and light trucks. This value is used as an input in the CAFE Model for both styles (cars and SUVs/vans/pickups). Finally, the rate of the pump flow can be calculated either as the total gallons pumped over the assumed variable time component (approximately 3 minutes) or as the difference in the average number of gallons filled between light trucks and passenger cars over the difference in the time to fill and pay between the two classes. The first methodology implies a rate between 3 and 4 gallons per minute. Although the second methodology implies a rate of 15 gallons per minute, there is a legal restriction on the flow of gasoline from pumps of 10 gallons per minute.[713] Thus, we assume the rate of gasoline pumps range between 4 and 10 gallons per minute, and use 7.5 gallons per minute—a value slightly above the midpoint of that range—as the average flow rate in the CAFE Model.

The calculations described above are repeated for each future calendar year in the analysis. As a vehicle ages, the refueling benefit attributable to it decreases—as older vehicles are typically driven less which means less fuel consumption and fewer refueling events[714]—until the vehicle is scrapped.

[713] 40 CFR 80.22 (j), Regulation of Fuels and Fuel Additives - subpart B. Controls and Prohibitions, *available at* https://www.law.cornell.edu/cfr/text/40/80.22. (Accessed: February 15, 2022).
[714] *See* 4.3.1.2.

As described in Chapter 4.2, more stringent regulatory alternatives cause fleet turnover to slow, and as a result older and less efficient vehicles are relied upon to drive additional miles. This shift of VMT from newer to older vehicles diminishes a portion of the refueling benefit accrued under stricter standards. The CAFE Model calculates the aggregate refueling costs for all vehicles—new and the existing fleet—and calculates the refueling benefit associated with more stringent standards as the difference in fleet-wide absolute refueling costs relative to the baseline.

The CAFE Model tracks the legacy fleet of light-duty vehicles by body style and vintage, using average measures for fuel economy. Estimating refueling costs for these vehicles requires measures of average fuel tank sizes by body style and vintage. We used publicly available data on fuel tank sizes of 17 high-volume nameplates to derive estimates of average fuel tank size over time. The tank sizes are averaged by body style, and these historical values are used as estimates of the average by body style and vintage. The vehicles included, their fuel tank sizes, and the averages are reported in Table 6-8 through Table 6-10 for cars, vans/SUVs, and pickups, respectively. The averages are used to represent the fuel tank sizes by vintage and vehicle body style. We used the fuel tank sizes from Table 6-8 to Table 6-10 to determine the number of refueling events and time spent refueling to compute refueling costs using the methodology described above.

Table 6-8 – Fuel Tank Size of High-Volume Car Models and Averages by Vintage

Model Year	Honda Civic	Honda Accord	Toyota Corolla	Toyota Camry	Ford Mustang	Chevy Corvette	Car Average
1975	10		13.2		12.4	17	13.2
1976	10	13.2	13.2		12.4	17	13.2
1977	10	13.2	13.2		12.4	17	13.2
1978	10.6	13.2	13.2		12.4	24	14.7
1979	10.6	13.2	13.2		12.5	24	14.7
1980	10.8	13.2	13.2	16.1	12.5	24	15.0
1981	10.8	13.2	13.2	16.1	12.5	24	15.0
1982	12.2	15.9	13.2	16.1	15.4	24	16.1
1983	12.2	15.9	13.2	14.5	15.4	24	15.9
1984	12.2	15.9	13.2	14.5	15.4	20	15.2
1985	12.2	15.9	13.2	14.5	15.4	20	15.2
1986	12.2	15.9	13.2	14.5	15.4	20	15.2
1987	12.2	15.9	13.2	15.9	15.4	20	15.4
1988	11.9	15.9	13.2	15.9	15.4	20	15.4
1989	11.9	15.9	13.2	15.9	15.4	20	15.4
1990	11.9	16.9	13.2	15.9	15.4	20	15.6
1991	11.9	16.9	13.2	15.9	15.4	20	15.6
1992	11.9	16.9	13.2	18.5	15.4	20	16.0
1993	11.9	16.9	13.2	18.5	15.4	20	16.0
1994	11.9	16.9	13.2	18.5	15.4	20	16.0
1995	11.9	16.9	13.2	18.5	15.4	20	16.0
1996	11.9	16.9	13.2	18.5	15.4	20	16.0
1997	11.9	16.9	13.2	18.5	15.4	19.1	15.8

Model Year	Honda Civic	Honda Accord	Toyota Corolla	Toyota Camry	Ford Mustang	Chevy Corvette	Car Average
1998	11.9	17.2	13.2	18.5	15.7	19.1	15.9
1999	11.9	17.2	13.2	18.5	15.7	19.1	15.9
2000	11.9	17.2	13.2	18.5	15.7	18.5	15.8
2001	13.2	17.2	13.2	18.5	15.7	18.5	16.1
2002	13.2	17.2	13.2	18.5	15.7	18.5	16.1
2003	13.2	17.2	13.2	18.5	15.7	18.5	16.1
2004	13.2	17.2	13.2	18.5	15.7	18	16.0
2005	13.2	17.2	13.2	18.5	16.6	18	16.1
2006	13.2	17.2	13.2	18.5	16.6	18	16.1
2007	13.2	17.2	13.2	18.5	16.6	18	16.1
2008	13.2	18.5	13.2	18.5	16.6	18	16.3
2009	13.2	18.5	13.2	18.5	16.6	18	16.3
2010	13.2	18.5	13.2	18.5	16	18	16.2
2011	13.2	18.5	13.2	18.5	16	18	16.2
2012	13.2	18.5	13.2	17	16	18	16.0
2013	13.2	17.2	13.2	17	16	18	15.8
2014	13.2	17.2	13.2	17	16	18.5	15.9
2015	13.2	17.2	13.2	17	16	18.5	15.9
2016	12.4	17.2	13.2	17	16	18.5	15.7

Table 6-9 – Fuel Tank Size of High-Volume Van/SUV Models and Averages by Vintage

Model Year	Jeep Wrangler	Ford Explorer	Jeep Grand Cherokee	Chevy Blazer	Ford Escape	Honda CR-V	Toyota Rav4	SUVs Average
1975				31				31.0
1976				31				31.0
1977				31				31.0
1978				31				31.0
1979				31				31.0
1980				31				31.0
1981				31				31.0
1982				31				31.0
1983				31				31.0
1984				31				31.0
1985				31				31.0
1986				31				31.0
1987	20			31				25.5
1988	20			31				25.5
1989	20			31				25.5
1990	20			31				25.5
1991	20	19.3		30				23.1
1992	20	19.3		30				23.1
1993	20	19.3	23	30				23.1

Model Year	Jeep Wrangler	Ford Explorer	Jeep Grand Cherokee	Chevy Blazer	Ford Escape	Honda CR-V	Toyota Rav4	SUVs Average
1994	20	19.3	23	30			15.3	21.5
1995	20	19.3	23	20			15.3	19.5
1996	20	21	23	19			15.3	19.7
1997	19	21	23	19		15.3	15.3	18.8
1998	19	21	23	19		15.3	15.3	18.8
1999	19	21	20.5	19		15.3	15.3	18.4
2000	19	21	20.5	19		15.3	15.3	18.4
2001	19	21	20.5	19	16	15.3	14.7	17.9
2002	19	22.5	20.5	19	16	15.3	14.7	18.1
2003	19	22.5	20.5	19	16	15.3	14.7	18.1
2004	19	22.5	20.5	19	16	15.3	14.8	18.2
2005	19	22.5	20.5	19	16.5	15.3	14.8	18.2
2006	19	22.5	20.5	22	16.5	15.3	15.9	18.8
2007	19	22.5	21.1	22	16.5	15.3	15.9	18.9
2008	22.5	22.5	21.1	22	16.5	15.3	15.9	19.4
2009	22.5	22.5	21.1	22	16.5	15.3	15.9	19.4
2010	22.5	22.5	21.1		16.5	15.3	15.9	19.0
2011	22.5	18.6	24.6		17.5	15.3	15.9	19.1
2012	22.5	18.6	24.6		17.5	15.3	15.9	19.1
2013	22.5	18.6	24.6		15.1	15.3	15.9	18.7
2014	22.5	18.6	24.6		15.1	15.3	15.9	18.7
2015	22.5	18.6	24.6		15.1	15.3	15.9	18.7
2016	22.5	18.6	24.6		15.1	15.3	15.9	18.7

Table 6-10 – Fuel Tank Size of High-Volume Pickup Models and Averages by Vintage

Model Year	Ford F150	Dodge Ram	Chevy Silverado	Ford Ranger	Pickups Average
1975	39.2				39.2
1976	39.2				39.2
1977	39.2				39.2
1978	39.2				39.2
1979	39.2				39.2
1980	37.5				37.5
1981	37.5	26			31.8
1982	37.5	26			31.8
1983	37.5	26		19	27.5
1984	37.5	26		19	27.5
1985	37.5	26		19	27.5
1986	37.5	26		19	27.5
1987	37.5	26		19	27.5
1988	37.5	26		19	27.5
1989	37.5	26		19	27.5

Model Year	Ford F150	Dodge Ram	Chevy Silverado	Ford Ranger	Pickups Average
1990	37.5	26		19	27.5
1991	37.5	26		19	27.5
1992	37.5	26		19	27.5
1993	37.5	30.5		18.8	28.9
1994	37.5	30.5		18.8	28.9
1995	37.5	30.5		18.8	28.9
1996	37.5	30.5		18.8	28.9
1997	30	30.5		18.8	26.4
1998	30	30.5		18.5	26.3
1999	30	30.5	30	18.5	27.3
2000	30	30.5	30	18.5	27.3
2001	30	30.5	30	18.5	27.3
2002	30	30.5	30	18.5	27.3
2003	30	30.5	30	18.5	27.3
2004	30	30.5	30	18.5	27.3
2005	30	30.5	30	18.5	27.3
2006	30	30.5	30	18.5	27.3
2007	30	30.5	30	18.5	27.3
2008	30	30.5	30	18.5	27.3
2009	26	29	30	18.5	25.9
2010	26	29	30	18.3	25.8
2011	26	29	30	18.3	25.8
2012	26	29	30		28.3
2013	26	29	30		28.3
2014	26	29	30		28.3
2015	23	29	30		27.3
2016	23	29	30		27.3

After calculating the aggregate value for each regulatory alternative using the methodology and inputs described above for both the new and legacy fleets, the model calculates the incremental value relative to the baseline as the refueling cost or benefit for that regulatory alternative. More efficient vehicles have to be refueled less often and refueling costs per vehicle decline.

6.1.4.3 Including Electric Vehicle Recharging

In addition to including the refueling costs associated with the "legacy fleet," the CAFE Model also adds the cost to recharge electric vehicles to the total refueling costs. As electric vehicles become a larger share of the on-road fleet, accounting for the cost of their refueling becomes increasingly relevant. In order to do so, it is important to first understand how many electric vehicle charging events will require the driver to wait and for how long. The answer to this question depends on the range of the electric vehicle and the length of the trip.[715] For trips

[715] While the range of EVs is dependent on a number of factors, such as driver habits, geography, and weather, NHTSA took a conservative approach and assumed a best-case scenario.

shorter than the range, the driver can recharge the vehicle at times that will not require them to be actively waiting and there would be no cost related to recharging. Only for trips where the vehicle is driven more miles than the range will the driver have to stop mid-trip, a time that is assumed to be inconvenient, to recharge the vehicle at least enough to reach the intended destination.

NHTSA used trip data from the National Household Transportation Survey (NHTS) to estimate the frequency and expected length of trips that exceed the range of the electric vehicle technologies in the simulation (200 and 300 mile ranges – which were extrapolated for longer battery ranges). The NHTS collects data on individual trips by mode of transportation from a representative random sample of U.S. households. A trip is defined by the starting and ending point for any personal travel, so that vehicle trips will capture any time a car is driven. The survey includes identification numbers for households, individuals, and vehicles, and mode of transportation (including the body style of the vehicle for vehicle trips), and the date of the trip. Although some trips made in the same day may allow for convenient charging in between trips, we assume that travel in the same day exceeding the range will involve the driver waiting for the vehicle to charge. Thus, the total number of miles driven by the same vehicle in a single day is summed, and we assume that charging stations are not conveniently available to the driver in between.

From the final body style datasets (which excludes taxis and rental cars), we calculated two measures that allow for the construction of the value of recharging time. First, the expected distance between trips that exceed the range of 200-mile and 300-mile BEVs (BEV200 and BEV300, respectively) was calculated. This is calculated as the quotient of the sum of total miles driven by each individual body style and the total number of trips exceeding the range, as shown in Equation 6-5.[716]

$$Charge\ Frequency_{Style,Range} = \frac{\sum_{Trip\ \epsilon\ Style} Trip\ Length}{\sum_{Trip\ \epsilon\ Style}[Trip\ Length > Range]}$$

Equation 6-5 – Calculation of En Route Charge Frequency

This calculates the expected frequency of en route recharging events, or the amount of miles traveled per inconvenient recharging event. It is used later to calculate the total expected time to recharge a vehicle.

The second measure needed to calculate the total expected recharging time is the expected share of miles driven that will be charged in the middle of a trip (causing the driver to wait and lose the value of time). In order to calculate this measure, we sum the difference of the trip length and range, conditional on the trip length exceeding the range for each body style. This figure is then divided by the sum of the length of all trips for that body style, as in Equation 6-6.

[716] The denominator counts the number of necessary recharging events by body style. It is not a measurement of VMT.

$$Share\ Charged_{Style,Range} = \frac{\sum_{Trip\ \epsilon\ Style}([Trip\ Length > Range] * (Trip\ Length - Range))}{\sum_{Trip\ \epsilon\ Style} Trip\ Length}$$

Equation 6-6 – Share of Battery Electric Range Charged

The calculated frequency of inconvenient charging events and share of miles driven that require the driver to wait for BEVs with 200 and 300-mile ranges are presented in Table 6-11, below. As the table shows, cars are expected to require less frequent inconvenient charges and a smaller share of miles driven will require the driver to charge the vehicle in the middle of a trip. Pickups and vans/SUVs have fairly similar measures, with vans and SUVs requiring slightly more inconvenient charging than pickups.

Table 6-11 – Electric Vehicle Recharging Thresholds by Body Style and Range

Body Style	Cars	Vans/SUVs	Pickups
Miles until mid-trip charging event, BEV200	2,000	1,500	1,600
Miles until mid-trip charging event, BEV300	5,200	3,500	3,800
Share of miles charged mid-trip, BEV200	6%	9%	8%
Share of miles charged mid-trip, BEV300	3%	4%	4%

The measures presented in Table 6-11, above, can be used to calculate the expected time drivers of electric vehicles of a given body style and range will spend recharging at a time that will require them to wait. First the agencies calculate the expected number of refueling events for a vehicle of a given style and range in a given calendar year. This is shown in Equation 6-7 as the expected miles driven by a vehicle in a given calendar year divided by the charge frequency of a vehicle of that style and range (from Table 6-11).[717]

$$Recharge\ Events_{CY,Veh\ \epsilon\ (Style\ \cup\ Range)} = \frac{Miles_{CY,Veh}}{Charge\ Frequency_{Style,Range})}$$

Equation 6-7 – Calculation of Recharge Events

We next calculate the number of miles charged for a vehicle of a given style and range in a specific calendar year. This is the product of the number of miles driven by the vehicle and the share of miles driven that require an inconvenient charge for a vehicle of that style and range (from Table 6-11), as presented in Equation 6-8.

$$Miles\ Charged_{CY,Veh\ \epsilon\ (Style\ \cup\ Range)} = Miles_{CY,Veh} * Share\ Charged_{Style,Range}$$

[717] Note that $\sum_{Trip\ \epsilon\ Style} Trip\ Length$ and $Miles_{CY,Veh}$ are different values. $Miles_{CY,Veh}$ is the estimated amount of VMT predicted by VMT while $\sum_{Trip\ \epsilon\ Style} Trip\ Length$ is the sum of trips observed by the NHTS study.

Equation 6-8 – Calculation of Miles Charged

Finally, we calculate the expected time that a driver of an electric vehicle (of a given style and range) will spend waiting for the vehicle to charge. This is the product of the fixed amount of time it takes to get to the charging station and the number of recharging events plus the quotient of the expected miles that will require inconvenient charging over an input assumption of the rate of which a vehicle of that style and range can be charged in a given calendar year (expressed in units of miles charged per hour). The fixed amount of time it takes to get to a charging station is set equal to the average time it takes for an ICE vehicle to get to a gas station for a refueling event, as discussed above.[718] This is shown in Equation 6-9.

$$\begin{aligned} &Charge\ Time_{CY,Veh\ \epsilon\ (Style\ \cup\ Range)} \\ &\qquad = (Fixed_{Veh} * Recharge\ Events_{CY,Veh}) + \frac{Miles\ Charged_{CY,Veh}}{Charge\ Rate_{CY,Veh}} \end{aligned}$$

Equation 6-9 – Calculation of Charging Time

The expected time that a driver will wait for their vehicle to charge can then be multiplied by the value of time estimate, as is done with gasoline, diesel, and E85 vehicles (see description above of the current approach to accounting for refueling time costs).

Plug-in hybrids are treated somewhat differently in the modelling. Presumably, plug-in hybrids that are taken on a trip that exceeds their electric range will be driven on gasoline and the driver will recharge the battery at a time that is convenient. For this reason, the electric portion of travel should be excluded from the refueling time calculation. The gasoline portion of travel is treated the same as other gasoline vehicles so that when the tank reaches some threshold, the vehicles is assumed to be refueled with the same fixed event time and the same rate of refueling flow.

6.1.5 Benefits of Additional Mobility

Increased travel provides benefits that reflect the value to drivers and their passengers of the added—or more desirable—social and economic opportunities to which it provides access. Under the regulatory alternatives considered in this analysis, the fuel cost per mile of driving would decrease as a consequence of the higher fuel economy levels they require, thus increasing the number of miles that buyers of new cars and light trucks would drive as a consequence of the well-documented fuel economy rebound effect.

The fact that drivers and their passengers elect to make more frequent or longer trips to gain access to these opportunities when the cost of driving declines demonstrates that the benefits they gain by doing so exceed the costs they incur. At a minimum, the benefits must be large enough to offset the cost of the fuel consumed to travel the additional miles (or they would not have occurred). Because the cost of fuel consumed by additional rebound-effect driving is has already been accounted for in the simulated fuel expenditures for each regulatory alternative, it is

[718] Given the current state charging infrastructure, this is likely a conservative estimate. Gas stations vastly outnumber publicly available recharging stations and are often in more convenient locations.

necessary to account separately for the benefits associated with the additional miles traveled.[719] The amount by which the benefits of this additional travel *exceed* its economic costs measures the net benefits drivers and their passengers experience, usually referred to as increased consumer surplus.

The structure of these additional benefits is described by Figure 6-2, below. In the figure, the triangle abc is the consumer surplus associated with the additional travel, and the area of the rectangle immediately below triangle abc represents the cost of the fuel consumed in the course of traveling the additional miles.[720] The rectangle immediately below that one represents the internalized benefit of increased exposure to vehicular crashes. While we assume that drivers consider the added safety risks they assume when they undertake additional trips, we assume that they do not *completely* internalize any risks they impose on other drivers when they travel more. So, unlike the corresponding benefit associated with the additional fuel cost of rebound travel, which fully offsets the cost, the offsetting benefit of safety risk only offsets 90 percent of the (social) cost of increasing safety risk.

While Figure 6-2 also shows travel costs related to maintenance, non-fuel operating costs, and the value of occupants' travel time, these other elements that accrue due to the rebound effect are not accounted for in the analysis. Because we do not estimate these additional costs of increased driving, there is no need to separately account for an offsetting benefit (as we do with other components of the mobility costs related to rebound travel).

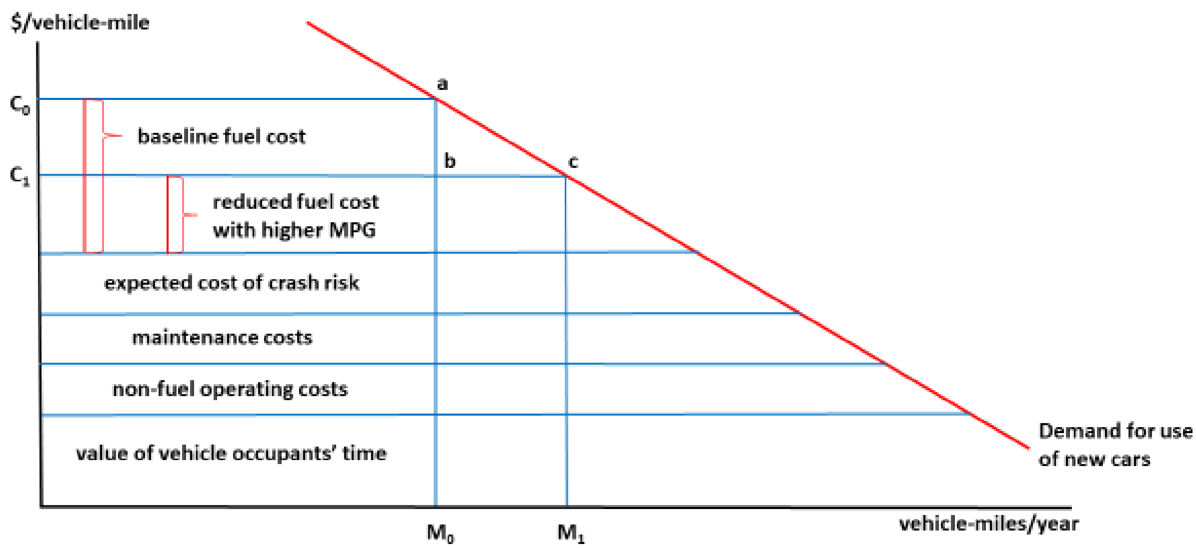

Figure 6-2 – The Benefit of Additional Mobility

[719] The benefits from additional travel must also offset the economic value of their (and their passengers') travel time, other vehicle operating costs, and the economic cost of safety risks due to the increase in exposure that occurs with additional travel.

[720] The CAFE Model tracks mileage accrual for new vehicles atomically, at the row level, and is thus able to separate the fuel cost of rebound travel on a per-vehicle basis. It then aggregates all of those individual benefits to construct the aggregate estimate of increased mobility.

In contrast to the societal cost-benefit analysis, calculation of average costs and benefits to consumers is done on a per-vehicle basis and is intended to describe how alternative standards affect the costs and benefits of owning vehicles from the consumers' perspective. The analysis for this rule adds an adjustment to the calculation of the value of additional mobility per vehicle that was missing in the NPRM. The adjustment is specific to the calculation of the per vehicle value of mobility and does not apply to the overall cost-benefit analysis.

In general, CAFE standards change the quantities of new vehicles sold in future years. When future vehicle sales differ from the baseline, the CAFE Model adjusts miles traveled per vehicle by vehicle type, model year and age to ensure that total miles traveled, prior to adjustments for the rebound effect, are the same across alternatives (see Chapter 4.3.2). When new vehicle sales decrease relative to the baseline, miles per vehicle increase because the same number of miles per year is driven by fewer vehicles. In the NPRM, the increase in fuel cost per vehicle due to these reallocated miles was included in the per vehicle costs, but no offsetting benefit was recognized. However, the reallocation of VMT to existing vehicles implies that consumers are willing to pay for the additional travel, which implies a corresponding per vehicle travel benefit at least as great as the fuel cost. That per vehicle benefit was not accounted for in the NPRM consumer welfare analysis but is included in the calculations for this rule.

Figure 6-2 illustrates the consumer benefit in question. D_0 is the per-vehicle travel demand curve in the baseline. Reallocating miles equal to $M_{Delta,Alt}$ - M_{Base} to the vehicle shifts the demand curve outward to D^*. This increases fuel expenditures by an amount equal to the reallocated miles times the fuel cost per mile for the vehicle in the alternative, i.e., the rectangle ($M_{Delta,Alt}$ - M_{Base})CPM_{Alt}. The increase in vehicle miles due to the rebound effect of lower fuel cost per mile ($CPM_{Alt} < CPM_{Base}$) also increases fuel costs by ($M_{Reb,Alt} – M_{Delta,Alt}$)$CPM_{Alt}$. Both increases in fuel costs are included when the total fuel costs by vehicle type, model year and age are divided by the corresponding number of vehicles. The benefit to the consumer of the miles induced by the rebound effect is accounted for by the method described above. However, in the NPRM the per vehicle benefit of the reallocated miles was not included in the consumer welfare analysis, although the fuel costs were.

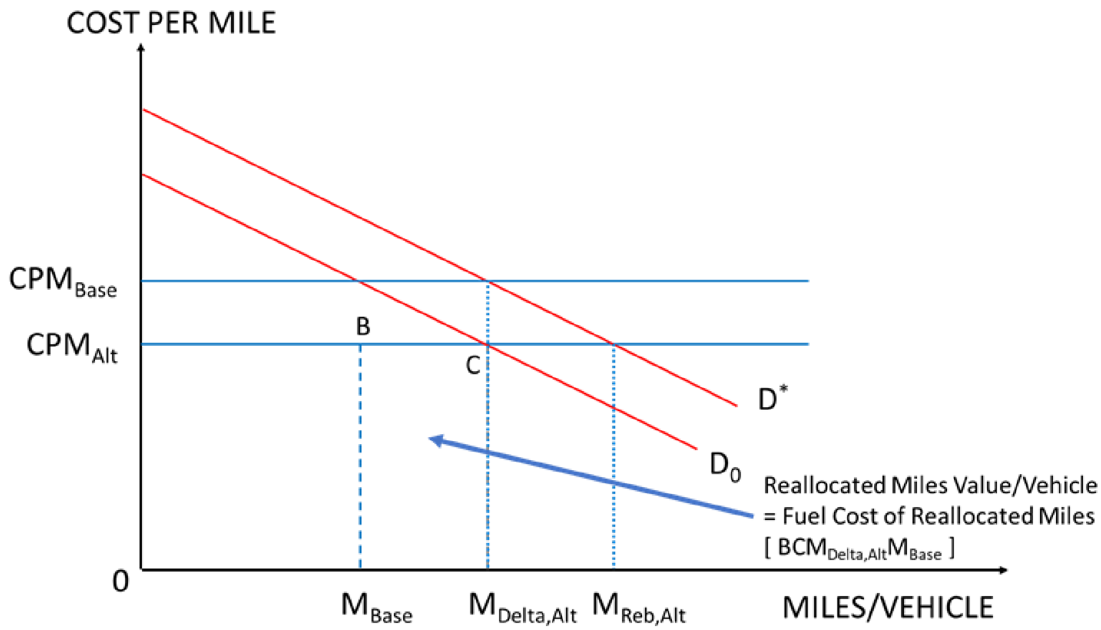

Figure 6-3 – Per Vehicle Change in Vehicle Travel as a Function of Cost-per-Mile

Because total non-rebound VMT does not change from the baseline to the alternatives, there is no change in consumers' surplus due to the reallocation of miles in the alternative cases. For this reason, we calculate only the portion of the value of reallocated miles that is equivalent to the fuel cost per vehicle associated with those miles in order to offset the increase in fuel costs per vehicle caused by the reallocated miles.[721] The mobility value of reallocated miles is calculated as, (Reallocated VMT Alternative - Reallocated VMT Baseline)(Alternative Cost per Mile), or in Figure 6-3, $(M_{Delta,Alt} - M_{Base})CPM_{Alt}$.[722] A detailed explanation of the method of calculation is available in the CAFE Model Documentation, Section S8.8.2.

6.2 External Benefits and Costs

In addition to the benefits and costs that establishing higher CAFE standards creates for manufacturers and buyers of new cars and light trucks, NHTSA's analysis evaluates a number of impacts its action is likely to have on the general public, the U.S. economy, and even global economic activity. The agency refers to these indirect impacts as "external" costs and benefits

[721] By reallocating every mile that would have been traveled by the vehicles not sold (in the case of a reduction in new vehicle sales), we implicitly assume that consumers are indifferent between travel in the new vehicles versus the existing vehicles to which the travel is reallocated. In general, some change in total travel would be expected due to the differences in the attributes of new and existing vehicles. However, by reallocating every mile we implicitly assume there is no change in consumers' welfare due to the reallocation. For this reason, we do not estimate a per-vehicle change in consumers' surplus associated with the reallocated miles beyond the value that effectively cancels the increase in fuel cost per vehicle.

[722] The VMT reallocated in the baseline ensures that baseline VMT is consistent with the forecasts of the FHWA VMT model by adjusting the VMT per vehicle type and age of the reference year fleet (see Chapters 4.3.1 and 4.3.2 above).

from establishing more stringent standards, because they extend well beyond the private businesses and households that experience the more direct effects of raising CAFE standards.

The most significant external benefit from reducing fuel consumption is lower GHG emissions and the consequent reduction in the expected economic damages caused by resulting changes in the future global climate. Chapter 5.2 and Chapter 5.3 explain how the agency estimates the reductions in emissions of GHGs that are likely to result from establishing stricter CAFE standards, and Chapter 6.2.1 explains how the agency values the associated reduction in future climate-related economic damages, which is likely to extend to nations and regions well outside U.S. borders.

As Chapter 5 discussed, changes in emissions of criteria air pollutants and the health damages they cause for the U.S. population are likely to result from raising CAFE standards. Chapter 6.2.2 below explains how NHTSA estimates the economic value of changes in health outcomes. Finally, Chapter 6.2.3 discusses how U.S. consumption and imports of petroleum can generate economic externalities that impose potential costs beyond those to consumers of petroleum products and describes how reducing gasoline consumption can limit the costs of these externalities, thus generating additional external benefits.

At the same time, raising CAFE standards is likely to impose some costs that extend beyond its private impacts on producers and buyers of new cars and light trucks, and beyond related economic transfers (such as sales taxes on new vehicle purchases) discussed above. As Chapter 4.3.3 describes, improving fuel economy is likely to increase the number of miles that new cars and light trucks are driven via the well-documented fuel economy rebound effect. This additional driving will contribute to increased traffic congestion and road noise, the impacts of which will extend to road users other than those traveling in new cars and light trucks, as well as to residents of areas surrounding streets and highways. Chapter 6.2.4 explains how NHTSA estimates of the costs of these congestion and noise externalities.

Some fraction of the safety risks that buyers of new cars and light trucks impose when they drive additional miles is likely to be borne by occupants of other vehicles using the same roads, as well as perhaps by pedestrians and bystanders. Chapter 7.4 describes how the agency estimates this "external" component of safety risks from additional rebound-effect driving, and how NHTSA calculates the fraction of costs from fatalities, injuries, and property damage to vehicles that are borne by road users other than drivers and passengers of new cars and light trucks.

Finally, reducing fuel consumption by raising CAFE standards will lower revenue to government agencies from fuel taxes. Taxes are considered a transfer in the analysis, so while we include the lost tax revenue as a societal cost in our accounting, consumers experience an exactly offsetting savings in fuel tax payments, which is included in our estimates of fuel cost savings.

6.2.1 Social Costs of Greenhouse Gas Emissions

The combustion of petroleum-based fuels to power cars and light trucks generates emissions of various greenhouse gases (GHGs), which contribute to changes in the global climate and the resulting economic damages. The processes of extracting and transporting crude petroleum, refining it to produce transportation fuels, and distributing fuel for retail sale each generate additional GHG emissions ("upstream" emissions), as does generating electricity that is used to power by plug-in hybrid (PHEVs) and battery-electric vehicles (BEVs). By reducing the volume of petroleum-based fuel produced and consumed by cars and light trucks, the final standards will reduce both direct GHG emissions from fuel consumption and upstream emissions from supplying petroleum-based fuels. By increasing sales and use of PHEVs and BEVs, however, raising CAFE standards will increase upstream emissions from generating the additional electricity they consume.

NHTSA's regulatory analysis supporting the final CAFE standards quantifies resulting changes in emissions of three important GHGs: carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O). For an extensive discussion of the definitions, sources, and impacts of these GHGs, see Chapter 5 of the Environmental Impact statement accompanying the final rule. Chapter 5 of this TSD details how NHTSA estimates changes in GHG emissions expected to result from the different rulemaking alternatives. The agency calculates the economic benefits and costs resulting from anticipated changes in emissions of each of these three GHGs using estimates of the social costs of greenhouse gases (SC-GHG) values reported by the federal Interagency Working Group on the Social Cost of Greenhouse Gases (hereinafter referred to as the IWG). Chapter 6.2.1.1 offers a brief overview of the IWG and the methods it uses to estimate the social costs of greenhouse gas emissions, while Chapter 6.2.1.2 explains the process NHTSA uses to integrate the IWG's SC-GHG values into the agency's CAFE Model, and the assumptions it makes regarding discounting of future economic benefits from reducing emissions of GHGs.

6.2.1.1 Estimating the Social Costs of GHG Emissions

In principle, SC-GHG includes the value of all climate change impacts, including (but not limited to) changes in net agricultural productivity, human health effects, property damage from increased flood risk and natural disasters, disruption of energy systems, risk of conflict, environmental migration, and the value of ecosystem services. The SC-GHG therefore, reflects the societal value of reducing emissions of the gas in question by one metric ton. The SC-GHG is the theoretically appropriate value to use in conducting benefit-cost analyses of policies that affect CO_2, CH_4, and N_2O emissions.

We estimate the global social benefits of CO_2, CH_4, and N_2O emission reductions expected from the final rule using the SC-GHG estimates presented in this TSD: Social Cost of Carbon, Methane, and Nitrous Oxide Interim Estimates under E.O. 13990. These SC-GHG estimates are interim values developed under E.O. 13990 for use in benefit-cost analyses until updated estimates of the impacts of climate change can be developed based on the best available science and economics.

The SC-GHG estimates presented here were developed over many years, using a transparent process, peer-reviewed methodologies, the best science available at the time of that process, and with input from the public. Specifically, in 2009, an interagency working group (IWG) that included the DOT and other executive branch agencies and offices was established to ensure that agencies were using the best available science and to promote consistency in the SC-GHG values used across agencies. The IWG published SC-GHG estimates in 2010 that were developed from an ensemble of three widely cited integrated assessment models (IAMs) that estimate global climate damages using highly aggregated representations of climate processes and the global economy combined into a single modeling framework. The three IAMs were run using a common set of input assumptions in each model for future population, economic, and CO_2 emissions growth, as well as equilibrium climate sensitivity (ECS) – a measure of the response to increased atmospheric CO_2 concentrations. These estimates were updated in 2013 based on new versions of each IAM. In August 2016 the IWG published estimates of the social cost of methane (SC-CH_4) and nitrous oxide (SC-N_2O) using methodologies that are consistent with the methodology underlying the SCGHG estimates.

E.O. 13990 (issued on January 20, 2021) re-established an IWG and directed it to publish updated interim SC-GHG values for CO_2, CH_4, and N_2O within thirty days. The E.O. also tasked the IWG with devising long-term recommendations to update the methodology used to estimate these SC-GHG values, based on "the best available economics and science," while incorporating principles of "climate risk, environmental justice, and intergenerational equity". The E.O. also instructed the IWG to take into account the recommendations from the National Academy of Sciences (NAS) committee that had been previously convened to address this topic, which were contained in the committee's 2017 report.

The February 2021 TSD provides a complete discussion of the IWG's initial review conducted under E.O. 13990. First, the IWG concluded that a global analysis is essential for SC-GHG estimates because climate impacts can directly and indirectly affect the welfare of U.S. citizens and residents through complex pathways that do not respect national borders. Examples of affected interests include direct effects on U.S. citizens and assets, investments located abroad, international trade, and tourism, and spillover pathways such as economic and political destabilization and global migration. In addition, assessing the benefits of U.S. GHG mitigation activities requires consideration of how those actions may affect mitigation activities by other countries, as those international mitigation actions will provide a benefit to U.S. citizens and residents by mitigating climate impacts that affect U.S. citizens and residents. Additionally, we note that NHTSA assumes the technology costs of the rule are passed through to consumers, reducing their consumption of other goods and services; and that the IWG SC-GHG estimated are reported as consumption-equivalent values. As a member of the IWG involved in the development of the February 2021 TSD, DOT agrees with the IWG and the NAS that the consumption rate of interest is the appropriate discounting approach for reductions in climate-related damages. Therefore, in this final rule DOT centers attention on a global measure of SC-GHG. This approach is the same as that taken in DOT regulatory analyses over 2009 through 2016. As noted in the February 2021 TSD, the IWG will continue to review developments in the literature, including more robust methodologies for estimating SC-GHG values, and explore ways to better inform the public of the full range of carbon impacts. As a member of the IWG, DOT will continue to follow developments in the literature pertaining to this issue.

Second, the IWG found that the use of the social rate of return on capital (7 percent under current OMB Circular A-4 guidance) to discount the future benefits of reducing GHG emissions inappropriately underestimates the impacts of climate change for the purposes of estimating the SC-GHG. Consistent with the findings of the National Academies and the economic literature, the IWG continued to conclude that the consumption rate of interest is the theoretically appropriate discount rate in an intergenerational context (IWG 2010, 2013, 2016a, 2016b), and recommended that discount rate uncertainty and relevant aspects of intergenerational ethical considerations be accounted for in selecting future discount rates. As a member of the IWG involved in the development of the February 2021 TSD, DOT agrees with this assessment and will continue to follow developments in the literature pertaining to this issue.

NHTSA uses the IWG's recommended interim SC-GHG values, which were published in a February 2021 technical support document, for the analysis of increasing CAFE standards it conducts in this rulemaking. Table 6-12, Table 6-13, and Table 6-14 below show the IWG's interim SC-CO_2, SC-CH_4, and SC-N_2O values for the period 2020-2050. The values shown in these tables differ slightly from those reported in the IWG's February 2021 TSD because they have been converted to 2018$ to be consistent with the remainder of the agency's analysis. For this purpose, NHTSA staff used the change in Bureau of Economic Analysis (BEA)'s implicit price deflator for U.S. GDP between 2018 and 2020, the year the IWG used to denominate its estimated social costs of GHGs.

Table 6-12 – SCC Interim Values (per ton, 2018$)

Year	Social Cost of CO_2 Discounted at 5%	Social Cost of CO_2 Discounted at 3%	Social Cost of CO_2 Discounted at 2.50%	Social Cost of CO_2 Discounted at 3%, 95th Percentile[723]
2020	14	50	74	148
2021	15	50	76	150
2022	15	51	77	154
2023	16	52	78	157
2024	16	53	80	161
2025	17	54	81	164
2026	17	55	82	168
2027	17	57	83	171
2028	17	58	84	175
2029	18	59	85	178
2030	18	60	86	182
2031	19	61	88	185
2032	20	62	89	188
2033	20	63	91	192
2034	21	64	92	196
2035	21	65	93	200
2036	22	67	95	204
2037	22	68	96	207
2038	23	69	97	211
2039	24	70	99	215
2040	24	71	100	218
2041	25	72	101	221
2042	25	73	103	225
2043	26	75	104	228
2044	27	76	105	232
2045	27	77	107	235
2046	28	78	108	239

[723] The IWG constructs these values based on the 95th percentile of estimates, using a 3 percent discount rate.

Year	Social Cost of CO_2 Discounted at 5%	Social Cost of CO_2 Discounted at 3%	Social Cost of CO_2 Discounted at 2.50%	Social Cost of CO_2 Discounted at 3%, 95th Percentile[723]
2047	29	79	109	242
2048	29	80	111	246
2049	30	82	112	248
2050	31	83	113	252

Table 6-13 – SC-CH_4 Interim Values (per ton, 2018$)

Year	Social Cost of CH_4 Discounted at 5%	Social Cost of CH_4 Discounted at 3%	Social Cost of CH_4 Discounted at 2.50%	Social Cost of CH_4 Discounted at 3%, 95th Percentile[724]
2020	650	1,456	1,941	3,786
2021	670	1,456	1,941	3,883
2022	699	1,553	2,038	4,077
2023	728	1,553	2,038	4,174
2024	747	1,650	2,136	4,271
2025	777	1,650	2,136	4,368
2026	806	1,747	2,233	4,562
2027	835	1,747	2,233	4,659
2028	854	1,844	2,330	4,756
2029	883	1,844	2,427	4,951
2030	912	1,941	2,427	5,048
2031	942	1,941	2,524	5,145
2032	971	2,038	2,524	5,339
2033	971	2,038	2,621	5,533
2034	1,068	2,136	2,718	5,630
2035	1,068	2,136	2,718	5,824
2036	1,068	2,233	2,815	5,921
2037	1,165	2,233	2,912	6,115
2038	1,165	2,330	2,912	6,212
2039	1,165	2,427	3,009	6,407
2040	1,262	2,427	3,009	6,504
2041	1,262	2,524	3,106	6,698
2042	1,359	2,524	3,203	6,795
2043	1,359	2,621	3,203	6,989
2044	1,359	2,621	3,300	7,086
2045	1,456	2,718	3,397	7,280
2046	1,456	2,718	3,397	7,377
2047	1,456	2,815	3,494	7,474
2048	1,553	2,912	3,592	7,668
2049	1,553	2,912	3,592	7,766

[724] The IWG constructs these values based on the 95th percentile of estimates, using a 3 percent discount rate.

Year	Social Cost of CH_4 Discounted at 5%	Social Cost of CH_4 Discounted at 3%	Social Cost of CH_4 Discounted at 2.50%	Social Cost of CH_4 Discounted at 3%, 95th Percentile[724]
2050	1,650	3,009	3,689	7,960

Table 6-14 – SC-N_2O Interim Values (per ton, 2018$)

Year	Social Cost of N_2O Discounted at 5%	Social Cost of N_2O Discounted at 3%	Social Cost of N_2O Discounted at 2.50%	Social Cost of N_2O Discounted at 3%, 95th Percentile[725]
2020	5,630	17,472	26,209	46,593
2021	5,824	18,443	27,179	47,564
2022	6,018	18,443	27,179	49,505
2023	6,212	19,414	28,150	50,476
2024	6,407	19,414	28,150	51,447
2025	6,601	20,384	29,121	52,417
2026	6,795	20,384	29,121	54,359
2027	6,989	20,384	30,091	55,329
2028	7,183	21,355	31,062	56,300
2029	7,377	21,355	31,062	57,271
2030	7,571	22,326	32,033	58,241
2031	7,766	22,326	32,033	60,183
2032	8,057	23,297	33,003	61,153
2033	8,251	23,297	33,974	62,124
2034	8,542	24,267	33,974	64,066
2035	8,736	24,267	34,945	65,036
2036	9,027	25,238	34,945	66,007
2037	9,222	25,238	35,916	67,948
2038	9,513	26,209	36,886	68,919
2039	9,707	26,209	36,886	70,860
2040	9,707	27,179	37,857	71,831
2041	10,678	27,179	37,857	72,802
2042	10,678	28,150	38,828	74,743
2043	10,678	28,150	39,798	75,714
2044	10,678	29,121	39,798	77,655
2045	11,648	29,121	40,769	78,626
2046	11,648	30,091	41,740	79,597
2047	11,648	30,091	41,740	81,538
2048	12,619	31,062	42,710	82,509
2049	12,619	31,062	43,681	84,450
2050	12,619	32,033	43,681	85,421

[725] The IWG constructs these values based on the 95th percentile of estimates, using a 3 percent discount rate.

The IWG's SC-GHG estimates reflect various sources of uncertainty. One major source is uncertainty regarding the effects of accumulating concentrations of GHGs in the earth's atmosphere on the stability of global climate systems, changes in climate-related indicators such as surface and ocean temperatures and precipitation levels, and increases in the frequency or severity of significant weather events. A second source is uncertainty about the effects of changes in climate indicators and severe weather events on the well-being of the global population, the overall level of economic activity and its distribution over the globe, and the social and political stability of nations and global regions.

The extent to which social, political, and economic systems will be able to adapt to changes in the global climate in ways that reduce potential disruptions and damage also introduces uncertainty into the IWGs' SC-GHG estimates. Finally, there is uncertainty about the most appropriate discounting approach in assessing climate damages due to the long time horizons involved, and because much of the damage caused by current GHG emissions is likely to occur in the distant future, choosing a discount rate can have an enormous effect on calculated SC-GHG values. Recognizing these many important sources of uncertainty, the IWG recommends that agencies consider the wide distribution of possible SC-GHG values rather than simply the mean or expected values when conducting regulatory analyses, and also reports estimates of each SC-GHG that reflect discount rates of 2.5, 3, and 5 percent, and NHTSA concurs.

6.2.1.2 How NHTSA Uses the Social Costs of GHG Emissions

Following the guidance of OMB Circular A-4, NHTSA discounts future costs and benefits of adopting higher CAFE standards at alternative rates of 3 and 7 percent; the former reflects OMB's estimate of the rate at which consumers discount future consumption opportunities to their present value, while the latter represents the opportunity cost of drawing capital from private investment opportunities. (Both rates are expressed in "real," or inflation-adjusted terms.)

NHTSA has not selected a primary discount rate for the social cost of greenhouse gases and instead presents non-GHG related impacts of the final rule discounted at 3 and 7 percent alongside estimates of the social cost of greenhouse gases valued at each of the discount rates prescribed by the IWG. This approach was selected because, as the IWG noted, the range of values provides useful information for decision-makers. The agency's analysis showing our primary non-GHG impacts at 3 and 7 percent alongside climate-related benefits discounted at each rate recommended by the IWG may be found in FRIA Chapter 6.5.6. For the sake of simplicity, most tables throughout today's analysis pair both the 3 percent and the 7 percent discount rates with a 3 percent value for the social costs of greenhouse gases.

6.2.2 Monetized Health Impacts from Changes in Criteria Pollutant Emissions

The CAFE Model estimates monetized health effects associated with emissions from three criteria pollutants: NO_X, SO_X, and $PM_{2.5}$. As discussed in Chapter 5, although other criteria pollutants are currently regulated, only impacts from these three pollutants are calculated since they are known to be emitted regularly from mobile sources, have the most adverse effects to human health, and there exist several papers from the EPA estimating the benefits per ton of reducing these pollutants. Other pollutants, especially those that are precursors to ozone, are more difficult to model due to the complexity of their formation in the atmosphere, and EPA does not calculate benefit-per-ton estimates for these. The CAFE Model computes the monetized impacts associated with health damages from each pollutant by multiplying monetized health impact per ton values by the total tons of these pollutants, which are emitted from both upstream and tailpipe sources. Chapter 5.2 includes a detailed description of the emission factors that inform the CAFE Model's calculation of the total tons of each pollutant associated with upstream and tailpipe emissions.

These monetized health impacts per ton values are closely related to the health incidence per ton values described in Chapter 5.4. We use the same EPA sources that provided health incidence values to determine which monetized health impacts per ton values to use as inputs in the CAFE Model. The EPA uses the value of a statistical life (VSL) to estimate premature mortality impacts, and a combination of willingness to pay estimates and costs of treating the health impact for estimating the morbidity impacts.[726] EPA's 2018 technical support document, "Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors,"[727] (referred to here as the 2018 EPA source apportionment TSD) contains a more detailed account of how health incidences are monetized. It is important to note that the EPA sources cited frequently refer to these monetized health impacts per ton as "benefits per ton" (BPT), since they describe these estimates in terms of emissions avoided. In the CAFE Model input structure, these are generally referred to as monetized health impacts or damage costs associated with pollutants emitted, not avoided, unless the context states otherwise.

The CAFE Model includes monetized impacts per ton for multiple pollutant sources, referred to here as source sectors or source categories (e.g. refineries, light truck mobile sources, electricity generation, etc.). Certain source sectors may be associated with higher monetized impacts per ton than others. Since the impacts for the different source sectors all are based on the emission of one ton of the same pollutants (NO_X, SO_X, and $PM_{2.5}$), the differences in the incidence per ton values between sectors arise from differences in the geographic distribution of the pollutants, a factor that affects the number of people impacted by the pollutants.[728]

The various emission source sectors included in the EPA papers cited do not always correspond exactly to the emission source categories used in the CAFE Model.[729] In those cases, we mapped multiple EPA sectors to a single CAFE source category and computed a weighted average of the health impact per ton values from those EPA sectors. The CAFE Model health impacts inputs are based partially on the structure of one of the EPA source papers (the 2018 EPA source apportionment TSD), which reported benefits per ton values for the years 2020, 2025, and 2030. For the years in between the source years used in the input structure, the CAFE

[726] Although EPA and DOT's VSL values differ, DOT staff determined that using EPA's VSL was appropriate here, since it was already included in these monetized health impact values, which were best suited for the purposes of the CAFE Model.
[727] *See* Environmental Protection Agency (EPA). 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. https://www.epa.gov/sites/production/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf. (Accessed: February 15, 2022).
[728] *See* Environmental Protection Agency (EPA). 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. https://www.epa.gov/sites/production/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf. (Accessed: February 15, 2022).
[729] The CAFE Model's emission source sectors follow a similar structure to the inputs from GREET. *See* Chapter 5.2 for further information.

Model applies values from the closest source year. For instance, the model applies 2020 monetized health impact per ton values for calendar years 2020-2022 and applies 2025 values for calendar years 2023-2027. For more information, see the CAFE Model documentation,[730] which contains additional details of the model's computation of monetized health impacts.

It is important to note that uncertainties and limitations exist at each stage of the emissions-to-health benefit analysis pathway (e.g., projected emissions inventories, air quality modeling, health impact assessment, economic valuation). The BPT approach to monetizing benefits relies on many assumptions; when uncertainties associated with these assumptions are compounded, even small uncertainties can greatly influence the size of the total quantified benefits. Some key assumptions associated with $PM_{2.5}$-related health benefits and uncertainties associated with the BPT approach are discussed above in Chapter 5.4.3.

The following subsections describe the sources that we used to provide the CAFE Model with monetized health impacts per ton values, and any calculations made in the process. Each subsection corresponds to one of the five upstream emission source sectors that the CAFE Model distinguishes between, and the tailpipe emission sources.

The emission source categories defined in the CAFE Model are as follows:

- Upstream emissions sources
  - Petroleum Extraction
  - Petroleum Transportation
  - Refineries
  - Fuel Transportation, Storage, and Distribution (Fuel TS&D)
  - Electricity Generation
- Tailpipe emissions sources
  - On-road light duty cars and motorcycles
  - On-road light duty trucks
  - On-road light duty diesel

Table 6-15 details the mapping between CAFE and EPA emission source sectors.

Table 6-15 – CAFE to EPA Emissions Source Sector Mapping

CAFE Model Upstream Component (per GREET)	Corresponding EPA Source Categories
Petroleum Extraction	Assigned to the "Oil and natural gas" sector from a 2018 EPA paper (Fann et al.).[731]

[730] https://www.nhtsa.gov/corporate-average-fuel-economy/compliance-and-effects-modeling-system. (Accessed: February 15, 2022).

[731] Fann et al. 2018. Assessing Human Health $PM_{2.5}$ and Ozone Impacts from U.S. Oil and Natural Gas Sector Emissions in 2025. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6718951. (Accessed: February 15, 2022).

CAFE Model Upstream Component (per GREET)	Corresponding EPA Source Categories
Petroleum Transportation	Assigned to several mobile source sectors from a 2019 EPA paper (Wolfe et al.)[732] and one source sector from the 2018 EPA source apportionment TSD.[733] The specific mode mappings are as follows: From Wolfe et al: • Rail sector (for GREET's rail mode) • C1&C2 marine vessels sector (for GREET's barge mode) • C3 marine vessels sector (for GREET's ocean tanker mode) • On-road heavy-duty diesel sector (for GREET's truck mode) From the 2018 EPA source apportionment TSD: • Electricity generating units (for GREET's pipeline mode) A weighted average of these different sectors was used to determine the overall health impact values for the sector as a whole.
Fuel TS&D	Assigned to several mobile source sectors from a 2019 EPA paper (Wolfe et al.)[734] and one source sector from the 2018 EPA source apportionment TSD.[735] The specific mode mappings are as follows: From Wolfe et al.: • Rail sector (for GREET's rail mode) • C1&C2 marine vessels sector (for GREET's barge mode) • C3 marine vessels sector (for GREET's ocean tanker mode) • On-road heavy-duty diesel sector (for GREET's truck mode) From the 2018 EPA source apportionment TSD: • Electricity generating units (for GREET's pipeline model) A weighted average of these different sectors was used to determine the overall health impact values for the sector as a whole.
Electricity Generation	Assigned to the electricity-generating units sector from the 2018 EPA source apportionment TSD.[736]

[732] Wolfe et al. 2019. Monetized health benefits attributable to mobile source emissions reductions across the United States in 2025. https://pubmed.ncbi.nlm.nih.gov/30296769. (Accessed: February 15, 2022). Health incidence per ton values corresponding to this paper were sent by EPA staff.

[733] 2018 EPA source apportionment TSD. https://www.epa.gov/sites/production/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf. (Accessed: February 15, 2022).

[734] Wolfe et al. 2019. Monetized health benefits attributable to mobile source emissions reductions across the United States in 2025. https://pubmed.ncbi.nlm.nih.gov/30296769. (Accessed: February 15, 2022).

[735] Environmental Protection Agency (EPA). 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. https://www.epa.gov/sites/production/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf. (Accessed: February 15, 2022).

[736] Environmental Protection Agency (EPA). 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. https://www.epa.gov/sites/production/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf. (Accessed: February 15, 2022).

6.2.2.1 Monetized Health Impacts per Ton Associated with the Petroleum Extraction Sector

We match the monetized health impact per ton values for the petroleum extraction sector to a 2018 oil and natural gas sector paper written by EPA staff (Fann et al.), which estimates monetized health impacts for this sector in the year 2025.[737] Fann et al. define emissions from the oil and natural gas sector as not only arising from petroleum extraction but also from transportation to refineries, while the CAFE /GREET component is composed of only petroleum extraction. We consulted with the authors at EPA and determined that this paper contained the best available estimates for the petroleum extraction sector, notwithstanding this difference. Therefore, these monetized values may slightly overestimate the cost of health impacts associated with emissions from this sector.

Fann et al. reported monetized health impact per ton values discounted at 3 percent, while the CAFE Model reports total health impact costs discounted at both 3 and 7 percent.[738] In order to match the structure of other health impact costs in the CAFE Model, we developed proxies for the 7 percent discounted values, using the ratio between a comparable sector's 3 and 7 percent discounted values. From the 17 sectors discussed in the 2018 EPA source apportionment TSD, the taconite mines sector most closely resembled the petroleum extraction sector in emission location characteristics, as both occur largely in rural areas.[739]

Fann et al. estimates monetized health impacts per ton values only for calendar year 2025, so DOT staff apply these values to all three years in the CAFE Model health impacts input structure: 2020, 2025, and 2030.[740] This implies an overestimation of damages in earlier years and an underestimation in 2030.

All monetized health impact per ton estimates reported by Fann et al. use 2015 dollars. We use implicit price deflators from the BEA to convert the estimates to 2018 dollars, in order to be consistent with the rest of the CAFE Model inputs.[741]

6.2.2.2 Monetized Health Impacts per Ton Associated with the Petroleum Transportation Sector

We use the same weighted average calculation used to determine the appropriate health incidence per ton values (see Chapter 5.4.1) for the petroleum transportation sector when estimating the monetized health impacts per ton values. All of the same sources and calculations

[737] Fann et al. 2018. Assessing Human Health $PM_{2.5}$ and Ozone Impacts from U.S. Oil and Natural Gas Sector Emissions in 2025. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6718951. (Accessed: February 15, 2022).
[738] Fann et al. 2018. Assessing Human Health $PM_{2.5}$ and Ozone Impacts from U.S. Oil and Natural Gas Sector Emissions in 2025. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6718951. (Accessed: February 15, 2022).
[739] Environmental Protection Agency (EPA). 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. https://www.epa.gov/sites/production/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf. (Accessed: February 15, 2022).
[740] These three years are used in the CAFE Model structure for health impact per ton values because it was originally based on the estimates provided in the 2018 EPA source apportionment TSD.
[741] Bureau of Economic Analysis. Table 1.1.9. Implicit Price Deflators for Gross Domestic Product. BEA. https://apps.bea.gov/iTable/iTable.cfm?reqid=19&step=2#reqid=19&step=2&isuri=1&1921=survey. (Accessed: February 15, 2022).

are used, the only difference being that this section deals strictly with monetized impacts per ton as opposed to incidences.

The petroleum transportation sector does not correspond to any single EPA source sector, so we use a weighted average of multiple different EPA sectors to determine the monetized health impact per ton values for the petroleum transportation sector as a whole. In calculating the weighted average, we mapped the petroleum transportation sector as described in GREET to a combination of different EPA mobile source sectors from two different papers, the 2018 EPA source apportionment TSD[742] and a 2019 mobile source sectors paper (Wolfe et al.).[743] See Table 6-15 for the exact mapping.

Wolfe et al. includes more specific sectors than the 2018 EPA source apportionment TSD; for instance, where 'Aircraft, Locomotive, and Marine Vessels' is a single category in the 2018 EPA source apportionment TSD, Wolfe et al. specify four: Aircraft, Rail, C1&C2 Marine Vessels, and C3 Marine Vessels. Therefore, the mapping uses sectors from Wolfe et al wherever possible and uses the 2018 EPA source apportionment TSD for the transportation mode mapping only when there are no appropriate sectors in the Wolfe et al. paper. Wolfe et al. only report impacts for the year 2025, but DOT staff determined that these values could be applied to the other years in the input structure, after communication with one of the authors at EPA. Therefore, this implies a slight overestimation of monetized health impacts in 2020 and a slight underestimation of monetized impacts in 2030.

We calculate the total monetized health costs per ton by pollutant using a weighted average of these different sectors, based on the percent of upstream emissions attributable to each transportation mode.

In GREET, the model that informs the CAFE upstream component categories, there are five types of petroleum products relevant to upstream emissions for gasoline:

- Conventional crude oil
- Synthetic crude oil (SCO)
- Dilbit
- Shale oil (Bakken)
- Shale oil (Eagle Ford)

[742] Environmental Protection Agency (EPA). 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. https://www.epa.gov/sites/production/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf. (Accessed: February 15, 2022).
[743] Wolfe et al. 2019. Monetized health benefits attributable to mobile source emissions reductions across the United States in 2025. https://pubmed.ncbi.nlm.nih.gov/30296769. (Accessed: February 15, 2022).

Table 6-16 – Petroleum Transportation Mode Shares in 2020[744]

Fuel Type[745]	Ocean Tanker	Barge	Pipeline	Rail	Truck
Conventional Crude Oil	10.3%	23.2%	79.9%	2.9%	0
Synthetic Crude Oil (SCO)	0	0	100%	0	0
Dilbit	0	0	100%	0	0
Shale Oil (Bakken)	0	0	50.0%	50.0%	100%
Shale Oil (Eagle Ford)	0	20.0%	65.0%	15.0%	100%

GREET provides the percentage of these five petroleum products transported by each mode, as shown in Table 6-16. Transportation both within the United States and outside of U.S. borders is included, provided that the destination of the transported products is the continental United States. The percentages add up to more than 100 percent because there are multiple stages of the transportation journey. For example, 50 percent of shale oil (Bakken) is transported by pipeline and the other 50 percent by rail during the first part of the journey to the refinery, but 100 percent of it is transported by truck on the second part of the journey.

GREET also provides emissions in grams/mmBtu of fuel transported attributable to each transportation mode. DOT staff multiply these emissions values by the percentage of petroleum product transported by each mode, as seen in Table 6-16, to obtain a weighted value. This calculation uses total emissions from each mode for all of the modes except ocean tanker. Health effects from ocean transport are concentrated in populated areas, rather than while the tankers are at sea. To address this, the ocean tanker mode includes only urban emissions. Additionally, using urban emissions for ocean tankers ensures that the emissions attributable to this mode are not underestimated, because the percentage of related health impacts decreases when using the high total emissions figure.

We multiply emissions by transportation mode share five times, once for each of the five petroleum types. Since the GREET Model projects that the transportation mode shares will change over time, different weights are used for years 2020, 2025, and 2030, based on the mode percentages GREET reports for those years.[746]

[744] These values are from the GREET 2021 Model, using baseline year 2020. In the Excel version, this information can be found in the T&D Flowcharts worksheet. *See* https://greet.es.anl.gov/ to download the model.
[745] Conventional crude oil is both extracted domestically and imported. SCO and Dilbit are oil sand products and are imported exclusively from Canada. Shale oil is exclusively domestic. *See* the 'T&D Flowcharts' worksheet in the GREET Model.
[746] These are the three years used in the CAFE Model inputs for health impacts, based on the structure of the 2018 EPA source apportionment TSD that originally informed the analysis. Baseline years may be changed in the 'Inputs' worksheet in the GREET Model.

Table 6-17 – Energy Share by Petroleum Type[747]

Conventional Crude Oil	SCO	Dilbit	Shale (Bakken)	Shale (Eagle Ford)
76.8%	3.4%	4.6%	8.2%	7.0%

Then, we multiply the energy share of each petroleum type by its corresponding emissions value to reflect how much of each emissions value should go into the weighted average. For example, using the energy share information in Table 6-17, the conventional crude emissions are multiplied by 76.8 percent, SCO emissions are multiplied by 3.4 percent, Dilbit emissions are multiplied by 4.6 percent, shale (Bakken) emissions are multiplied by 8.2 percent, and shale (Eagle Ford) emissions are multiplied by 7.0 percent.

Next, we sum the resulting weighted emissions values by pollutant to represent the total upstream emissions in grams/mmBtu of petroleum product transported. With that information, the percentages of each pollutant attributable to each mode for petroleum transportation overall can be calculated. DOT staff calculate these percentages three times, for each different base year (2020, 2025, and 2030). Table 6-18 shows these percentages, using base year 2020 as an example.

Table 6-18 – Percent of Emissions Attributable to each Mode for the Petroleum Transportation Category[748]

Mode	EPA source category	NO_X	SO_X	$PM_{2.5}$
Ocean Tanker	C3 marine vessels	5.04%	13.87%	9.10%
Barge	C1 & C2 marine vessels	56.47%	1.70%	39.83%
Pipeline	Electricity-generating units	24.82%	83.62%	45.79%
Rail	Rail	12.31%	0.59%	4.79%
Truck	On-road heavy duty diesel	1.36%	0.22%	0.48%

Finally, we calculate the weighted average of monetized health impacts by multiplying the percentages of emissions by mode by the monetized health costs per ton from the relevant EPA sector that matches each mode. Equation 6-10 illustrates this process, using incidences of asthma exacerbation as an example. The variables beginning with "%" represent the percent of SO_X emissions attributable to each specified mode. The other variables indicate the incidences per ton resulting from SO_X emissions coming from each sector: *C3marine* corresponds to C3 marine vessels, *C1&C2* marine to C1&C2 marine vessels, *EGU* corresponds to electricity-generating units, *Rail* to railroad, and *Truck* corresponds to on-road heavy-duty diesel.

$$Asthma\ Exacerbation\ incidents\ per\ ton\ from\ SOx\ in\ Petroleum\ Transportation =$$

$$(\%\ SOx\ ocean\ tanker * C3marine) + (\%\ SOx\ barge * C1\&C2\ marine) + (\%SOx\ pipeline * EGU) + (\%\ SOx\ rail * Rail) + (\%\ SOx\ truck * Truck)$$

Equation 6-10 – Weighted Average of Health Incidences from the Petroleum Transportation Sector

[747] Taken from the Petroleum tab of the GREET Excel Model, using 2020 as a base year.
[748] These percentages are calculated using the 2020 base year in GREET.

Following guidance from the 2018 EPA source apportionment TSD, DOT staff round the final health impact costs per ton to two significant digits.[749]

6.2.2.3 Monetized Health Impacts per Ton Associated with the Fuel TS&D Sector

As in the case of the previous section, this section closely echoes the approach taken in the corresponding Fuel TS&D section in Chapter 5.4, since we calculate the monetized health impacts per ton described in this section using the same sources and the same weighted averaging process. The Fuel TS&D sector, like the Petroleum Transportation sector, corresponds to several different EPA source sectors, so DOT staff use the same weighted average approach as described in Chapter 6.2.2.2. Gasoline blendstocks and finished gasoline are the two components of the Fuel TS&D category described in GREET. DOT staff map these components to five different transportation source sectors from two EPA papers, the 2018 EPA source apportionment TSD and the 2019 mobile source emission sectors paper, Wolfe et al.[750]

GREET provides the percentage of each fuel type transported by each mode, and as in the case of the petroleum transportation calculations, the percentages change based on the year. In the case of the "gasoline blendstocks" fuel type, the mode shares add up to more than 100 percent because multiple modes are taken during the distinct parts of the trip. As an example, Table 6-16 shows the estimated mode shares in 2020.

Table 6-19 – Transportation Mode Shares for the Fuel TS&D Sector[751]

Mode Share	Gasoline Blendstocks	Finished Gasoline
Ocean Tanker	3.0%	0%
Barge	31.2%	0%
Pipeline	67.6%	0%
Rail	2.2%	0%
Truck	100%	100%

We multiply the emissions by pollutant attributed to each mode (measured in grams/mmBtu), by these mode share percentages to create weighted emissions values.

Next, we add the weighted emissions from trucks transporting gasoline blendstocks to the emissions arising from finished gasoline transportation (100 percent truck mode). Using that information, the total emissions per pollutant may be calculated in order to find the percentage of

[749] Environmental Protection Agency (EPA). 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. https://www.epa.gov/sites/production/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf; p.14. (Accessed: February 15, 2022).
[750] Environmental Protection Agency (EPA). 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. https://www.epa.gov/sites/production/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf; p.14. (Accessed: February 15, 2022)
Wolfe et al. 2019. Monetized health benefits attributable to mobile source emissions reductions across the United States in 2025. https://pubmed.ncbi.nlm.nih.gov/30296769. (Accessed: February 15, 2022).
[751] Using baseline year 2020 in GREET. These values can be found in the 'T&D Flowcharts' tab of the GREET Model.

emissions attributable to each mode for Fuel TS&D overall. Table 6-20 provides an example of these percentages.

Table 6-20 – Percent of Emissions Attributable to each Mode for the Petroleum Transportation Category[752]

Mode	EPA source category	NO_X	SO_X	$PM_{2.5}$
Ocean Tanker	C3 marine vessels	5.04%	13.87%	9.10%
Barge	C1 & C2 marine vessels	56.47%	1.70%	39.83%
Pipeline	Electricity-generating units	24.82%	83.62%	45.79%
Rail	Rail	12.31%	0.59%	4.79%
Truck	On-road heavy duty diesel	1.36%	0.22%	0.48%

The Fuel TS&D calculations follow the same process as the petroleum transportation category, matching the modes to EPA sectors and using the calculated percentages to create a weighted average of monetized health impacts associated with emissions of each pollutant. We completed these calculations three times, for years 2020, 2025, and 2030. As stated previously, the sectors in the 2019 mobile sources paper only showed monetized health costs per ton estimated for the year 2025, but analysts determined that this information should be applied to all years, as it was the most up-to-date available, after communicating with EPA staff. The use of 2025 monetized impacts for all three years implies a slight overestimation of monetized health impacts in 2020 and a slight underestimation in 2030.

Wolfe et al report all monetized impacts per ton values in 2015$. We use BEA deflators to convert these values to 2018$, in order to ensure consistency with the rest of the CAFE Model inputs.[753]

6.2.2.4 Monetized Health Impacts per Ton Associated with the Refineries Sector

We match the monetized health impacts per ton values associated with the refineries sector in the 2018 EPA source apportionment TSD to the petroleum refining emissions category in the CAFE Model. BEA deflators are used to convert the values to 2018$[754] Table 6-21 shows the various types of health effects per ton corresponding to each pollutant emitted from the refineries sector. These estimates are based on the study cited in the 2018 EPA source apportionment TSD.[755]

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[752] These percentages are calculated using the 2020 base year in GREET.
[753] Bureau of Economic Analysis. Table 1.1.9. Implicit Price Deflators for Gross Domestic Product. BEA. https://apps.bea.gov/iTable/iTable.cfm?reqid=19&step=2#reqid=19&step=2&isuri=1&1921=survey. (Accessed: February 15, 2022).
[754] Bureau of Economic Analysis. Table 1.1.9. Implicit Price Deflators for Gross Domestic Product. BEA. https://apps.bea.gov/iTable/iTable.cfm?reqid=19&step=2#reqid=19&step=2&isuri=1&1921=survey. (Accessed: February 15, 2022).
[755] Environmental Protection Agency (EPA). 2018. Estimating the Benefit per Ton of Reducing $PM_{2.5}$ Precursors from 17 Sectors. https://www.epa.gov/sites/production/files/2018-02/documents/sourceapportionmentbpttsd_2018.pdf;.14. (Accessed: February 15, 2022).

Table 6-21 – Monetized Health Impacts per Ton from Refineries, 3 Percent Discount Rate[756]

Calendar Year	Upstream Emissions (Refineries Sector)		
	NO_X	SO_X	$PM_{2.5}$
2020	$8,100	$81,000	$380,000
2025	$8,800	$90,000	$420,000
2030	$9,600	$98,000	$450,000

6.2.2.5 Monetized Health Impacts per Ton Associated with the Electricity Generation Sector

The 2018 EPA source apportionment TSD contains monetized health impacts per ton values associated with emissions of NO_X, SO_X, and $PM_{2.5}$ arising from electricity-generating units (EGUs), reported in 2015$. We mapped these to the electricity generation sector in the CAFE Model and converted the values to 2018$ using BEA deflators, to ensure consistency with the rest of the CAFE Model inputs[757] Table 6-22 shows the health effects per ton associated with the emissions of criteria pollutants from this sector.

Table 6-22 – Monetized Health Impacts per ton from Electricity-Generating Units, 3 Percent Discount Rate[758]

Calendar Year	Upstream Emissions (Electricity Generation Sector)		
	NO_X	SO_X	$PM_{2.5}$
2020	$6,500	$44,000	$160,000
2025	$7,100	$48,000	$180,000
2030	$7,600	$52,000	$190,000

6.2.2.6 Monetized Health Impacts per Ton Associated with Tailpipe Emissions

The CAFE Model follows a similar process for computing monetized health impacts resulting from tailpipe emissions as it does for calculating monetized health impacts from the upstream emissions sectors. The analysis relies on a 2019 paper from EPA (Wolfe et al.) that computes monetized per ton damage costs for mobile sources in several categories, based on vehicle type and fuel type. Wolfe et al. did not report incidences per ton, but that information was obtained through communications with EPA staff. We match three source categories from the 2019 paper to the CAFE Model tailpipe emissions inventory: "on-road light duty gas cars and motorcycles," "on-road light duty gas trucks," and "on-road light duty diesel" Table 6-23 shows the monetized impacts by criteria pollutant for these three categories. As in the case of the other monetized

756 Based on the Krewski et al values in the 2018 EPA TSD. See Section III.F of the preamble for further discussion of the benefit-per-ton reporting.

757 Bureau of Economic Analysis. Table 1.1.9. Implicit Price Deflators for Gross Domestic Product. BEA. https://apps.bea.gov/iTable/iTable.cfm?reqid=19&step=2#reqid=19&step=2&isuri=1&1921=survey. (Accessed: February 15, 2022).

758 Based on the Krewski et al values in the 2018 EPA TSD. See Section III.F of the preamble for further discussion of the benefit-per-ton reporting.

impacts from Wolfe et al., we used BEA deflators to convert monetized values from 2015$ to 2018$.[759]

Table 6-23 – Monetized Impacts per Ton from Tailpipe Source Categories

	On-road Light Duty Gas Cars & Motorcycles			On-road Light Duty Gas Trucks			On-road Light Duty Diesel		
	NO_X	SO_X	$PM_{2.5}$	NO_X	SO_X	$PM_{2.5}$	NO_X	SO_X	$PM_{2.5}$
2025	$7,500	$130,000	$740,000	$6,800	$110,000	$620,000	$6,100	$320,000	$510,000

6.2.3 Social Costs of Congestion and Noise

If more driving of new cars and light trucks results from the fuel economy rebound effect, it will add to the levels of traffic congestion and roadway noise caused by overall motor vehicle use. The resulting increases in delays to vehicles traveling in congested traffic, and the noise impacts on areas surrounding roadways would impose additional economic costs that are attributable to the agency's action to establish higher fuel economy standards. Only a small fraction of these increases in delay and noise costs is likely to be experienced by the buyers of new cars and light trucks whose decisions about how much more to drive – and where and when to do so – cause the increases in congestion delays and traffic noise. Thus, the agency's analysis treats increases in the costs of congestion delays and noise impacts as external costs from requiring higher fuel economy, as distinguished from private costs such as the higher prices buyers of new cars and light trucks pay.

To estimate the economic costs associated with increases in congestion delays and roadway noise caused by increased rebound-effect driving, the agency uses estimates of incremental (or "marginal") congestion and noise costs from increased automobile and light truck use that were originally developed by FHWA as part of its 1997 Highway Cost Allocation Study.[760] The marginal congestion cost estimates reported in the 1997 FHWA study were intended to measure the costs of increased congestion resulting from incremental growth in automobile and light truck use and the delays it causes to drivers, passengers, and freight shipments.

As the 1997 study explained, the distinction between marginal and average congestion costs is extremely important: while average congestion costs on a roadway are calculated as total congestion costs experienced by all vehicles divided by the total number of miles they travel, marginal congestion costs are calculated as the increase in congestion costs resulting from an incremental increase in the number of vehicle-miles traveled. When roads are already crowded, marginal congestion costs can be much higher that their average value, because while each additional vehicle slows travel speeds only slightly, it does so for a very large number of vehicles, so the resulting increase in total delay experienced by all vehicles on the road can be

[759] Bureau of Economic Analysis. Table 1.1.9. Implicit Price Deflators for Gross Domestic Product. BEA. https://apps.bea.gov/iTable/iTable.cfm?reqid=19&step=2#reqid=19&step=2&isuri=1&1921=survey. (Accessed: February 15, 2022).

[760] Federal Highway Administration, 1997 Highway Cost Allocation Study, Chapter V, Tables V-22 and V-23, available at https://www.fhwa.dot.gov/policy/hcas/final/five.cfm. (Accessed: February 15, 2022). The agency previously employed these same cost estimates to analyze the impacts of its actions establishing new CAFE standards in 2010, 2012, 2016, and 2020.

extremely large. As a consequence, increases in total delay and congestion costs associated with additional driving are generally more than proportional to the changes in traffic volumes that cause them.

The 1997 FHWA study's estimates of marginal noise costs reflected the variation in noise levels resulting from incremental changes in travel by autos and light trucks and the estimated economic value of annoyance and other adverse impacts from noise, including those on pedestrians and residents of the surrounding area as well as vehicle occupants.

Because the action the agency is finalizing will increase the stringency of CAFE standards for MYs 2024-2026 and the fuel economy of new cars and light trucks, the number of miles new cars and light trucks are driven is likely to increase relative to the No-Action Alternative. To calculate the incremental costs of congestion and noise caused by this added driving, the agency multiplies FHWA's "middle" estimates of marginal congestion and noise costs per mile of auto and light truck travel by the increase in new car and light truck travel. As with the estimates of various other parameters used throughout this analysis, the agency updated the original 1997 FHWA estimates of congestion costs during the proposal to account for changes in travel activity and economic conditions since they were originally developed, as well as to express them in 2018 dollars for consistency with other economic inputs.

One factor affecting marginal congestion costs from additional travel include traffic volumes and their relationship to roadway capacity, since this determines how travel speeds and delays will change in response to incremental growth in traffic. The agency approximated the effect of growth in traffic on congestion and resulting delays using the increase in annual vehicle-miles of travel per lane-mile on major U.S. highways that occurred between 1997, the date of FHWA's original estimates of marginal congestion costs, and 2017.[761] Other important factors include the typical number of occupants riding in each vehicle and the economic value of their travel time, since these combine to determine the average hourly cost of congestion delays.[762] The agency estimated growth in the hourly cost of delays from 1997 to 2017 by combining growth in the DOT-recommended value of travel time with the change in average occupancy of cars and light trucks.[763]

[761] Traffic volumes, as measured by the annual number of vehicle-miles traveled per lane-mile of roads and highways nationwide, rose by 53 percent between 1997 and 2017. Calculated from FHWA, Highway Statistics, 1998 and 2018, Tables VM-1 and HM-48, available at https://www.fhwa.dot.gov/policyinformation/statistics.cfm. (Accessed: February 15, 2022).

[762] Fuel consumption and other operating costs can also increase during travel in congested conditions, but their relationship to the frequent changes in speed that typically occur in congested travel is less well understood, and in any case, they vary by far smaller amounts than the value of vehicle occupants' travel time.

[763] Measured in inflation-adjusted terms, the average hourly value of travel time increased by 22 percent between 1997 and 2017, including light-duty vehicle occupants as well as truck drivers and passengers; see U.S. Department of Transportation, "Departmental Guidance for the Valuation of Travel Time in Economic Analysis," April 9, 1997, Table 4, and U.S. Department of Transportation, "Benefit-Cost Analysis Guidance for Discretionary Grant Programs," December 2018, Table A-3. From 1995 to 2017, the average number of occupants traveling in household vehicles increased by 3 percent; values were tabulated from FHWA, Nationwide Personal Transportation Survey, 2005 and 2017, using on-line table designer available at https://nhts.ornl.gov/ and https://nhts.ornl.gov/index9.shtml. (Accessed: February 15, 2022).

The agency applied these adjustments to FHWA's 1997 estimates of marginal congestion costs to update those original values to reflect current travel and economic conditions. Expressed in 2018 dollars for consistency with the other economic values used to analyze this final rule, the agency's updated values of external congestion costs are \$0.135 per vehicle-mile of increased travel by cars and \$0.121 per vehicle-mile for light trucks. The agency adjusted FHWA's 1997 estimate of marginal noise costs only to account for inflation since its original publication since little research is available to indicate how noise levels or the economic costs of noise might have changed.[764] Because marginal noise costs are so small—less than \$0.001 per mile of travel for both cars and light trucks—the change in noise resulting from the final rule will have a minimal impact.

The agency's estimates of incremental congestion and noise costs from added car and light truck use are assumed to remain constant (in real or inflation-adjusted terms) throughout the analysis period.

6.2.4 Benefits from Increased U.S. Energy Security

U.S. consumption and imports of petroleum products has three potential effects on the domestic economy that are often referred to collectively as "energy security externalities," and increases in their magnitude are sometimes cited as possible social costs of increased U.S. demand for petroleum. First, any increase in global petroleum prices that results from higher U.S. gasoline demand will cause a transfer of revenue from consumers of petroleum products to oil producers worldwide, because consumers throughout the world are ultimately subject to the higher global prices for petroleum and refined products that results. Although this transfer is simply a shift of resources that produces no change in global economic output or welfare, the financial drain it produces on the U.S. economy is sometimes cited as an external cost of increased U.S. petroleum consumption.

As the United States has approached self-sufficiency in petroleum production in recent years (AEO 2021 projects the nation to be a net exporter of petroleum and other liquids through 2050), this transfer is increasingly *from U.S. consumers of refined petroleum products to U.S. petroleum producers*, so any price increase that results from increased domestic petroleum demand not only leaves welfare unaffected, but even ceases to be a financial burden on the U.S. economy.[765] In fact, as the United States has become a net petroleum exporter, the transfer from global consumers to petroleum producers created by higher world oil prices are a net financial *benefit* to the U.S. economy. Nevertheless, uncertainty about the nation's long-term import-export balance makes it difficult to project precisely how these effects might change in response to changes in U.S. domestic consumption of petroleum products. However, the welfare gain experienced by

[764] The agency's revised estimates of congestion and noise costs were adjusted to 2018 dollars using the change in the implicit price deflator for U.S. GDP between the year in which they were originally denominated (1994 dollars) and 2018; see Bureau of Economic Analysis, NIPA Table 1.1.9 Implicit Price Deflators for Gross Domestic Product, available at https://apps.bea.gov/iTable/index_nipa.cfm. (Accessed: February 15, 2022).
[765] The United States became a net exporter of oil on a weekly basis several times in late 2019, and EIA's subsequent analyses continue to project that it will do so on a sustained, long-term basis after 2020; see EIA, AEO 2021 Reference Case, Table 11, https://www.eia.gov/outlooks/archive/aeo21/tables_ref.php. (Accessed: February 15, 2022).

U.S. consumers as a result of fuel economy improvements that lower world oil prices is important to acknowledge.

Increased U.S. consumption of refined products such as gasoline can also expose domestic users of other petroleum products – whose consumption would be unrelated to changes in CAFE standards – to increased economic risks from sudden changes in their prices or interruptions in their supply. Users of petroleum products are unlikely to consider any effect their consumption has on other consumers, and the expected economic cost of that increase in risk is often cited as an external cost of increased U.S. petroleum consumption. Finally, some analysts argue that domestic demand for imported petroleum may also influence U.S. military spending; because any increase in the cost of military activities necessary to enable additional petroleum imports would not be reflected in the price paid at the gas pump. This is often alleged to represent a third category of external costs form increased U.S. petroleum consumption.

Each of these three costs may decline – although probably only modestly – as a consequence of the reduction in U.S. petroleum consumption likely to result from these final standards. This section describes the extent to which each of these three costs may change as a result of this action, whether that change would represent a significant net economic benefit for the United States as a whole (or simply reduce transfers of resources), and how the agency measures each cost and incorporated it into the analysis.

6.2.4.1 U.S. Petroleum Demand and its Effect on Global Prices

Figure 6-4 illustrates the effect of a decrease in U.S. fuel and petroleum demand on worldwide demand for petroleum and its global market price. The reduction in domestic demand from adopting more stringent CAFE standards is represented by an inward shift in the U.S. demand curve for petroleum from its initial position at $D_{US,0}$ with the baseline standards in effect, to $D_{US,1}$ with the higher standards replacing them. Because global demand is simply the sum of what each nation would purchase at different prices, the inward shift in U.S. demand causes an identical shift in the global demand schedule, as the figure shows.[766]

[766] The figure exaggerates the U.S. share of total global consumption, which currently stands at 20 percent, for purposes of illustration.

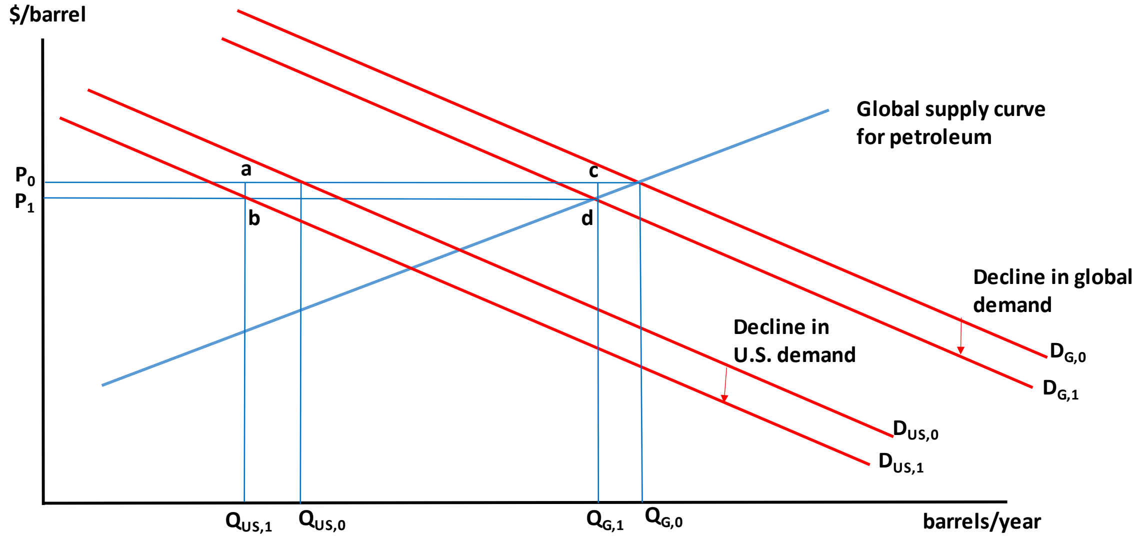

Figure 6-4 – U.S. Petroleum Demand and its Effect on Global Prices

The global supply curve for petroleum shown in Figure 6-5 slopes upward, reflecting the fact that it is progressively costlier for oil-producing nations to explore for, extract, and deliver additional supplies of oil to the world market.[767] Thus the downward shift in the U.S. and world demand schedules leads to a decrease in the global price for oil, from P_0 to P_1 in the figure.[768] Lower domestic demand reduces U.S. purchases of petroleum from $Q_{US,0}$ to $Q_{US,1}$, and global consumption from $Q_{G,0}$ to $Q_{G,1}$. The resulting savings to U.S. consumers consist mainly of what they previously spent to purchase the quantity they no longer consume, which is measured by the product of the original price P_0 and the decline in consumption ($Q_{US,0} - Q_{US,1}$).

At the same time, the decline in the global price of petroleum means that domestic consumers also save that amount on each barrel they *continue* to buy; their resulting savings is the product of the decline in price (P_0-P_1) and the amount they continue to use ($Q_{US,1}$), or the area P_0abP_1.[769,770] This additional savings is sometimes cited as an economic benefit of U.S. conservation measures such as raising CAFE standards, but is more properly interpreted as reducing the transfer of revenue from U.S. consumers to petroleum producers worldwide. Reducing this transfer is thus a purely "pecuniary" externality resulting from lower U.S. demand, which has no effect on total economic output or welfare, either within or outside the United

[767] The figure depicts the relationship between the global supply of petroleum and its worldwide price during a single time period. The global supply curve for petroleum has been shifting outward over time in response to increased investment in exploration, the ability of refineries to utilize feedstocks other than conventional petroleum, and technological innovations in petroleum extraction. The combination of these developments may also have reduced its upward slope, meaning that global supply now increases by more in response to increases in the world price than it once did.
[768] While U.S. demand influences prices, price is determined by global demand.
[769] Foreign petroleum users also pay the lower global price P_1 for each barrel they continue to consume, so in total they save (P_0-P_1) times ($Q_{G,1} - Q_{US,1}$) or the area acdb in the figure, as a consequence of reducing U.S. demand.
[770] Sometimes this benefit is expressed in terms of per barrel of reduced domestic consumption. Under this approach, the amount is expressed as by the reduction in U.S. consumption divided by the elasticity of oil (the change in demand divided by the change in price).

States.[771] However, as noted above, this analysis focuses on impacts to U.S. consumers, and as such, the benefit to U.S. consumers of lower oil prices caused by enhanced fuel economy is important to acknowledge.

Much of the reduction in payments by domestic users of petroleum products would once have represented a loss to foreign-owned oil producers and would thus have reduced the financial drain on the U.S. economy from using and importing petroleum. To a growing extent, however, lower payments by U.S. consumers that result from downward pressure on the world oil price are a transfer *entirely within* the Nation's economy, because a growing fraction of domestic petroleum consumption is supplied by U.S. producers. The United States recently became a net exporter of petroleum, and as it approached that situation an increasing share of any savings to U.S. petroleum consumers resulting from lower global oil prices became a loss to U.S. oil producers.[772] Once the United States became self-sufficient in petroleum supply (which occurred in 2020), the savings to U.S. petroleum users that results from reducing oil prices effectively reduced a transfer from domestic petroleum consumers to domestic producers. Stated another way, the financial burden that transfers from U.S. consumers to foreign oil producers once placed on the U.S. economy has been eased and ultimately erased by growing U.S. petroleum production, so reducing domestic demand no longer reduces that burden.[773]

Figure 6-5, which is a more detailed version of the previous figure, illustrates this situation. As in Figure 6-4, raising CAFE standards shifts the U.S. petroleum demand curve shifts inward from $D_{US,0}$ to $D_{US,1}$ causing an inward shift in global demand for petroleum from $D_{G,0}$ to $D_{G,1}$ and reducing the world oil price from P_0 to P_1. Before the decline in U.S. and global demand, domestic petroleum consumers purchase the entire output of U.S producers, $S_{US,0}$ barrels, and the U.S imports $Q_{US,0}$ - $S_{US,0}$ to meet the remainder of domestic demand. In response to the decline in the global petroleum price, U.S. producers reduce their output to $S_{US,1}$ barrels and foreign producers continue to supply the remainder of domestic demand, or $Q_{US,1} – S_{US,1}$ barrels.

[771] The decline is petroleum prices caused by lower U.S. demand does have consequences for economic welfare, because it leads to increases in consumer surplus to both domestic and foreign petroleum users. However, lower prices also reduce producer surplus to domestic and overseas suppliers of petroleum, and in total these losses in producer surplus exceed gains in consumer surplus to petroleum users. How domestic economic welfare changes depends on the U.S. petroleum import situation, which as discussed below has changed rapidly in recent years. The agency's analysis of this action does not attempt to estimate the net effect of these changes in domestic consumer and producer surplus.

[772] The U.S. Energy Information Administration EIA estimates that the United States exported more total crude oil and petroleum products in September and October of 2019, and expects the United States to continue to be a net exporter. *See Short Term Energy Outlook November 2019*, available at https://www.eia.gov/outlooks/steo/archives/nov19.pdf. (Accessed: February 15, 2022).

[773] In fact, much of that transfer has been reversed, so that reducing global petroleum prices may *lower* revenue to U.S. producers by more than it saves domestic consumers.

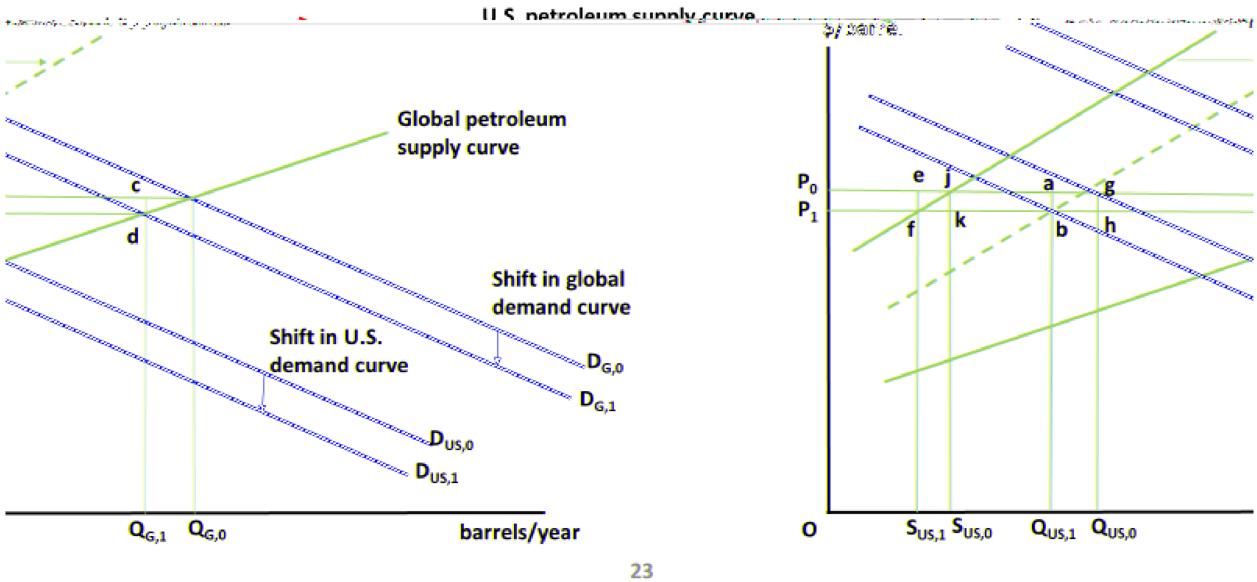

Figure 6-5 – Effect of Change in United States to Net Exporter of Petroleum

The decline in the global price of petroleum reduces "monopsony" payments by U.S. consumers for the quantity they originally purchased by $(P_1 - P_0)*Q_{US,0}$, or area P_0ghP_1 in Figure 6-5. Of this savings, the part P_0jkP_1 represents a revenue loss to U.S. producers, and the remaining component jghk represents lower revenue to foreign suppliers on their exports to the United States. From a global standpoint, this is simply a reduction in financial transfers that produces no change in welfare, although from a domestic perspective it does represent a reduced financial drain on the U.S. economy.

As the U.S. supply curve for petroleum has gradually shifted outward, the fraction of monopsony payments by U.S. consumers going to U.S. producers (which was P_0jkP_1/P_1ghP_0 before tighter CAFE standards reduced U.S. demand) gradually increased, while the fraction received by foreign producers ($jghk/P_0ghP_1$) gradually fell. When the U.S. supply curve reached the position shown by the dashed line in Figure 6-5 – indicating that all U.S. petroleum consumption could be supplied via domestic production, all monopsony payments by U.S. consumers became revenue to U.S. producers. As a consequence, any reduction in their value resulting from declining U.S. demand and the resulting fall in global petroleum prices – that is, the "monopsony effect" of reducing domestic consumption – became a financial transfer entirely within the U.S. economy.[774]

[774] As this occurred, the numerator and denominator of the fraction P_0jkP_1/P_1ghP_0 became identical so the value of this fraction approached 1.0, while the numerator of $jghk/P_0ghP_1$ and the value of that fraction approached zero.

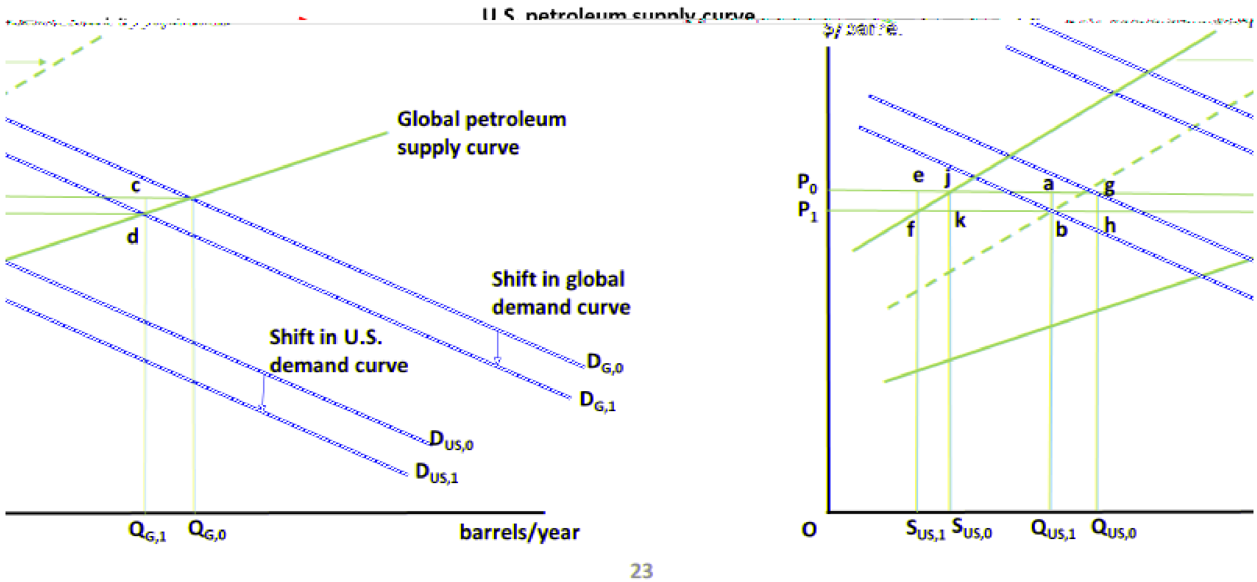

Figure 6-6 – Effect of Reducing U.S. Petroleum Demand on Domestic Monopsony Payments

Over most of the period spanned by the analysis, any decrease in domestic spending for petroleum caused by the effect of lower U.S. fuel consumption and petroleum use on world oil prices is expected to remain largely or entirely a transfer within the U.S. economy and thus produce no net impact on domestic economic resources. For this reason—and because in any case, such transfers do not create real economic costs or benefits—lower U.S. spending on petroleum products that results from the effect of raising CAFE standards on U.S. gasoline demand and the downward pressure it places on global petroleum prices is not included among the economic benefits accounted for in this final rule.

6.2.4.2 Macroeconomic Costs of U.S. Petroleum Consumption

In addition to influencing global demand and prices, U.S. petroleum consumption imposes further costs that are unlikely to be reflected in the market price for petroleum, or in the prices paid by consumers of refined products such as gasoline.[775] Petroleum consumption imposes external economic costs by exposing the U.S. economy and U.S. consumers to increased risks of rapid increases in prices triggered by global events – which may also disrupt the supply of imported oil – and U.S. consumers of petroleum products seem unlikely to take these costs into account when making their decisions about how much to consume.

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[775] *See, e.g.*, Bohi, D. R. & W. David Montgomery (1982), *Oil Prices, Energy Security, and Import Policy* Washington, D.C. - Resources for the Future, Johns Hopkins University Press; Bohi, D. R., & M. A. Toman (1993), "Energy and Security - Externalities and Policies," *Energy Policy* 21:1093-1109; and Toman, M. A. (1993). "The Economics of Energy Security - Theory, Evidence, Policy," in A. V. Kneese and J. L. Sweeney, eds. (1993), *Handbook of Natural Resource and Energy Economics, Vol. III*, Amsterdam - North-Holland, pp. 1167–218.

Interruptions in oil supplies and sudden increases in oil prices can impose significant economic costs not only because they raise the costs of commodities whose production and distribution relies on petroleum, but also because they temporarily reduce the level of output that the U.S. economy can produce (often called "potential GDP"). The magnitude of the resulting reduction in U.S. economic output depends on the extent and duration of increases in prices for petroleum products that result from disruptions to global oil supplies. Of course, it also depends on whether and how rapidly prices return to their pre-disruption levels, which in turn depends partly on the petroleum industry's capacity to respond to localized supply disruptions by increasing production elsewhere. Even if prices for oil return completely to their original levels, economic output will be at least temporarily reduced from the level that would have been possible with uninterrupted oil supplies and stable prices, so the U.S. economy will bear some transient losses it cannot subsequently recover.

Supply disruptions and price increases caused by global political events tend to occur suddenly and unexpectedly, so they can also force businesses and households to adjust their use of petroleum products more rapidly than if the same price increase occurred gradually. Rapid substitutions between different forms of energy and between energy and other inputs, as well as other changes such as adjusting production levels and downstream prices, can be costly for businesses to make. As with businesses, sudden changes in energy prices and use are also difficult for households to adapt to quickly or smoothly, and being forced to do so may cause at least temporary losses in other consumption.

Interruptions in oil supplies and sudden increases in petroleum prices are both uncertain prospects, so the costs of the disruptions they can cause must be weighted or adjusted by the probability that they will occur, as well as for their uncertain duration. The agency relies on estimated costs of such disruptions that reflect the probabilities that price increases of different magnitudes and durations will occur, as well as the resulting costs of lower U.S. economic output and abrupt adjustments to sharply higher prices. Any *change* in the probabilistic "expected value" of such costs that can be traced to lower U.S. fuel consumption and petroleum demand stemming from increased CAFE standards represents an external benefit of adopting them.

A variety of mechanisms are available to businesses and households to "insure" against sudden increases in petroleum prices and reduce their costs for adjusting to them. Examples include making purchases or sales in oil futures markets, adopting energy conservation measures, diversifying the fuel economy levels within the set of vehicles individual households own, locating where public transit provides a viable alternative to driving, and installing technologies that permit rapid fuel switching. Growing reliance on such measures, coupled with continued improvements in energy efficiency throughout the economy, has reduced the vulnerability of the U.S. economy to the costs of oil shocks in recent decades, and there is now considerable debate about the potential magnitude and continued relevance of economic damages from sudden increases in petroleum prices. However, as discussed in the preamble, domestic gasoline prices are currently linked to globalized oil markets, and as such, increased U.S. oil production does not insulate against price spikes and disruptions in the global oil market. Given that linkage, it is the reduction in the oil-intensity of the U.S. economy, delivered by policies like fuel economy standards, that reduce the exposure of U.S. consumers to those disruptions.

As one indicator of the U.S. economy's declining vulnerability to such disruptions, the agency analyzed how the amount of energy needed to produce the same level of U.S. economic output has changed over time. Figure 6-7 shows that U.S. GDP measured in real or inflation-adjusted dollars increased more than 800 percent between 1950 and 2020, while the nation's total energy consumption grew about 150 percent over that same period. As a consequence, the amount of energy required to produce each dollar of U.S. GDP fell by about 70 percent, reflecting both continuing improvements in the energy efficiency of production and shifts in the composition of GDP toward less energy-intensive products and services. AEO 2021 forecasts a continuing decline in U.S. energy intensity, with the energy/GDP ratio projected to decline a further 38 percent from 2020 through 2050. This forecast reflects anticipated energy efficiency improvements throughout the U.S. economy, including among passenger cars and light trucks.

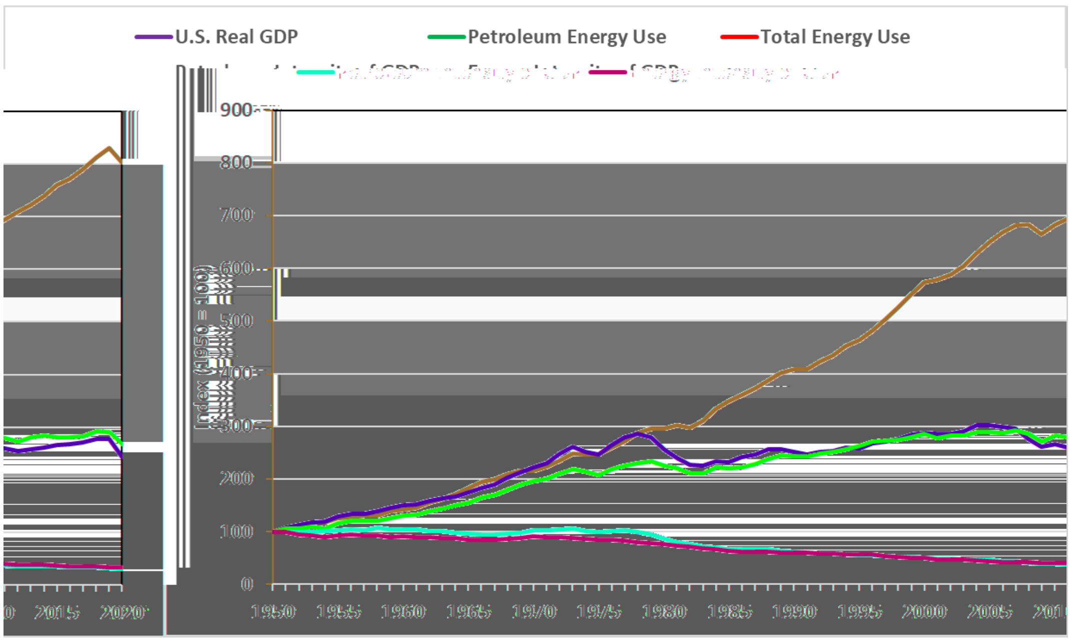

Figure 6-7 – U.S. Energy Intensity, 1950 - 2020[776]

As with the overall energy intensity of the U.S. economy, the *petroleum* intensity of U.S economic output has also declined significantly over time, while at the same time global oil prices have fallen to levels dramatically lower than when analysts first identified and quantified the risks they create to the U.S. economy. As Figure 6-7 illustrates, U.S. GDP and the nation's consumption of petroleum-based energy grew almost exactly the same rate from 1950 through 1980, after which petroleum consumption leveled off while GDP continued to grow steadily. As a consequence, petroleum energy consumption per dollar of U.S. economic output declined steadily from 1980 through 2020. AEO 2021 projects that the petroleum intensity of U.S. GDP

[776] Sources: U.S. GDP: Department of Commerce, Bureau of Economic Analysis, National Income and Product Accounts for the U.S., Interactive Data: GDP and Personal Income, Section 1: Domestic Product and Income, Table 1.1.6, https://apps.bea.gov/iTable/iTable.cfm?reqid=19&step=2#reqid=19&step=2&isuri=1&1921=survey (Accessed: March 24, 2022); U.S. Petroleum and Energy Consumption: Energy Information Administration, Annual Energy Review, Total Energy, Table 1.3 Energy Consumption by Source, https://www.eia.gov/totalenergy/data/browser/index.php?tbl=T01.03#/?f=A&start=1949&end=2020&charted=3. (Accessed: March 24, 2022).

will fall by another 40 percent from its current level over the next three decades. Further, not only has the United States dramatically increased its own petroleum supply, but other new global suppliers have emerged as well, and both of these developments reduce the potential impact of disruptions in the unstable or vulnerable regions of the globe that have historically represented critical sources of supply.

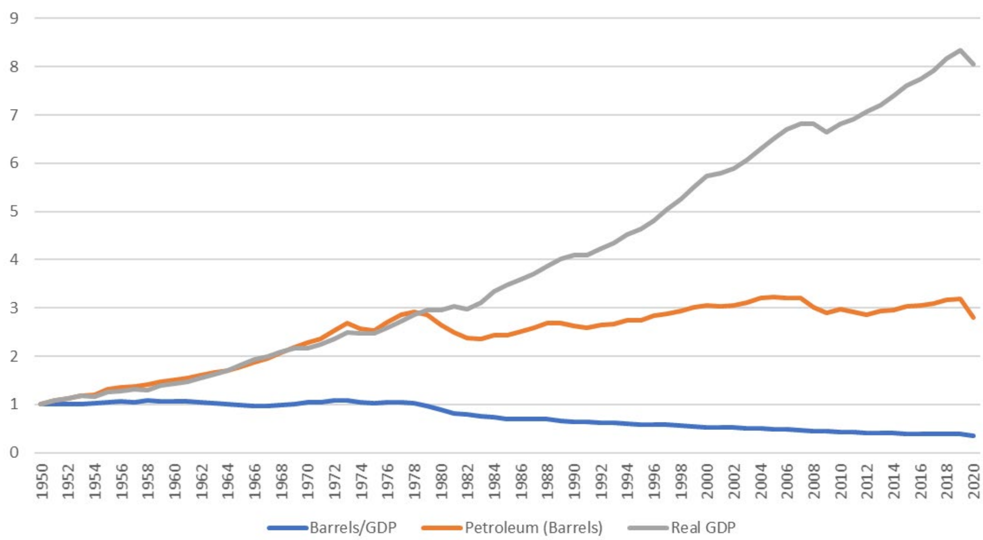

Figure 6-8 – Petroleum Intensity of U.S. GDP, 1950 - 2020[777]

As a consequence, the potential macroeconomic costs of sudden increases in oil prices are now likely to be considerably smaller than when they were originally identified and estimated. Recognizing this situation, the National Research Council (2009) argued that non-environmental externalities associated with dependence on foreign oil are now small, and perhaps trivial.[778] Research by Nordhaus and by Blanchard and Gali has also questioned how harmful recent oil price shocks have been to the U.S. economy, noting that the U.S. economy actually *expanded* rapidly following the most recent oil price shocks, and that there was little evidence of higher energy prices being passed through into higher wages or prices.[779]

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[777] Source: GDP data from Federal Reserve Bank, FRED series GDPC1 and petroleum consumption data from EIA, by sector, https://www.eia.gov/totalenergy/data/annual. (Accessed: February 15, 2022).

[778] National Research Council, *Hidden Costs of Energy - Unpriced Consequences of Energy Production and Use,* National Academy of Sciences, Washington, D.C. (2009).

[779] Nordhaus (2010) argues that one reason for limited vulnerability to oil price shocks is that monetary policy has become more accommodating to the price impacts, while another is that U.S. consumers and businesses may determine that such movements are temporary and abstain from passing them on as inflationary price increases in other parts of the economy. He also notes that changes in productivity in response to recent oil price increases have been extremely modest, observing that "energy-price changes have no effect on multifactor productivity and very little effect on labor productivity." at p. 19. Blanchard and Gali (2010) contend that improvements in monetary policy, more flexible labor markets, and the declining energy intensity of the U.S. economy (combined with an absence of concurrent shocks to the economy from other sources) lessened the impact of oil price shocks after 1980. They find that "the effects of oil price shocks have changed over time, with steadily smaller effects on prices and

Since these studies were conducted, the petroleum intensity of the U.S. economy has continued to decline, while domestic energy production has increased in ways and to an extent that experts failed to predict, so that the United States became the world's largest producer in 2018.[780] The U.S. shale oil revolution has both established the potential for energy independence and placed downward pressure on prices. Lower oil prices are also a result of sustained reductions in U.S. consumption and global demand resulting from energy efficiency measures, many undertaken in response to previously high oil prices and, more recently, the pandemic.

Reduced petroleum intensity and higher U.S. production have combined to produce a dramatic decline in U.S. petroleum imports, permitting U.S. supply to act as a buffer against artificial or natural restrictions on global petroleum supplies due to military conflicts or natural disasters. In addition, the speed and relatively low incremental cost with which U.S. oil production has increased suggests that both the magnitude and (especially) the duration of future oil price shocks may be limited.

While some risk of price shocks certainly still exists, even the *potential* for a large and relatively rapid U.S. production response may be limiting the extent of price shocks attributable to external events. For example, the large-scale attack on Saudi Arabia's Abqaiq processing facility—the world's largest crude oil processing plant—on September 14, 2019, caused "the largest single-day [crude oil] price increase in the past decade" ($7-8 per barrel), according to EIA.[781] The Abqaiq facility has the capacity to process 7 million barrels per day, or about 7 percent of global crude oil production capacity. By September 17, however – only three days after the incident – Saudi Aramco reported that Abqaiq was producing 2 million barrels per day, and they expected its entire output capacity to be fully restored by the end of September 2019. In addition, Saudi Aramco stated that crude oil deliveries would continue by drawing on available inventories and increasing crude oil production from other fields. Tanker loading estimates from third-party data sources indicate that loadings at two Saudi Arabian export facilities had already been restored to the pre-attack levels by September 17 and, likely driven by news of the expected return of the lost production capacity, both Brent and West Texas Intermediate crude oil prices fell sharply on that same day.[782]

Thus, the largest single-day oil price increase in the past decade was largely resolved within a week; assuming that average crude oil prices were approximately $70/barrel in September 2019 (slightly higher than their actual average), an increase of $7/barrel would have represented a 10 percent increase as a result of the Abqaiq attack. This contrasts sharply with the 1973 Arab oil

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wages, as well as on output and employment...The message…is thus optimistic in that it suggests a transformation in U.S. institutions has inoculated the economy against the responses that we saw in the past." at p. 414; *See* William Nordhaus, "Who's Afraid of a Big Bad Oil Shock?" Available at https://www.brookings.edu/wp-content/uploads/2007/09/2007b_bpea_nordhaus.pdf; and Blanchard, Olivier and Jordi Gali, J., "The Macroeconomic Effects of Oil price Shocks - Why are the 2000s so Different from the 1970s?," in Gali, Jordi and Mark Gertler, M., eds., *The International Dimensions of Monetary Policy*, University of Chicago Press, February (2010), pp. 373–421, available at http://www.nber.org/ses/c0517.pdf. (Accessed: February 15, 2022).

[780] *See* U.S. Energy Information Administration EIA, *Today in Energy August 20, 2019*, available at https://www.eia.gov/todayinenergy/detail.php?id=40973; *Today in Energy September 12, 2018,* available at https://www.eia.gov/todayinenergy/detail.php?id=37053. (Accessed: February 15, 2022).

[781] https://www.eia.gov/todayinenergy/detail.php?id=41413. (Accessed: February 15, 2022).

[782] *Id*.

embargo, which lasted several months and raised prices nearly 350 percent.[783] Saudi Arabia could have taken advantage of increased revenue resulting from higher prices following the Abqaiq attack, but instead moved rapidly to restore production and tap its domestic reserves to control the risk of resulting price increases. In doing so, the Saudis likely recognized that sustained, long-term price increases would reduce their ability to control global supply (and thus to affect global prices and their own revenues) by relying on their lower cost of production.[784]

Some have asserted that U.S. shale oil resources cannot serve as "swing supply" to provide stability in the face of a sudden, significant global supply disruption. Despite its greater responsiveness to price changes, some argue that lead time to bring new shale resources to market (6-12 months) is inferior to "true spare capacity" (like Saudi Arabia's large oil fields) because it cannot be deployed quickly enough to mitigate the economic consequences resulting from rapidly rising oil prices.[785] However, shale oil projects' lead times are still shorter—and possibly much shorter—than conventional oil resource development. So, while new U.S. oil resources may take some time to respond to supply disruptions, they are nevertheless likely to provide some stabilizing influence on price increases.

This is likely to be especially true for price increases that occur more slowly. When Beccue and Huntington updated their 2005 estimates of supply disruption probabilities in 2016,[786] they found that the probability distribution had generally "flattened," meaning that supply disruptions of most potential magnitudes were less likely to occur under today's market conditions than they had estimated previously in 2005. In particular, Beccue and Huntington found that supply disruptions of between two and four million barrels per day were significantly less likely to occur in 2016 than their previous estimates for 2005 had suggested. Although their recent study also estimated that larger supply disruptions (nine or more million barrels per day) are now slightly more likely to occur than in previous estimates, in their view disruptions of this magnitude remain extremely unlikely under either set of estimates.

DOT thus concludes that while shale resources may not be able to stabilize oil markets sufficiently to prevent price increases that originate from rapid, very large supply disruptions elsewhere in the world, U.S. resources are likely to be adequate to stabilize most smaller or less rapid disruptions.

6.2.4.3 Potential Effects of Petroleum Imports on U.S. Military Spending

A third potential effect of decreasing U.S. demand for petroleum is a decrease in U.S. military spending to secure the supply of oil imports from potentially unstable regions of the world and protect against their interruption. If a decrease in fuel consumption that results from adopting

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783 *See* Jeanne Whalen, "Saudi Arabia's oil troubles don't rattle the U.S. as they used to," Washington Post, September 19, 2019, available at https://www.washingtonpost.com/business/2019/09/19/saudi-arabias-oil-troubles-dont-rattle-us-like-they-used. (Accessed: February 15, 2022).

784 *See*, *e.g*., "Dynamic Delivery: America's Evolving Oil and Natural Gas Transportation Infrastructure," National Petroleum Council (2019) at p. 18, available at: https://dynamicdelivery.npc.org/downloads.php. (Accessed: February 15, 2022).

785 For such a cautionary analysis, see Richard G. Newell and Brian C. Prest, "The Unconventional Oil Supply Boom: Aggregate Price Response from Microdata," NBER Working Paper No. 23973, October 2017.

786 Beccue, Phillip, Huntington, Hillard, G., 2016. An Updated Assessment of Oil Market Disruption Risks: Final Report. Energy Modeling Forum, Stanford University.

higher CAFE standards enables any military spending that is clearly attributable to protecting flows of imported oil to be scaled back, this reduction in outlays would represent an additional external benefit of NHTSA's action. Such benefits could also include decreased costs to maintain the U.S. Strategic Petroleum Reserve (SPR), because it is intended to cushion the U.S. economy against disruptions in the supply of imported oil or sudden increases in the global price of oil.

Some have argued that U.S. military expenditures are uniquely attributable to securing U.S. supplies of petroleum from unstable regions of the globe – the Middle East, in particular. However, such a perspective appears to confuse those costs with the *marginal* impact of changes in oil consumption of the scale likely to result from this final action on U.S. military activity and its costs. Incrementally reducing domestic petroleum consumption does not seem likely to significantly decrease military spending to protect those resources and ensure their safe and reliable distribution throughout the world. An analysis by Crane *et al*. reached exactly this conclusion, stating that "our analysis addresses the incremental cost to the defense budget of defending the production and transit of oil. It does not argue that a partial reduction of the U.S. dependence on imported oil would yield a proportional reduction in U.S. spending that is focused on this mission. The effect on military cost from such changes in petroleum use would be minimal."[787] NHTSA thus does not believe that any incremental reduction in petroleum consumption that may result from this final action will influence whatever U.S. defense spending might be uniquely ascribed to protecting the global oil network.

Eliminating petroleum imports (to both the United States and its national security allies) *entirely* might permit the Nation to scale back its military presence in oil-supplying regions of the globe, but only to the extent that maintaining this presence is necessitated by narrow concerns for oil production and transportation, rather than reflecting broader geopolitical considerations. There is little evidence that U.S. military activity and spending in those regions have varied over history in response to fluctuations in the Nation's oil imports or are likely to do so over the future period spanned by this analysis. Figure 6-9 shows that military spending as a share of total U.S. economic activity has gradually declined over the past several decades, and that any temporary—although occasionally major—reversals of this longer-term decline have been closely associated with U.S. foreign policy initiatives or overseas wars.

[787] Crane, K., A. Goldthau, M. Toman, T. Light, S. E. Johnson, A. Nader, A. Rabasa, & H. Dogo, *Imported Oil and U.S. National Security*, Santa Monica, CA, The RAND Corporation (2009) available at https://www.rand.org/pubs/monographs/MG838.html. (Accessed: February 15, 2022).

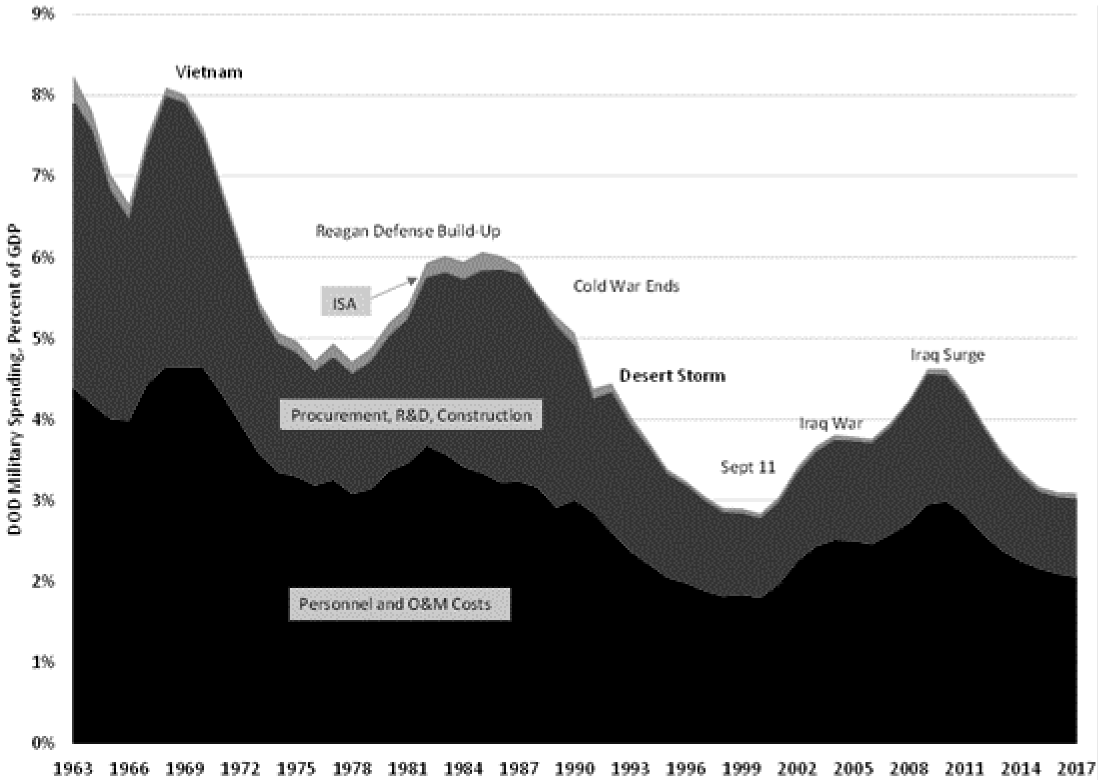

Figure 6-9 – Historical Variation in U.S. Military Spending (Percent of U.S. GDP)

Figure 6-10 superimposes U.S. petroleum consumption and imports on the history of military spending shown in the previous figure. Doing so shows that variation in U.S military spending throughout this period has had little association with the historical pattern of domestic petroleum purchases, changes in which instead primarily reflected the major increases in global petroleum prices that occurred in 1978-79, 2008, and 2012-13. More important, Figure 6-10 also shows that U.S. military spending varied *almost completely independently* of the nation's imports of petroleum over most or all this period. This history suggests that U.S. military activities—even in regions of the world that have historically represented vital sources of oil imports—serve a far broader range of security and foreign policy objectives than simply protecting oil supplies. Thus, reducing the nation's consumption or imports of petroleum is unlikely by itself to lead to reductions in military spending.

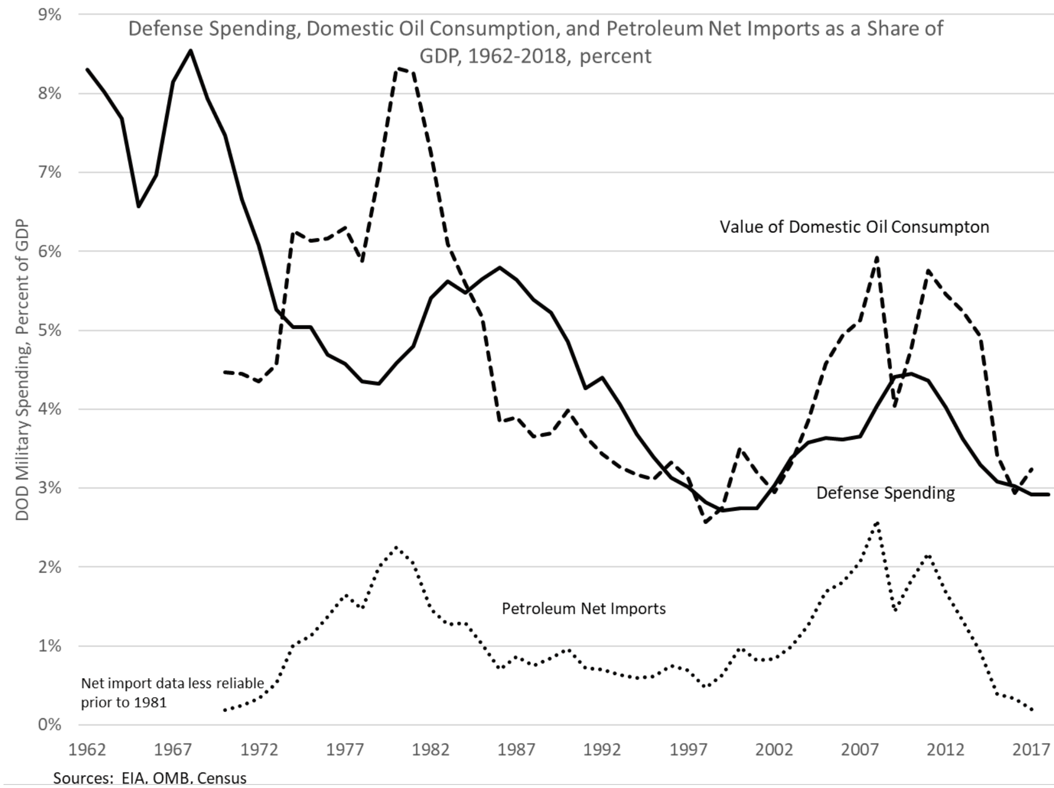

Figure 6-10 – Historical Variation in U.S. Military Spending in Relation to U.S. Petroleum Consumption and Imports (Percent of U.S. GDP)

Further, the agency was unable to find any record of the U.S. government attempting to calibrate U.S. military expenditures, force levels, or deployments to any measure of the Nation's petroleum use and the fraction supplied by imports, or to an assessment of the potential economic consequences of hostilities in oil-supplying regions of the world that could disrupt the global market.[788] Instead, changes in U.S. force levels, deployments, and spending in such regions appear to have been governed by purposeful foreign policy initiatives, unforeseen political events, and emerging security threats, rather than by shifts in U.S. oil consumption or imports.[789] The agency thus concludes that U.S. military activity and expenditures are unlikely

[788] Crane et al. (2009) analyzed reductions in U.S. forces and associated cost savings that could be achieved if oil security were no longer a consideration in military planning and disagree with this assessment. After reviewing recent allocations of budget resources, they concluded that "the United States *does* include the security of oil supplies and global transit of oil as a prominent element in its force planning" at p. 74 (emphasis added). Nevertheless, their detailed analysis of individual budget categories estimated that even eliminating the protection of foreign oil supplies *completely* as a military mission would reduce the current U.S. defense budget by approximately 12-15 percent. *See* Crane, K., A. Goldthau, M. Toman, T. Light, S. E. Johnson, A. Nader, A. Rabasa, & H. Dogo, *Imported Oil and U.S. National Security*., Santa Monica, CA, The RAND Corporation (2009) available at https://www.rand.org/pubs/monographs/MG838.html. (Accessed: February 15, 2022).

[789] Crane et al. (2009) also acknowledge the difficulty of reliably allocating U.S. military spending by specific mission or objective, such as protecting foreign oil supplies. Moore et al. (1997) conclude that protecting oil supplies cannot be distinguished reliably from other strategic objectives of U.S. military activity, so that no clearly separable component of military spending to protect oil flows can be identified, and its value is likely to be near

to be affected by even relatively large changes in consumption of petroleum-derived fuels by light duty vehicles. Certainly, the historical record offers no suggestion that U.S. military spending is likely to adjust significantly in response to the decrease in domestic petroleum use that result from increasing CAFE standards.

Nevertheless, it is possible that more detailed analysis of military spending might identify some relationship to historical variation in U.S. petroleum consumption or imports. A number of studies has attempted to isolate the fraction of total U.S. military spending that is attributable to protecting overseas oil supplies.[790] These efforts have produced varying estimates of how much it might be reduced if the United States no longer had *any* strategic interest in protecting global oil supplies; however, none has identified an estimate of spending that is likely to vary *incrementally* in response to changes in U.S. petroleum consumption or imports. Nor have any of these studies tracked specific changes in spending that can be attributed to protecting U.S. interests in foreign oil supplies over a prolonged period, so they have been unable to identify whether their estimates of such spending vary in response to fluctuations in domestic petroleum consumption or imports.

NHTSA thus concludes from this review of research that U.S. military commitments in the Persian Gulf and other oil-producing regions of the world contribute to worldwide economic and political stability, and insofar as the costs of these commitments are attributable to petroleum use, they are attributable to oil consumption throughout the world, rather than simply U.S. oil consumption or imports. It is thus unlikely that military spending would decline in response to any decrease in U.S. imports, or consumption, that did result from the final standards. As a consequence, the agency's evaluation of today's final CAFE standards assumes that there would be no reduction in government spending to support U.S. military activities in response to the anticipated reduction in gasoline use and U.S. petroleum consumption.

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zero. Similarly, the U.S. Council on Foreign Relations (2015) takes the view that significant foreign policy missions will remain over the foreseeable future even without any imperative to secure petroleum imports. A dissenting view is that of Stern (2010), who argues that other policy concerns in the Persian Gulf derive from U.S. interests in securing oil supplies, or from other nations' reactions to U.S. policies that attempt to protect its oil supplies. *See* Crane, K., A. Goldthau, M. Toman, T. Light, S.E. Johnson, A. Nader, A. Rabasa, and H. Dogo, *Imported Oil and U.S. National Security*., Santa Monica, CA, The RAND Corporation (2009) available at https://www.rand.org/pubs/monographs/MG838.html (Accessed: February 15, 2022); Moore, John L., E.J. Carl, C. Behrens, and John E. Blodgett, "Oil Imports - An Overview and Update of Economic and Security Effects," Congressional Research Service, Environment and Natural Resources Policy Division, Report 98, No. 1 (1997), pp. 1-14; Council on Foreign Relations, "Automobile Fuel Economy Standards in a Lower-Oil-Price World," November 2015; and Stern, Roger J. "United States cost of military force projection in the Persian Gulf, 1976–2007," *Energy Policy* 38, no. 6 (June 2010), pp. 2816-25, https://www.sciencedirect.com/science/article/pii/S0301421510000194?via%3Dihub. (Accessed: February 15, 2022).

[790] These include Copulos, M R. "America's Achilles Heel - The Hidden Costs of Imported Oil," Alexandria VA - The National Defense Council Foundation, September 2003 - 1-153, available at http://ndcf.dyndns.org/ndcf/energy/NDCFHiddenCostsofImported_Oil.pdf; Copulos, M R. "The Hidden Cost of Imported Oil--An Update." The National Defense Council Foundation (2007) available at http://ndcf.dyndns.org/ndcf/energy/NDCF_Hidden_Cost_2006_summary_paper.pdf; Delucchi, Mark A. & James J. Murphy. "US military expenditures to protect the use of Persian Gulf oil for motor vehicles," *Energy Policy* 36, no. 6 (June 2008), pp. 2253-64; and National Research Council Committee on Transitions to Alternative Vehicles and Fuels, *Transitions to Alternative Vehicles and Fuels* (2013).

Similarly, while the ideal size of the SPR from the standpoint of its potential stabilizing influence on global oil prices may be related to the level of U.S. petroleum consumption or imports, its actual size has not appeared to vary in response to either of those measures. The budgetary costs for maintaining the SPR are thus similar to U.S. military spending in that, while they are not reflected in the market price for oil (and thus do not enter consumers' decisions about how much to use), they do not appear to have varied in response to changes in domestic petroleum consumption or imports. Recognizing these findings, NHTSA's analysis of the final rule does not include any reduction in the cost to maintain a (possibly) smaller SPR as an external benefit of the expected reduction in gasoline and petroleum consumption. This view aligns with the conclusions of most recent studies of military-related costs to protect U.S. oil imports, which generally conclude that savings in military spending are unlikely to result from incremental reductions in U.S. consumption of petroleum products on the scale of those that would resulting from adopting higher CAFE standards.

6.2.4.4 Petroleum Imports and U.S. Energy Security

Although the vulnerability of the U.S. economy to oil price shocks depends on the nation's aggregate *consumption* of petroleum rather than on the level of its oil imports, variation in U.S. imports may have some independent effect on the frequency, size, or duration of sudden oil price increases. Insofar as it does, the expected value of potential economic costs from supply or price disruptions would also depend partly on the fraction of U.S. petroleum use that is supplied by imports rather than by domestic production. In addition, the estimates of these costs that NHTSA has relied upon in past regulatory analyses—and continues to employ in this analysis—are expressed per unit (barrel) of petroleum *imported into the U.S*, rather than total U.S. consumption. After converting them to a per-gallon basis, the agency applies these costs both to fuel that is imported in refined form, and that refined domestically from imported crude petroleum. To support these calculations, NHTSA is required to make specific assumptions about how imports of refined gasoline and crude petroleum are likely to change in response to reductions in gasoline consumption of the magnitude expected to result from the finalized CAFE standards.

There are three supply "pathways" for fuel consumed by the U.S. light-duty vehicle fleet:

1. Importing fuel that has been refined overseas into the United States.
2. Refining fuel within the United States from imported crude petroleum.
3. Refining fuel within the United States from domestically produced crude petroleum.[791]

NHTSA assumed that 50 percent of any change in domestic fuel consumption by cars and light trucks would be reflected in changes in the volume of fuel supplied by imports of refined fuel (pathway 1), while the remaining 50 percent would be reflected in changes in the volume of fuel refined domestically (pathways 2 and 3). In turn, the agency assumed that 90 percent of any change in the volume of fuel refined domestically would be reflected in changes in the volume of crude petroleum imported into the United States, while the remaining 10 percent would be

[791] We assume that all fuel refined outside the United States and then imported into the United States is refined from petroleum that was also produced outside the United States. Although some of it could be refined from crude petroleum produced in the United States and exported, we assume the fraction supplied via this pathway is negligible.

reflected in changes in the volume produced within the United States This combination of assumptions implied that for a change in domestic fuel consumption of 100 gallons, U.S. imports of refined fuel (pathway 1) would change by 50 gallons, while the volume of fuel supplied by domestic refining of imported crude oil (pathway 2) would change by 45 gallons, and the volume supplied by domestic refining of domestically produced crude oil (pathway 3) would change by 5 gallons. In the proposal, the agency reviewed its previous assumption that 90 percent of any reduction in domestic petroleum refining to produce gasoline that results from the proposal would reduce U.S. petroleum imports, with the remaining 10 percent reducing domestic production.

The agency's assumption was based on forecasts of changes in future U.S. fuel consumption and petroleum imports originally published in AEO 2012. For most of the past half-century, the United States has been a large net importer of crude petroleum, importing the volume necessary to meet the difference between U.S. demand for refined petroleum products and domestic petroleum supply. Throughout this period, the United States has also been largely self-sufficient in refining, meaning that any gap between domestic demand for refined products and the volumes refined from U.S. crude petroleum was primarily met by refining imported crude oil, supplemented by minor imports of refined gasoline. The agency's assumptions about the impacts of conserving fuel on U.S. petroleum imports and refining reflected the expected continuation of this situation.

In the past decade, this situation has changed dramatically. U.S. production of crude petroleum has more than doubled since 2008, making the nation one of the world's largest producers, while net imports of crude oil and refined products have declined more than 75-percent.[792] Domestic gasoline consumption declined by more than 6 percent between 2007 and 2012, recovering to its 2007 levels only as recently as 2016 and remaining near or slightly below that level since. As a consequence, the United States shifted from being a net importer of refined petroleum products to a net exporter in 2011 and has become a net exporter of gasoline and "blending stock" since 2016.[793]

Over the past decade, increased availability of crude petroleum and other refinery feedstocks in combination with declining gasoline consumption has presented U.S. refiners with a choice between continuing to produce gasoline at or near their capacity while boosting exports or

[792] All petroleum statistics are calculated from data at: (EIA, Petroleum and Other Liquids, 2019). Net U.S. imports are the difference between the nation's total (or gross) imports from elsewhere in the world and the volumes it exports to other nations.

[793] Another recent change in petroleum markets has been the increasing production and trade in gasoline blendstock in domestic and international petroleum trade. While in earlier periods refineries normally produced finished gasoline and shipped it to local storage terminals for distribution and retailing, in recent years, refineries have increasingly shifted to producing standardized gasoline blendstocks, such as Reformulated Blendstock for Oxygenate Blending (or "RBOB"), which are then shipped and blended with ethanol or other additives to make finished gasoline that meets local regulatory requirements or customer specifications. Although this process has clear cost and operational advantages, particularly with extensive geographic and seasonal variation in gasoline formulations, it complicates the tabulation and comparison of petroleum statistics. In both EIA and most international trade statistics, finished gasoline and blendstocks are treated as separate products, and as reported in EIA statistics, large volumes of finished gasoline are now produced from blendstocks by local "blenders," rather than by more centralized "refiners." In addition, the volume of refinery production of gasoline and blendstock is now systematically lower than consumption of finished gasoline, because up to 10 percent of the volume of gasoline sold at retail can be made up of ethanol that is blended into gasoline after it leaves the refinery.

cutting back on refinery output. As gasoline consumption declined from 2007 through 2012, U.S. refiners elected not to cut back on their production of gasoline; instead, they increased the volume they refined and have continued to do so since 2012 as domestic demand recovered. Overall, refinery and blender production of gasoline increased by 9 percent between 2007 and 2018, while, as noted, consumption has only recently recovered to its 2007 level.

The resulting excess of gasoline production over domestic consumption has partly displaced previous gasoline and blendstock imports, with the remainder taking the form of increased U.S. exports. As Figure 6-11 shows, the decline in U.S. gasoline consumption after 2007 has not led to a corresponding decline in refinery production, and the nation now has a capacity to produce gasoline that considerably exceeds its current domestic consumption. Further, this surplus of gasoline appears likely to increase in the coming years, as EIA's *Annual Energy Outlook 2019* reference case (EIA, 2019) anticipates that domestic gasoline consumption will continue to decline until nearly 2040. Thus, unless domestic refinery capacity is significantly curtailed, the United States seems likely to remain a net exporter of gasoline through the next three decades.

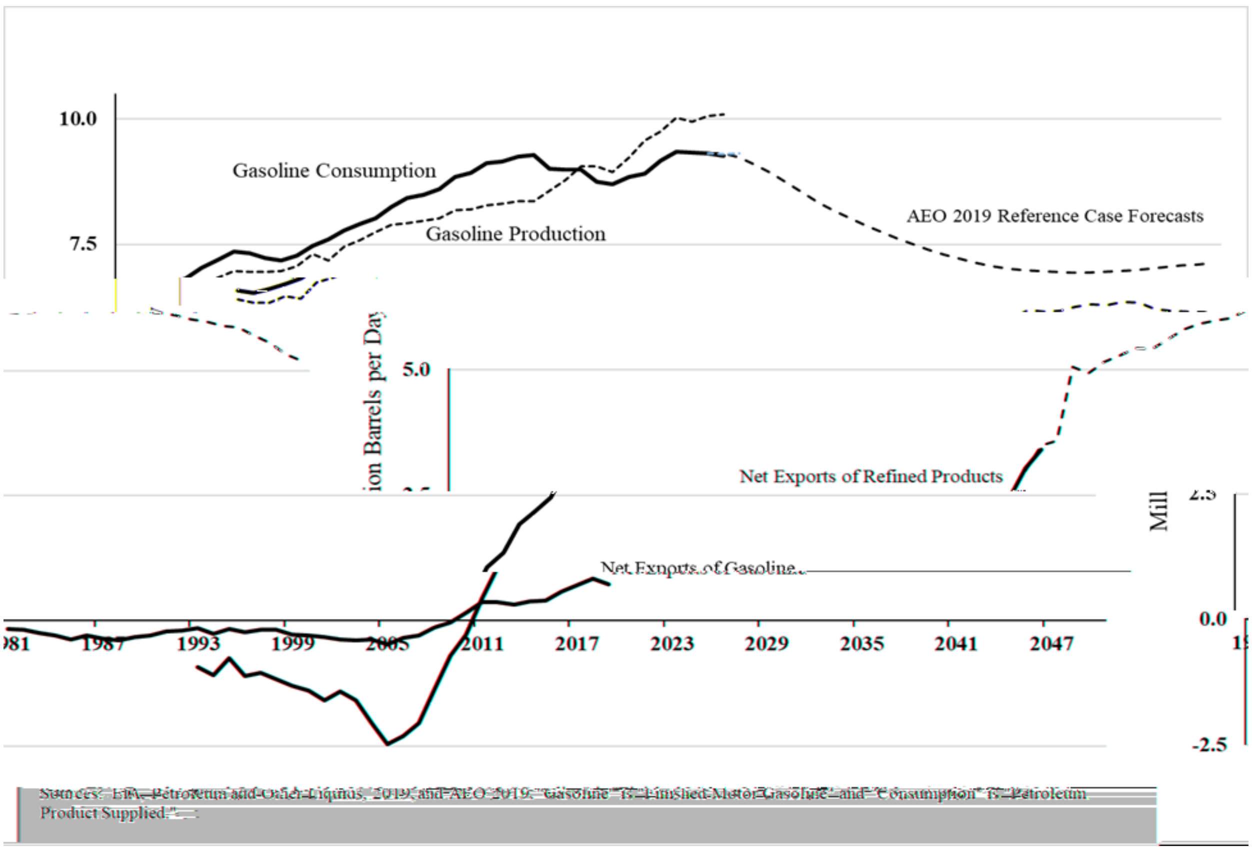


Figure 6-11 – U.S. Gasoline Consumption, Production, and Net Exports: Historical and Forecast

Although EIA's AEO does not include separate forecasts of gasoline exports and imports, that same agency's *Short Term Energy Outlook* projects that U.S. gasoline exports will continue to rise through 2020 (EIA, 2019).[794] Taken together, the forecasts of declining U.S. gasoline

[794] AEO does not forecast gasoline refining, imports, or exports separately, instead reporting them as part of total refined petroleum products.

consumption and rising net exports of refined petroleum products reported in AEO 2019 suggest that that EIA expects the United States to grow as a net exporter of refined petroleum products – including gasoline – through nearly 2040. In turn, this suggests that any decrease in domestic gasoline consumption that would result is likely to accelerate growth in U.S. exports slightly, rather than decrease domestic refining and associated upstream emissions.

As Figure 6-12 below shows, gasoline production along the East Coast has increased rapidly in recent years, while shipments into the region from the remainder of the United States and imports (mainly from Canada) declined as the gap between consumption and local supply within Petroleum Administration for Defense District (PADD) 1 has closed. In June 2019, however, press reports suggested that that one of the largest East Coast refineries (Philadelphia Energy Solutions, which represents some 28 percent of East Coast refining capacity) would be closed.[795] At the same time, construction of new refineries continues to be hindered by the density of population concentrations and commercial development along the nation's East Coast, casting doubt on the potential for continued increases in local gasoline refining and supply within PADD 1.

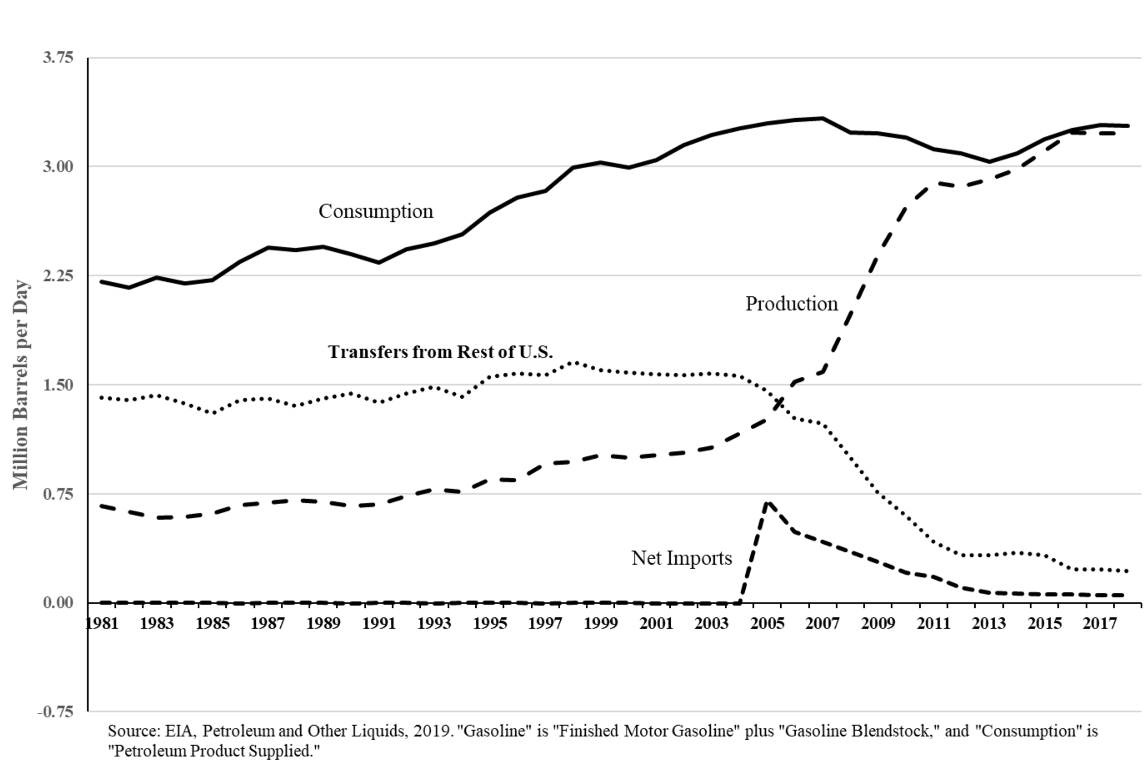


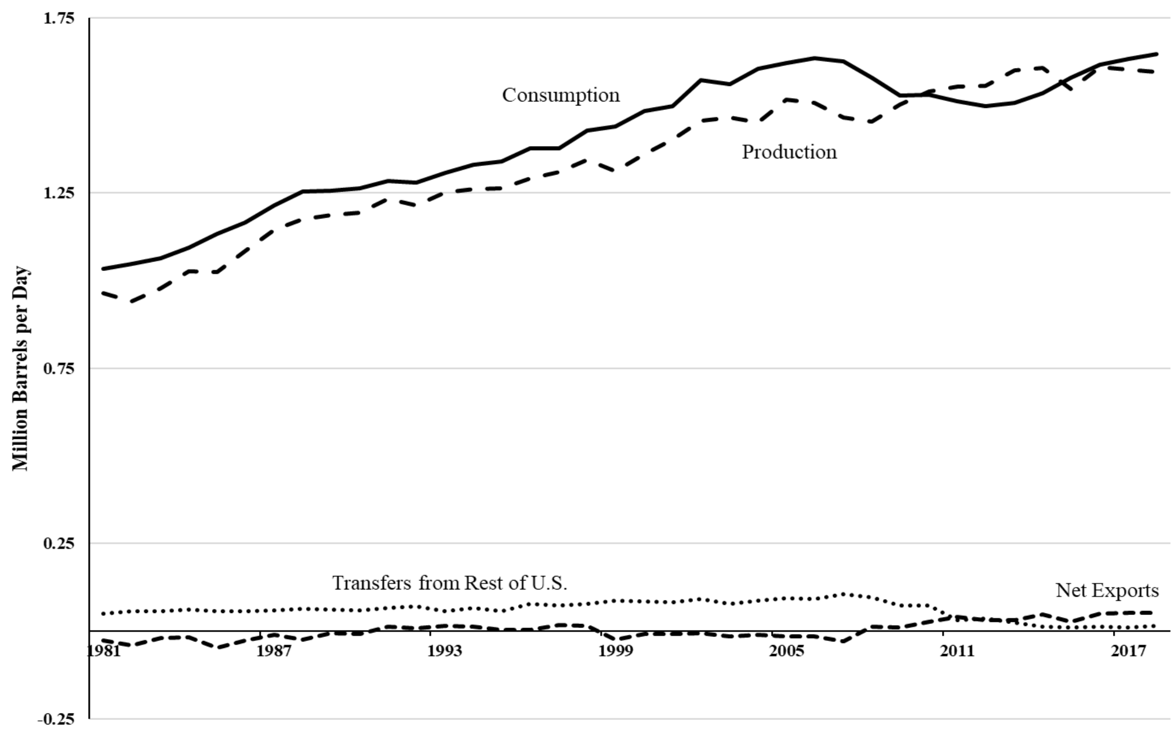
Figure 6-12 – U.S. East Coast (EIA PADD 1) Gasoline Production, Consumption, Transfers from Rest of U.S., and Net Exports

As a consequence, it seems likely that any decrease in gasoline consumption along the nation's East Coast in response to the final action would diminish the need to rely upon foreign imports

[795] Seba, E. (2019, July 5). Philadelphia refinery closing reverses two years of U.S. capacity gains. Retrieved September 19, 2019, from Reuters: https://www.reuters.com/article/us-usa-refinery-blast-capacity/philadelphia-refinery-closing-reverses-two-years-of-u-s-capacity-gains-idUSKCN1U0283. (Accessed: February 15, 2022).

or resumption of once-large transfers from the Gulf Coast. Pipelines available to transport refined petroleum products from Gulf Coast refineries to the East Coast may also face capacity limitations, in which case most of any decrease in gasoline consumption there would diminish the need of imports from abroad.

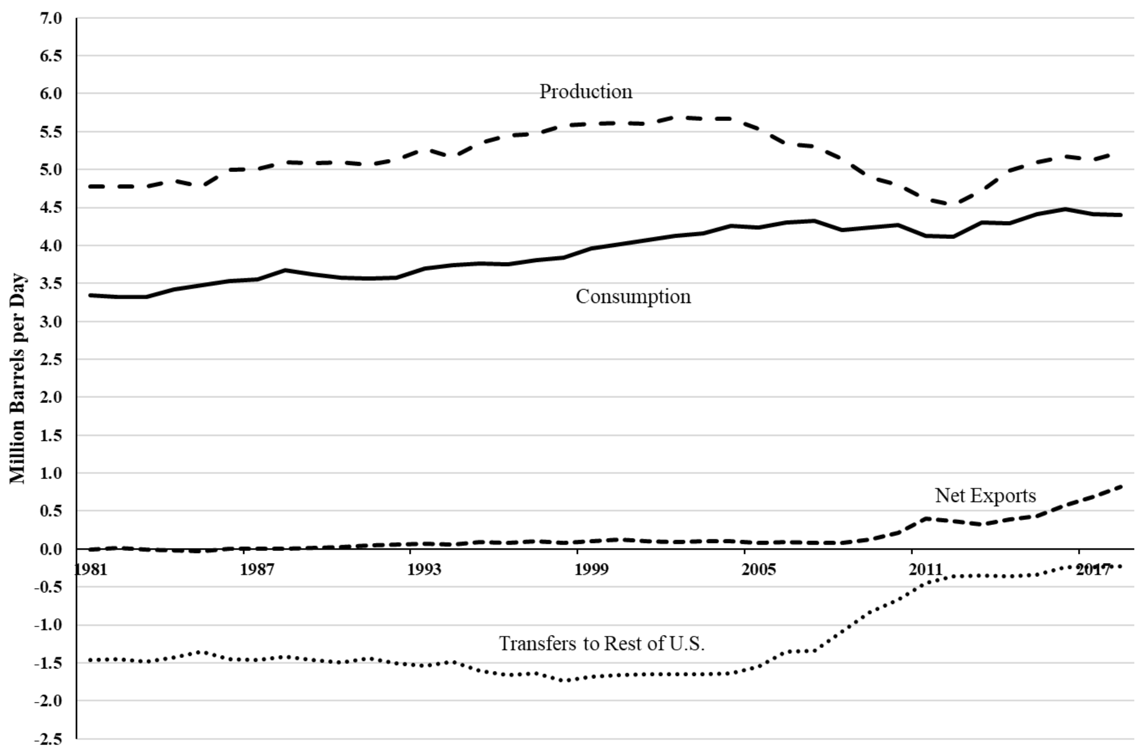
The West Coast, which includes Nevada and Arizona (EIA's PADD 5), currently accounts for 18 percent of U.S. gasoline consumption. Almost all of the gasoline consumed in that region is also refined within it, although small volumes are shipped into Arizona from neighboring PADDs by pipeline, and small volumes are also exported to Latin America by tanker. Since the West Coast is relatively isolated from other U.S. sources of refined gasoline by long transportation distances and limited pipeline capacity, while import terminals for crude petroleum are relatively numerous, it appears more likely that marginal increases in gasoline consumption from the rule will be met from increases in local (i.e., within-PADD) refining. Figure 6-13 shows that this has been the case in recent decades, as growth in gasoline production within PADD 5 throughout that period has closely paralleled growth in local consumption, while net exports have remained minimal.



Source: EIA, Petroleum and Other Liquids, 2019. "Gasoline" is "Finished Motor Gasoline" plus "Gasoline Blendstock," and "Consumption" is "Petroleum Product Supplied."

Figure 6-13 – U.S. West Coast (EIA PADD 5) Gasoline Production, Consumption, Transfers from Rest of United States, and Net Exports

The central region of the United States (PADDs 2-4) accounts for the remaining 47 percent of U.S. gasoline consumption, and almost 80 percent of the nation's production of gasoline and blendstock. Although as Figure 6-14 shows the central region was a minor net exporter of gasoline as recently as 2007, it now exports some 800,000 barrels per day of gasoline and blendstock (primarily to Mexico and other Latin American countries) and has accounted for virtually all of the recent growth in U.S. exports of these two categories of refined products. Recent press reports indicate that firms are currently making significant new investments to add refining capacity on the Gulf Coast to process the growing supply of U.S. shale oil (Douglas, 2019), and with the projected future decline in U.S. consumption, any additional gasoline refined there is likely to increase U.S. exports. Thus, future decreases in gasoline consumption in the central region of the United States of the magnitude reasonably attributable to the final rule would easily allow additional gasoline exports, even in the absence of additional refinery investments.



Source: EIA, Petroleum and Other Liquids, 2019. "Gasoline" is "Finished Motor Gasoline" plus "Gasoline Blendstock," and "Consumption" is "Petroleum Product Supplied."

Figure 6-14 – U.S. Central Region (EIA PADDs 2-4) Gasoline Production, Consumption, Transfers to Rest of United States, and Net Exports

To summarize, based on changes in the various sources of supply that have accompanied recent changes in consumption within different regions of the United States, the agencies anticipate that:

- Most of any reduction in gasoline consumption resulting from the final rule that occurs on the East Coast of the United States, which currently accounts for slightly more than one-third (35 percent) of total U.S. consumption, will be met in the near term by reduced transfers of gasoline refined in other regions of the United States or lower foreign imports, and possibly by reduced domestic refining activity over the longer term;

- Most of any decline in U.S. gasoline consumption that occurs on the West Coast, which now accounts for about one-sixth (18 percent) of U.S. gasoline consumption, will be reflected in reduced gasoline refining within that region; and

- Most or all of any reduction in U.S. gasoline consumption that occurs in the Central region, which currently accounts for nearly half (47 percent) of total U.S. consumption, will be met by increasing exports to foreign markets.

With these expectations and acknowledging the uncertainty surrounding them, NHTSA concludes that assuming 50 percent of any reduction in U.S. gasoline consumption resulting from the final rule will lead to lower domestic refining activity continues to be reasonable. Thus, the agency continues to use this assumption in its central analysis from the proposal, and to examine the sensitivity of its results to varying this fraction over the entire possible range, from zero to 100 percent.

As indicated in the proposal, the agency believes that recent changes in the U.S. petroleum production situation and in the global petroleum market may justify changing its previous assumption that 90 percent of any reduction in domestic refining of crude petroleum to produce gasoline would reduce U.S. oil imports to 100 percent, meaning that changes in domestic refining activity would leave U.S. petroleum production unaffected. U.S. oil production is primarily a function of development opportunities identified during prior exploration programs, innovations in the technology for drilling and extracting crude petroleum, producer's expectations regarding future world petroleum prices, and the U.S. tax and regulatory situations surrounding petroleum exploration and production.

Crude oil is a fungible, non-perishable commodity, and can usually be transported among local oil markets around the globe at modest cost; as a consequence the price of oil in a U.S. domestic market such as Texas is highly correlated with its price in markets located in Northern Europe, the Far East, and the Middle East. In contrast, U.S. gasoline consumption depends on a broad array of factors that overlap only partially with the determinants of U.S. crude petroleum production. These include domestic economic growth and its consequences for transportation demand, current and future vehicle fuel economy, gasoline prices, excise and sales taxes levied on gasoline, technological and cultural changes, vehicle prices, and the evolution of transportation systems and the built environment.

Recognizing these differences, changes in U.S. consumption and supply of petroleum products seem likely to be reflected primarily in changes in the destination of domestically produced crude petroleum, rather than in its total volume. To the extent that lower U.S. gasoline demand affects domestic refining activity, this is likely to be reflected in larger U.S. exports of crude oil, rather than in a change in U.S. *production* of crude oil. Any changes in U.S. crude oil production would arise primarily from second-order impacts of increased domestic gasoline demand, such as local changes in the relative prices refiners pay for crude petroleum, or minor changes in global oil prices, and these second-order impacts are in turn likely to have relatively small effects on U.S. petroleum production.

For example, localized and temporary changes in production might arise in response to capacity limitations or transportation bottlenecks associated with particular regions or refineries, temporarily creating a localized market for higher-priced crude oil. However, these situations would normally be localized and prevail for only a limited time.[796] At the same time, the effects of any change in domestic petroleum consumption on world oil prices would be attenuated, because the impact of increased domestic consumption would be felt on prices and volumes supplied in the much larger global petroleum market, rather than confined to the much smaller U.S. market. Any resulting changes in global oil prices and petroleum production would inevitably be small when viewed on a world scale, and likely to prompt only minimal responses in U.S. petroleum supply.

As one indication of the likely minimal impacts of higher U.S. gasoline consumption on U.S. production of crude petroleum, EIA's *Annual Energy Outlook 2018* included a side case called "No New Efficiency Requirements," which included a freeze on U.S. fuel economy standards beginning in 2020. Comparing its results to those from the AEO 2018 reference case illustrates the insensitivity of domestic crude oil production to changes in domestic gasoline consumption, as represented in EIA's National Energy Modeling System (NEMS). Figure 6-15 below presents such a comparison, showing historical trends is U.S gasoline consumption and petroleum production, and comparing their projected future trends in the AEO 2018 Reference Case and No New Efficiency Requirements alternative. As it illustrates, the large increase in U.S. gasoline consumption under the latter scenario relative to the Reference Case is accompanied by an almost indiscernible change in U.S. crude petroleum production, for exactly the reasons described above.

[796] A recent example occurred in May 2021 when a major East Coast oil pipeline owned by Colonial Pipeline was subject to a ransomware attack which raised gasoline prices temporarily in response to regional shortages in the Southeast. *See* https://www.eia.gov/todayinenergy/detail.php?id=47996. (Accessed: February 15, 2022).

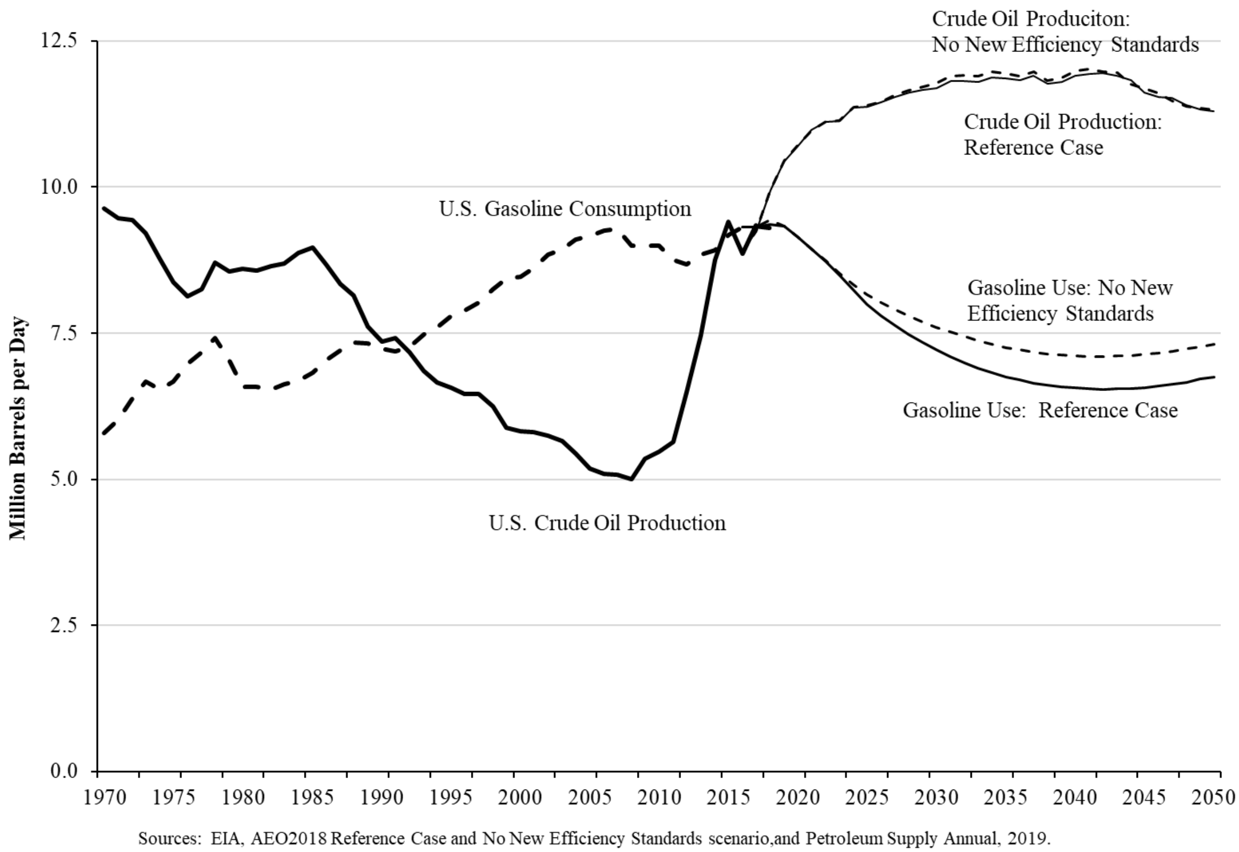


Figure 6-15 – Projected U.S. Gasoline Consumption and Crude Oil Production under AEO 2018 Reference and no New Efficiency Standards Scenario Cases

Considering the factors that influence U.S. petroleum supply and comparing EIA's forecasts of future changes in domestic petroleum production under very different levels of domestic gasoline consumption, NHTSA believes that in the context of the current global petroleum market, reductions in U.S. gasoline demand on the scale likely to result from this final rule are unlikely to prompt significant changes in domestic petroleum production, fuel refining, or net U.S. petroleum exports. Instead, they are likely to affect mainly the distribution of crude petroleum and gasoline produced within the United States between domestic consumption and U.S. exports to serve global markets, reducing the volumes supplied to U.S. markets and increasing exports. As a consequence, the agency's analysis assumes that the anticipated reduction in domestic gasoline consumption is unlikely by itself to significantly affect domestic crude oil production, gasoline refining, or U.S. exports and imports of crude petroleum. While we continue to analyze these relationships, the analysis continues to assume that 90 percent of any change in the volume of fuel refined domestically will be reflected in changes in the volume of crude petroleum imported into the United States, while the remaining 10 percent will be reflected in changes in the volume produced within the United States.[797]

6.2.4.5 Emerging Energy Security Considerations

As discussed above, energy security has traditionally referred to the nation's ability to reliably acquire petroleum in sufficient quantities to meet domestic demand, and to do so at an acceptable cost. However, as the number of electric vehicles on the road continues to increase, the concept of energy security is likely to expand to encompass the United States' ability to supply the additional electricity necessary to meet demand for the use of these vehicles. While nearly all electricity in the United States is generated through the conversion of domestic energy sources, the electric vehicles also require sophisticated batteries to store and deliver that electricity. Currently, the most commonly used vehicle battery chemistries include materials that are either scarce or expensive, are sourced from overseas sites, and can pose environmental challenges during extraction and conversion to usable material.

Most vehicle electrification is enabled by lithium-ion batteries. Lithium-ion battery global production chains have several phases: sourcing (mining/extraction); processing/refining; cell manufacturing; battery manufacturing; installation of batteries in an EV; and recycling.[798] Because lithium-ion battery materials have a wide global diversity of origin, accessing them can pose varying geopolitical challenges.[799] The U.S. International Trade Commission (USITC) recently summarized 2018 data from the U.S. Geological Survey on the production/sourcing of the four key lithium-ion battery materials, as shown in Table 6-24.

Table 6-24 – Lithium-ion Battery Materials Mining Production, 2018[800]

Lithium-ion Battery Material Ores and Concentrates	Countries with Largest Mining Production (share of global total)	U.S. Mining Production (share of global total)
Lithium	Australia (60 percent), Chile (19 percent), China (9 percent), Argentina (7 percent)	USITC staff estimates less than 1 percent
Cobalt	Democratic Republic of Congo (64 percent), Cuba (4 percent), Russia (4 percent), Australia (3 percent)	Less than 0.5 percent
Graphite (natural)	China (68 percent), Brazil (10 percent), India (4 percent)	0 percent

[797] The agency conducted a sensitivity analysis to examine how much an impact changing its assumption that the agency assumed that 90 percent of any change in the volume of fuel refined domestically would be reflected in changes in the volume of crude petroleum imported into the United States to 100 percent. As explained in FRIA Chapter 7, the change produces less than a 0.1 percent change in total and net benefits.
[798] Scott, Sarah, and Robert Ireland, "Lithium-Ion Battery Materials for Electric Vehicles and their Global Value Chains," Office of Industries Working Paper ID-068, U.S. International Trade Commission, June 2020, at p. 7. *Available at* https://www.usitc.gov/publications/332/working_papers/gvc_overview_scott_ireland_508_final_061120.pdf (Accessed: February 15, 2022) and in the docket for this rulemaking, NHTSA-2021-0053.
[799] *Id*. at p. 8.
[800] *Id*., citing U.S. Geological Survey, Mineral Commodity Summaries, Feb. 2019.

Lithium-ion Battery Material Ores and Concentrates	Countries with Largest Mining Production (share of global total)	U.S. Mining Production (share of global total)
Nickel	Indonesia (24 percent), Philippines (15 percent), Russia (9 percent)	Less than 1 percent

Of these sources, the USITC notes that while "lithium has generally not faced political instability risks," "because of the [Democratic Republic of Congo's] ongoing political instability, as well as poor labor conditions, sourcing cobalt faces significant geopolitical challenges."[801] Nickel is also used extensively in stainless steel production, and much of what is produced in Indonesia and the Philippines is exported to China for stainless steel manufacturing.[802] Obtaining graphite for batteries does not currently pose geopolitical obstacles, but the USITC notes that Turkey has great potential to become a large graphite producer, which would make its political stability a larger concern.[803] Thus, as the final column of Table 6-24 illustrates, the United States is currently at a disadvantage with respect to domestic sources and capacity of some materials critical for producing electric vehicle batteries.

For materials processing and refining, China is the largest importer of unprocessed lithium, which it then transforms into processed or refined lithium.[804] It is also the leading producer of refined cobalt (with Finland a distant second),[805] one of the leading producers of primary nickel products (along with Indonesia, Japan, Russia, and Canada), and one of the leading refiners of nickel into nickel sulfate, the chemical compound used for cathodes in lithium-ion batteries.[806] Finally, China is also one of the leading processors of graphite intended for use in lithium-ion batteries as well.[807] In all regions, increasing attention is being given to vertical integration in the lithium-ion battery industry from material extraction, mining and refining, battery materials, cell production, battery systems, reuse, and recycling. The United States is lagging in upstream capacity; although the United States has some domestic lithium deposits, it has very little capacity in mining and refining any of the key raw materials. However, there can be benefits and drawbacks in terms of environmental consequences associated with increased domestic mining, refining, and battery production.

President Biden issued an E.O. on "America's Supply Chains," aiming to strengthen the resilience of America's supply chains, including those for automotive batteries.[808] Reports are to be developed within one year of issuance of the E.O., and the agency will monitor these findings as they develop. However, obstacles to increasing domestic capacity for these critical materials have already emerged. The proposed development of the Rhyolite Ridge lithium deposits in Nevada, one of the most significant known deposits in the United States, has been complicated by the discovery of an indigenous species of buckwheat, Tiehm's buckwheat flower. The Center

[801] *Id*. at p. 8, 9.
[802] *Id*. at p. 9.
[803] *Id*.
[804] *Id*.
[805] *Id*. at p. 10.
[806] Id.
[807] *Id*.
[808] E.O. 14017, "America's Supply Chains," Feb. 24, 2021. 86 Fed. Reg. 11849 (Mar. 1, 2021).

for Biological Diversity (CBD) opposed the development of the mine and submitted an emergency petition to the U.S. Fish and Wildlife Service to protect Tiehm's buckwheat under the Endangered Species Act and further complicate permitting of the proposed lithium mine. CBD's Patrick Donnelly was quoted as saying, "The Biden administration is at a crossroads and the Tiehm's buckwheat is a symbol of our times." On June 4, 2021, Tiehm's buckwheat flower was designated an endangered species.[809]

China and the EU are also major consumers of lithium-ion batteries, along with Japan, Korea, and others. Lithium-ion batteries are used not only in light-duty vehicles, but in many portable consumer electronic devices, and are eventually likely to be used in other forms of transportation as well. Thus, securing sufficient batteries to enable large-scale shifts to electrification in the U.S. light-duty vehicle fleet may face new challenges as vehicle companies compete with other new sectors, and the transition to electric vehicles may increasingly call for the development of domestic sources of critical raw materials and production capacity. The agency will continue to monitor these issues going forward and determine whether access to these materials constitutes a new form of energy security for which future analyses must account.

6.2.5 Changes in Labor Utilization

Changes in vehicle prices and fuel costs resulting from CAFE technologies will affect new vehicle sales, which will in turn affect employment associated with those sales. Conversely, production of new technologies used to improve fuel economy will create new demand for production. NHTSA's analysis includes estimates of automobile industry employment under each of the regulatory alternatives.

The following sections describe the assumptions, data and calculations used to estimate the final rule's impact on labor utilization. Chapter 6.2.5.1 characterizes the baseline and describes the data used to obtain the relevant labor estimates for the CAFE Model inputs. Chapter 6.2.5.2 describes how NHTSA estimates labor within the three employment categories included in the analysis—dealership labor, assembly labor, and labor associated with additional fuel saving technologies. Chapter 6.2.5.2.4 contains a description of the calculations done to integrate the labor estimates into the CAFE Model.

6.2.5.1 Labor Utilization Assumptions and Data Description

The analysis considers the direct labor effects that the CAFE standards have across the automotive sector. The facets of the automotive labor market considered include (1) dealership labor related to new light-duty vehicle unit sales; (2) assembly labor for vehicles, engines, and transmissions related to new vehicle unit sales; and (3) labor related to mandated additional fuel savings technologies, accounting for new vehicle unit sales. The labor utilization analysis is intentionally narrow in its focus and does not represent an attempt to quantify the overall labor or economic effects of this rulemaking.

[809] Department of the Interior, U.S. Fish and Wildlife Service, Notification of Finding on a Petition to List the Tiehm's Buckwheat as Threatened or Endangered. 86 Fed. Reg. 29975 (Jun. 4, 2021).

All labor effects are estimated and reported at a national level, in person-years, assuming 2,000 hours of labor per person-year.[810] These labor hours are not converted into monetized values because we assume that the labor costs are included into a new vehicle's purchasing price. The analysis estimates labor effects from the forecasted CAFE Model technology costs and from review of automotive labor for the MY 2020 fleet. NHTSA uses information about the locations of vehicle assembly, engine assembly, and transmission assembly, and the percent of U.S. content of vehicles collected from American Automotive Labeling Act (AALA) submissions for each vehicle in the reference fleet.[811] The analysis assumes the portion of parts that are made in the United States will remain constant for each vehicle as manufacturers add fuel-savings technologies. This should not be misconstrued as a prediction that the percentage of U.S. made parts—and by extension U.S. labor— will remain constant in actuality, but rather that the agency does not have a clear basis to project where future productions may shift.

From this foundation, the CAFE Model estimates automotive labor effects after estimating how manufacturers could add fuel economy technology and then estimating impacts on future sales of passenger and light trucks. The model estimates sales in response to the different regulatory alternatives, by considering changes in new vehicle prices and new vehicle fuel economy levels.[812] As vehicle prices rise and fuel consumption falls, we expect vehicle sales to be affected. For this analysis, we assume that if manufacturers sell fewer vehicles, the manufacturers may need less labor to produce the vehicles and dealers may need less labor to sell the vehicles. However, as manufacturers add equipment to each new vehicle, the industry will require labor resources to develop, sell, and produce additional fuel-saving technologies.[813] We also account for the possibility that new standards could shift the relative shares of passenger cars and light trucks in the overall fleet (see Chapter 4.2.1.3). Since the production of different vehicles involves different amounts of labor, this shift impacts the quantity of estimated labor. We take into account the anticipated changes in vehicle sales, shifts in the mix of passenger cars and light trucks, and the addition of fuel-savings technologies that result from the regulation.

For this analysis, NHTSA assumes that some observations about the production of MY 2020 vehicles will carry forward into the future. We further assume that assembly labor hours per unit will remain at estimated MY 2020 levels for vehicles, engines, and transmissions, and that the factor between direct assembly labor and parts production labor will remain the same. NHTSA makes these simplifying assumptions for modeling purposes and recognizes that they may not reflect actual automotive practices. When considering shifts from one technology to another, we assume that revenue per employee from suppliers and original equipment manufacturers will remain in line with MY 2020 levels, even as manufacturers add fuel-saving technologies and experience cost reductions from learning.

NHTSA focuses this analysis on automotive labor because adjacent employment factors and consumer spending factors for other goods and services are uncertain and difficult to predict. We do not consider how direct labor changes may affect the macro economy and potentially change employment in adjacent industries. For instance, we do not consider possible labor

[810] The agencies recognize a few local production facilities may contribute meaningfully to local economies, but the analysis reports only on national effects.
[811] 49 CFR part 583.
[812] *See* Chapter 4.2.1.
[813] For the purposes of this analysis, NHTSA assumes a linear relationship between labor and production volumes.

changes in vehicle maintenance and repair, nor does it consider changes in labor at retail gas stations. We also do not consider possible labor changes due to raw material production, such as production of aluminum, steel, copper, and lithium, nor does NHTSA consider possible labor impacts due to changes in production of oil and gas, ethanol, and electricity.

Finally, NHTSA makes no assumptions regarding part-time-level of employment in the broader economy and the availability of human resources to fill positions. When the economy is at full employment, a fuel economy regulation is unlikely to have much impact on net overall U.S. employment; instead, labor would primarily be shifted from one sector to another. These shifts in employment impose an opportunity cost on society, as regulation diverts workers from other market-based activities in the economy. In this situation, any effects on net employment are likely to be transitory as workers change jobs (e.g., some workers may need to be retrained or require time to search for new jobs, while short-term labor shortages in some sectors or regions could result in firms bidding up wages to attract workers). On the other hand, if a regulation comes into effect during a period of less-than-full employment, a change in labor demand due to regulation would affect net overall U.S. employment because the labor market is not in equilibrium. Schmalensee and Stavins point out that net positive employment effects are possible in the near term when the economy is at less than full employment due to the potential hiring of idle labor resources by the regulated sector to meet new requirements (e.g., to install new equipment) and new economic activity in sectors related to the regulated sector longer run.[814] However, the net effect on employment in the long run is more difficult to predict and will depend on the way in which the related industries respond to regulatory requirements. For that reason, we do not include multiplier effects but instead focus on labor impacts in the most directly affected industries, which would face the most concentrated labor impacts.

The data used for these calculations include the National Automotive Dealers Association (NADA) annual report[815] and AALA reports, which are available on the NHTSA website.[816] The NADA report includes information regarding dealership employment related to new light duty vehicle sales, which serves as the basis for estimating dealership labor hours. The AALA reports list the passenger vehicles labeled with their percent U.S./Canadian parts content, the source of their engine and transmission, and the location of final assembly. These values serve as the basis for estimating final assembly and parts production labor.

6.2.5.2 Estimating Labor for Fuel Economy Technologies, Vehicle Components, Final Assembly, and Retailers

The following sections discuss NHTSA's approaches to estimating the individual factors related to dealership labor, final assembly labor and parts production, and fuel economy technology labor.

[814] Schmalensee, Richard, and Robert N. Stavins. "A Guide to Economic and Policy Analysis of EPA's Transport Rule." White paper commissioned by Exelon Corporation, March 2011 (Docket EPA-HQ-OAR-2010-0799-0676).
[815] National Automotive Dealers Association. (2016). *NADA Data 2016: Annual Financial Profile of America's Franchised New-Car Dealerships*, available at https://www.nada.org/2016NADAdata. (Accessed: February 14, 2022).
[816] https://www.nhtsa.gov/part-583-american-automobile-labeling-act-reports. (Accessed: February 14, 2022).

6.2.5.2.1 Dealership Labor

The labor utilization analysis evaluates dealership labor related to new light-duty vehicle sales and estimates the labor hours per new vehicle sold at dealerships. For the analysis, NHTSA considers changes in dealership labor related to sales, finance, insurance, and management. NHTSA does not include maintenance, repair, and parts department labor,[817] as their effect on new car sales is expected to be limited.

To estimate the labor hours dealerships spend per new vehicle sold, NHTSA uses data from the NADA annual report, which provides franchise dealer employment by department and function.

We calculate the average labor hours per new vehicle sold by using several values provided in the NADA annual report, including the total number of employees at dealerships, the percentages of employees involved in sales, the percentage of supervisors, new and total sales values, and the number of new vehicles sold in dealerships. We estimate that slightly less than 20 percent of dealership employees' work relates to new vehicle sales (the remaining approximately 80 percent of work is related to service, parts, and used car sales). Using these values, we estimate the number of employees involved with new vehicle sales, either as salespeople or in supervisory positions. Equation 6-11 shows how the final labor hours per vehicle value is calculated.

$$labor\ hours\ per\ new\ vehicle\ sold\ = \frac{annual\ labor\ hours * new\ vehicle\ sales\ jobs}{new\ vehicles\ sold}$$

Where:
Annual labor hours = hours of labor assumed per employee (2,000)
New vehicle sales jobs = number of employees estimated to be involved with new vehicle sales, in salesperson or supervisory positions
New vehicles sold = total number of new vehicles sold in dealerships

Equation 6-11 – Calculation of Labor Hours per New Vehicle Sold

We estimate that on average, dealership employees working on new vehicle sales labor for 27.8 hours per new vehicle sold. This labor hours per new vehicle value can be found in the Market Data file. For the CAFE Model's total jobs outputs, dealership labor scales directly with sales. See Chapter 6.2.5.2.4 for further discussion of these outputs.

6.2.5.2.2 Final Assembly Labor and Parts Production

As new vehicle sales increase or decrease, the amount of labor required to assemble parts and vehicles changes accordingly. NHTSA evaluates how the quantity of assembly labor and parts production labor will increase or decrease in the future as new vehicle unit sales increase or decrease. As a result of the analysis, manufacturing and assembly jobs scale directly with new vehicle unit sales, adjusted for origin of manufacturer. As part of this analysis, NHTSA identifies specific assembly locations for final vehicle assembly, engine assembly, and

[817] These are other labor components reported by the NADA's reports. For instance, a dealership might have a department dedicated to vehicle parts and body shop services.

transmission assembly for each MY 2020 vehicle, to determine the number of assembly labor hours relevant to U.S. employment. In some cases, manufacturers assemble products in more than one location, and the analysis identifies such products and considers parallel production in the labor analysis. For context, Figure 6-16 shows the average percent of U.S. (and Canadian) content, weighted by sales, of passenger cars and light trucks in MY 2020.

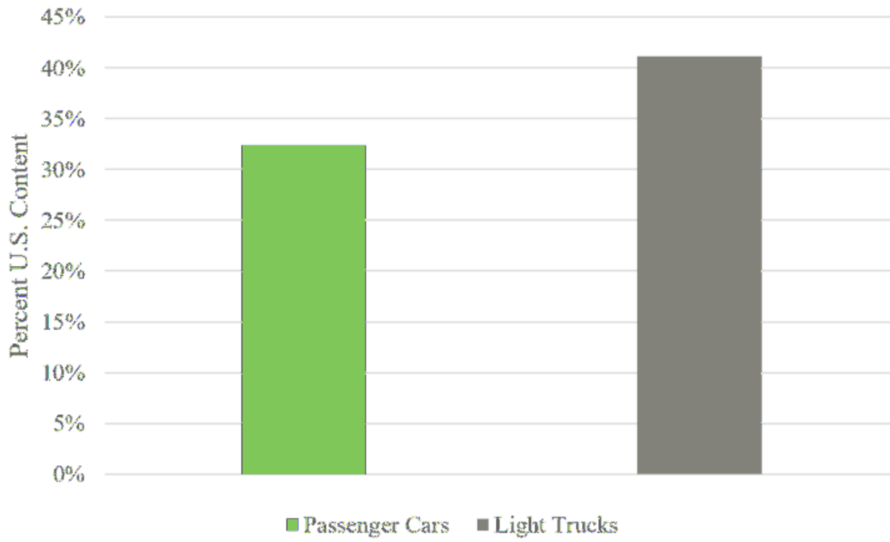


Figure 6-16 – Sales Weighted Percent U.S. Parts Content by Regulatory Class (MY 2020)

We estimate average direct assembly labor per vehicle (30 hours), per engine (four hours), and per transmission (five hours), based on a sample of U.S. assembly plant employment and production statistics and other publicly available information. NHTSA uses the AALA reports described in Chapter 6.2.5.1 to determine the assembly location of the final vehicle, engine, and transmission.[818]

NHTSA uses the assembly locations and the averages for labor per vehicle to estimate U.S. assembly labor hours for each vehicle in the Market Data file. U.S. assembly labor hours per vehicle range from as high as 39 hours if the manufacturer assembles the vehicle, engine, and transmission at U.S. plants, to as low as zero hours if the manufacturer imports the vehicle, engine, and transmission. Equation 6-12 shows the how NHTSA calculates the U.S. assembly employment hours associated with each vehicle in the Market Data file.

$$\begin{aligned} U.S.\,Assembly\ Employment\ hours \\ &= (Vehicle\ Assembly\ location * 30) + (Engine\ Assembly\ location * 4) \\ &+ (Transmission\ Assembly\ location * 5) \end{aligned}$$

Where:
Vehicle assembly location = Portion of U.S. content, 1 = fully U.S.
Engine assembly location = Portion of U.S. content, 1 = fully U.S.
Transmission assembly location = Portion of U.S. content, 1 = fully U.S.

[818] https://www.nhtsa.gov/part-583-american-automobile-labeling-act-reports. (Accessed March 26, 2022).

Equation 6-12 – Calculation of U.S. Assembly Employment Hours

The analysis also considers labor for parts production. We surveyed motor vehicle and equipment manufacturing labor statistics from the U.S. Census Bureau, the Bureau of Labor Statistics, and other publicly available sources. We found that the historical average ratio of vehicle assembly manufacturing employment to employment for total motor vehicle and equipment manufacturing for new vehicles was roughly constant over the period from 2001 through 2013, at a ratio of 5.26.[819] Observations from 2001-2013 included many combinations of technologies and technology trends, and many economic conditions, yet the ratio remained about the same over time. Accordingly, we scaled up estimated U.S. assembly labor hours by a factor of 5.26 to consider U.S. parts production labor in addition to assembly labor for each vehicle. The estimates for vehicle assembly labor and parts production labor for each vehicle scaled up or down as unit sales scaled up or down over time in the CAFE Model.

6.2.5.2.3 Fuel Economy Technology Labor

As manufacturers spend additional dollars on fuel-saving technologies, parts suppliers and manufacturers require labor to bring those technologies to market. Manufacturers may add, shift, or replace employees in ways that are difficult for the agencies to predict. However, it is expected that the revenue per labor hour at original equipment manufacturers (OEMs) and suppliers will remain about the same as in MY 2020 even as manufacturers include additional fuel-saving technology. To estimate the average revenue per labor hour at OEMs and suppliers, the analysis looked at financial reports from publicly traded automotive businesses.[820] Based on recent figures, NHTSA estimates that OEMs will add one labor year per each $633,066 increment in revenue and that suppliers will add one labor year per $247,648 in revenue.[821]

NHTSA applies these global estimates to all revenues, and the share of U.S. content is applied as a later adjustment.[822] NHTSA assumes that these ratios will remain constant for all technologies rather than that the increased labor costs would be shifted toward foreign countries. However, NHTSA acknowledges that this simplifying assumption might not always hold true. For instance, domestic manufacturers may react to increased labor costs by searching for lower-cost labor in other countries.

The additional labor hours associated with fuel-saving technology are calculated by the CAFE Model based on the values seen in Equation 6-13 and reported as part of the total labor hour outputs (see the Vehicles Report).

[819] NAICS Code 3361, 3363.

[820] The analysis considered suppliers that won the Automotive News "PACE Award" from 2013-2017, covering more than 40 suppliers, more than 30 of which are publicly traded companies. Automotive News gives "PACE Awards" to innovative manufacturers, with most recent winners earning awards for new fuel-savings technologies.

[821] The analysis assumed incremental OEM revenue as the RPE for technologies, adjusting for changes in sales volume. The analysis assumed incremental supplier revenue as the technology cost for technologies before RPE mark-up, adjusting for changes in sales volume.

[822] U.S. content information is found in the AALA reports discussed in Chapter 6.2.5.1.

$$\begin{aligned} &\mathit{Fuel\ economy\ tech\ labor\ hours} \\ &\quad = \left(\frac{\mathit{Vehicle\ tech\ cost}}{\mathit{OEM\ revenue}} + \frac{\frac{\mathit{Vehicle\ tech\ cost}}{\mathit{Supplier\ revenue}}}{\mathit{RPE}}\right) * \mathit{Percent\ US\ content} \\ &\quad * \mathit{Annual\ labor\ hours} \end{aligned}$$

Where:
Fuel economy tech labor hours = labor hours spent on additional fuel-saving technologies (for both OEMs and suppliers)
Vehicle tech cost = cost of technology for each vehicle in the analysis, reported in the CAFE Model outputs
OEM revenue = increment in OEM revenue estimated to correspond to the addition of one labor year
Supplier revenue = increment in supplier revenue estimated to correspond to the addition of one labor year
RPE = revenue per employee
Percent U.S. content = percent of vehicle components built within the United States
Annual labor hours = number of hours assumed to correspond to one labor year

Equation 6-13 – Calculation for Fuel Economy Technology Labor Hours

6.2.5.2.4 Labor Calculations in the CAFE Model

NHTSA estimates the total labor effect as the sum of the three components described in the previous chapters: changes to dealership hours, final assembly and parts production, and labor for fuel-economy technologies (at OEMs and suppliers) that are due to the change in CAFE standards. The CAFE Model calculates additional labor hours for each vehicle, based on current vehicle manufacturing locations, simulation outputs for additional technologies, and sales changes. While NHTSA does not consider a multiplier effect of all U.S. automotive-related labor on non-auto related U.S. jobs, the analysis does incorporate a "global multiplier" that can be used to scale up or scale down the total labor hours. We set the value of this parameter at 1.00 (see the Parameters file). Equation 6-14, Equation 6-15, and Equation 6-16 illustrate how the CAFE Model calculates base hours (assembly and dealership), innovation hours (associated with additional fuel-saving technology), and total hours, respectively. The labor utilization analysis's final outputs, total U.S. jobs and thousands of labor hours, can be found in the compliance report and the Vehicles Report.

$$\begin{aligned} \mathit{Base\ hours} = (&\mathit{Vehicle\ U.S.Assembly\ Hours} * \mathit{U.S.Assembly\ Multiplier} \\ &+ \mathit{Vehicle\ Dealership\ Hours}) \end{aligned}$$

Equation 6-14 – Calculation of Base Work Hours per Vehicle

$$Innovation\ hours = \frac{Vehicle\ tech\ cost}{OEM\ revenue} + \frac{Vehicle\ tech\ costs}{Supplier\ \frac{revenue}{RPE}} * Percent\ US\ content * Annual\ labor\ hours$$

Equation 6-15 – Calculation of Innovation Hours per Vehicle

$$Total\ hours = (Base\ hours + Innovation\ hours) * Vehicle\ Sales$$

Equation 6-16 – Calculation of Total Labor Hours per Vehicle

Section S5.9 of the CAFE Model documentation (U.S. Employment) also describes these U.S. labor utilization calculations.

See Chapter 6.3.3 of the FRIA for further discussion of the total labor impacts associated with this rulemaking analysis.

7 Safety Impacts of Regulatory Alternatives

The primary objective of CAFE standards is to achieve maximum feasible fuel economy, thereby reducing fuel consumption. In setting standards to achieve this intended effect, the potential of the standards to affect vehicle safety is also considered. As a safety agency, NHTSA has long considered the potential for adverse safety consequences when establishing CAFE standards. Safety consequences include all impacts from motor vehicle crashes, including fatalities, nonfatal injuries, and property damage.

Safety trade-offs associated with increases in fuel economy standards have occurred in the past—particularly before CAFE standards became attribute-based—because manufacturers chose to comply with stricter standards by building smaller and lighter vehicles.[823] Historically, in cases where fuel economy improvements were achieved through reductions in vehicle size and mass, the smaller, lighter vehicles did not protect their occupants as effectively in crashes as larger, heavier vehicles, on average. Although NHTSA now uses attribute-based standards, in part to reduce the incentive to downsize vehicles to comply with CAFE standards, the agency continues to be mindful of the possibility of safety-related trade-offs.

This safety analysis includes the comprehensive measure of safety impacts from three factors:

1. **Changes in Vehicle Mass.** Similar to previous analyses, NHTSA analyzes whether there is any safety impact of changes in vehicle mass made to reduce fuel consumption and comply with the standards. Statistical analysis of historical crash data indicates reducing mass in heavier vehicles generally improved safety, while reducing mass in lighter vehicles generally reduced safety. NHTSA's crash simulation modeling of vehicle design concepts for reducing mass revealed similar effects. As discussed below in this analysis, NHTSA was not able to estimate an

[823] Effectiveness and Impact of Corporate Average Fuel Economy (CAFE) Standards (NRC, 2002).

effect of changes in mass on safety with sufficient precision to distinguish them from zero at standard confidence levels accepted in the scientific literature.

2. **Impacts of Vehicle Prices on Fleet Turnover.** Vehicles have become safer over time through a combination of new safety regulations and voluntary safety improvements. The agency expects this trend to continue as emerging technologies, such as advanced driver assistance systems (ADAS), are incorporated into new vehicles. Safety improvements will likely continue regardless of changes to CAFE standards.

As discussed in Chapter 4.2, technologies added to comply with fuel economy standards have an impact on vehicle prices, therefore slowing the acquisition of newer vehicles and retirement of older ones. A delay in fleet turnover resulting from higher new vehicle prices is assumed to affect safety by slowing the penetration of new safety technologies into the fleet.

The standards also influence the composition of the light-duty fleet. As the safety provided by light trucks, SUVs and passenger cars responds differently to technology that manufacturers employ to meet the standards—particularly mass reduction—fleets with different compositions of body styles will have varying numbers of fatalities, so changing the share of each type of light-duty vehicle in the projected future fleet impacts safety outcomes.

3. **Increased driving because of better fuel economy.** The "rebound effect" predicts consumers will drive more when the cost of driving declines. More stringent standards reduce vehicle operating costs, and in response, some consumers may choose to drive more. Additional driving increases exposure to risks associated with motor vehicle travel, and this added exposure translates into higher fatalities and injuries.

The contributions of the three factors described above generate the differences in safety outcomes among regulatory alternatives.[824] The agency's analysis makes extensive efforts to allocate the differences in safety outcomes between the three factors. Fatalities expected during future years under each alternative are projected by deriving a fleet-wide fatality rate (fatalities per vehicle mile of travel) that incorporates the effects of differences in each of the three factors from baseline conditions and multiplying it by that alternative's expected VMT. Fatalities are converted into a societal cost by multiplying fatalities with the DOT-recommended VSL supplemented by economic impacts that are external to VSL measurements. Traffic injuries and property damage are also modeled directly using the same process and valued using costs that are specific to each injury severity level.

Only two of the factors—changes in vehicle mass and in the composition of the light-duty fleet in response to changes in vehicle prices—impose increased risks on drivers and passengers that are not compensated for by accompanying benefits. In contrast, increased driving associated

[824]The terms safety performance and safety outcome are related but represent different concepts. When we use the term safety performance, we are discussing the intrinsic safety of a vehicle based on its design and features, while safety outcome is used to describe whether a vehicle has been involved in a crash and the severity of the accident. While safety performance influences safety outcomes, other factors such as environmental and behavioral characteristics also play a significant role in safety outcomes.

with the rebound effect is a consumer choice that reveals the benefit of additional travel. Consumers who choose to drive more have apparently concluded that the utility of additional driving exceeds the additional costs for doing so—including the crash risk that they perceive additional driving involves. As discussed in Chapter 7.4, the benefits of rebound driving are accounted for by offsetting a portion of the added safety costs.

The agency categorizes safety outcome through three measures of light-duty vehicle safety: fatalities to occupants occurring in crashes, serious injuries sustained by occupants, and the number of vehicles involved in crashes that cause property damage but no injuries. Counts of fatalities to occupants of automobiles and light trucks are obtained from NHTSA's Fatal Accident Reporting System (FARS). Estimates of the number of serious injuries to drivers and passengers of light-duty vehicles are tabulated from NHTSA's General Estimates System (GES), an annual sampling of motor vehicle crashes occurring throughout the United States. Weights for different types of crashes were used to expand the samples of each type to estimates of the total number of crashes occurring during each year. Finally, estimates of the number of automobiles and light trucks involved in property damage-only (PDO) crashes each year were also developed using GES.

7.1 Projecting Future Fatalities and the Safety Baseline

To estimate the impact of the standards on safety, the agency uses statistical models that explicitly incorporate variation in the safety performance of individual vehicle model years. The agency uses separate models for fatalities, non-fatal injuries, and property damage to vehicles, each of which tracks vehicles from when they are produced and sold, enter the fleet, gradually age and accumulate usage (and for most vehicles, change in ownership as they age), and are ultimately retired from service. We also consider how newer technologies are likely to affect the safety of both individual vehicles and the combined fleet. The overall safety of the light-duty vehicle fleet during any future calendar year is determined by the safety performance of the individual model year cohorts comprising it at the ages they will have reached during that year, the representation of each model year cohort in that (calendar) year's fleet, and a host of external factors that fluctuate over time, such as driver demographics and behavior, economic conditions, traffic levels, and emergency response and medical care. Combining forecasts of future crash rates for individual model year cohorts at different ages with the composition of the vehicle fleet produces baseline forecasts of fatalities, non-fatal injuries, and vehicles incurring property damage. Regulatory alternatives that establish new CAFE standards for future model years change these forecasts by altering the representation of different model year cohorts making up the future light-duty fleet.

7.1.1 Historical Trends

The relationships among vehicle age, model year, and safety risks to occupants are significant, and have persisted over time. In a 2020 Research Note, NHTSA's National Center for Statistics and Analysis (NCSA) concluded that an occupant of a 7-11 year-old vehicle is 11 percent more likely to be severely injured in a crash than the driver of a vehicle 1-6 years old, after accounting for the vehicle's model year and various factors related to the severity of the crash. The increase in risk is even more pronounced for the oldest vehicles in use, with occupants of vehicles 15 years or older being 23 percent more likely to be severely injured in crashes than occupants of new vehicles (again after controlling for the model years of vehicles involved in crashes).[825]

At the same time, new vehicles have become consistently safer over time, most likely because of advancements in safety technology, like side-impact airbags, electronic stability control, and (more recently) sophisticated crash avoidance systems starting to work their way into the vehicle population. NHTSA's 2020 study showed that occupants of cars and light trucks produced in model years 1995-2011 were 15 percent more likely to sustain serious injuries in crashes than were occupants of vehicles from more recent model years (2012-18), and that occupants of pre-1987 cars and light trucks were 50 percent more likely to be seriously injured in crashes than occupants of vehicles from the most recent model years. These results account for the model year when the vehicles involved in crashes were produced and illustrate that the relationship between vehicles' age and the safety risks to their occupants when they are involved in crashes has persisted as new vehicles have become safer.

7.1.2 Model Framework

The agency's model uses an "age-period-cohort" framework, where vehicles produced during a single model year – sometimes referred to as "vintages" –represent the cohorts making up the vehicle fleet (or "population"). The safety performance of each model year cohort differs from its predecessors, as successive model years entering the light-duty vehicle fleet have generally become safer over time due to improvements in their design, increased durability resulting from changes in materials and manufacturing methods, and the effects of the agency's safety regulations. In addition, the safety performance of each individual model year cohort evolves as it ages, accumulates use, and the vehicles comprising it are acquired by new owners. The "age-period-cohort" approach disaggregates the evolution of fleet-wide safety improvements into changes over time, the evolution of each model year's safety performance from the time it is new as it ages, and the influence of factors that vary over time (such as seat and shoulder belt use) and affect the safety of all model years in the fleet as they change.[826]

The safety performance of individual model-year cohorts tends to follow a common pattern as they age, accumulate use, and for most vehicles, experience changes in ownership and locations

[825] Liu, C., & Subramanian, R. (2020, March). The relationship between passenger vehicle occupant injury outcomes and vehicle age or model year in police-reported crashes (Traffic Safety Facts Research Note. Report No. DOT HS 812 937). National Highway Traffic Safety Administration.

[826] For a detailed explanation of the rationale and methods for age-period-cohort analysis, see for example Columbia University Mailman School of Public Health, Population Health Methods: Age Period-Cohort Analysis, available at https://www.publichealth.columbia.edu/research/population-health-methods/age-period-cohort-analysis. (Accessed: February 15, 2022); and Kupper, Lawrence L. et al., ''Statistical age-period-cohort analysis: A review and critique,'' Journal of Chronic Diseases 38:10 (1985), at pp. 811–30, available at https://www.sciencedirect.com/science/article/abs/pii/0021968185901055. (Accessed: February 15, 2022). Previous applications of the age-period-cohort framework vehicle safety include Anderson, R. W. G., & Searson, D. J. (2015). Use of age-period-cohort models to estimate effects of vehicle age, year of crash and year of vehicle manufacture on driver injury and fatality rates in single vehicle crashes in New South Wales, 2003-2010. Accident Analysis and Prevention, 75: 202-210; Eun, Sang Jun (2020), "Trends in mortality from road traffic injuries in South Korea, 1983–2017: Joinpoint regression and age-period-cohort analyses," Accident Analysis and Prevention 134: 1-7; and Langley, J., Samaranayaka, A., Begg, D.J., (2013), "Age, period and cohort effects on the incidence of motorcyclist casualties in traffic crashes," Injury Prevention 19 (3), 153–57. https://doi.org/10.1136/injuryprev-2012-040345. (Accessed: February 14, 2022).

where they are driven. Historically, vehicles' safety appears to deteriorate gradually through approximately age 20, level off for some period, and in some cases improve thereafter. The causes of this pattern are not completely understood, but the agency believes that the major influences are the transition of older vehicles to ownership by habitually riskier drivers, or a shift in where vehicles are driven to geographic areas where road conditions are less safe and travel speeds higher.

Figure 7-1 illustrates the age-period-cohort framework as applied to the safety of light-duty vehicle travel. New model years introduced into the fleet have generally become progressively safer, and these improvements tend to persist throughout their lifetimes in the fleet (a cohort effect). As indicated previously, vehicles tend to gradually be involved in more frequent and dangerous accidents as they age and accumulate use, and this effect – which is surprisingly consistent across successive model years – represents an aging effect. Finally, changes in driver demographics and driving behavior, as well as external events such as gradual improvements in emergency crash response or transient periods of economic stress can affect the safety performance of the entire driver population and vehicle fleet. Such time-varying factors – which are the period effects in age-period-cohort analysis – influence fleet-wide safety *independently of and in addition to* the effects of safer new vehicles entering the fleet and the gradual aging of vehicles from previous model years. As the figure suggests, these three effects are conceptually independent, but interact in ways that combine to produce observed historical evolution in the overall safety of the light-duty vehicle fleet.

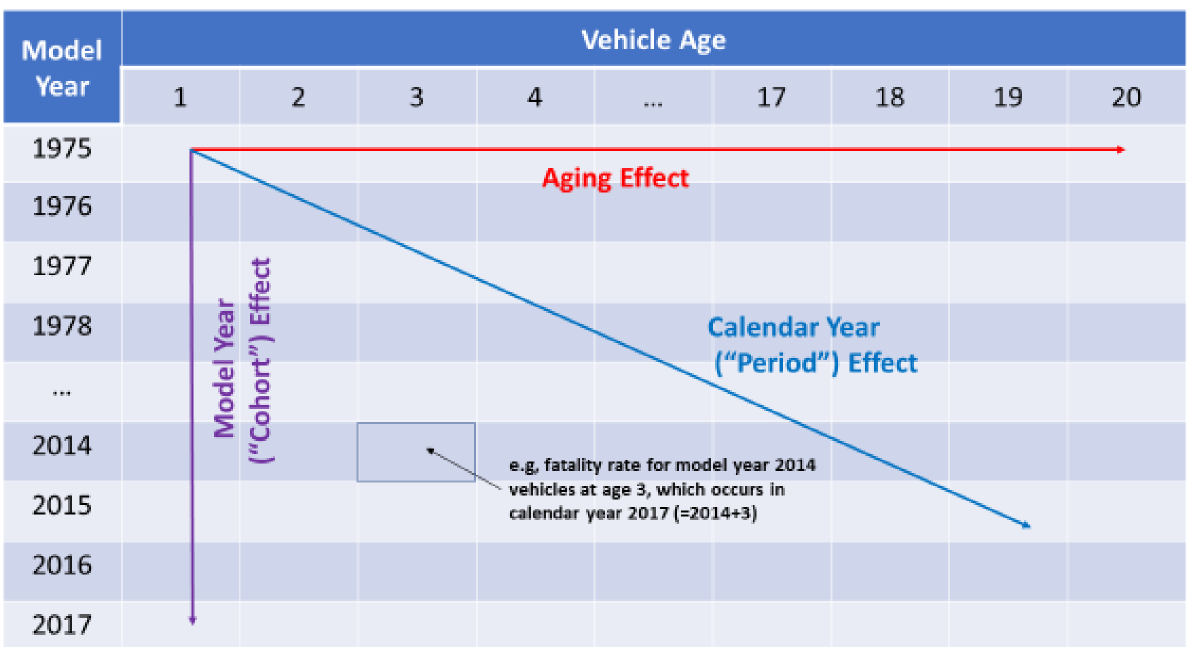


Figure 7-1 – Age, Cohort, and Period Effects on Safety of Light-Duty Vehicle Fleet

7.1.3 The Aging Effect

Figure 7-2 illustrates changes in the safety performance of selected recent model years of cars and light trucks as each model year cohort ages, using fatalities per billion miles driven as a measure of safety.[827] It shows a pattern of gradually increasing fatality rates through approximately age 20, after which fatality rates level off, and for some model years ultimately decline. Again, the increase in fatality rates is generally thought to result from transferring ownership of used vehicles to riskier drivers and driving locations, although structural fatigue with increased usage and mechanical failure also plays some small role in explaining the increase.[828] The decline in fatality rates for some very old vehicles may result because the small share of vehicles that remain in use beyond ages 20-25 tend to be owned by their original purchasers, carefully maintained, and driven on a limited basis under relatively safe conditions.

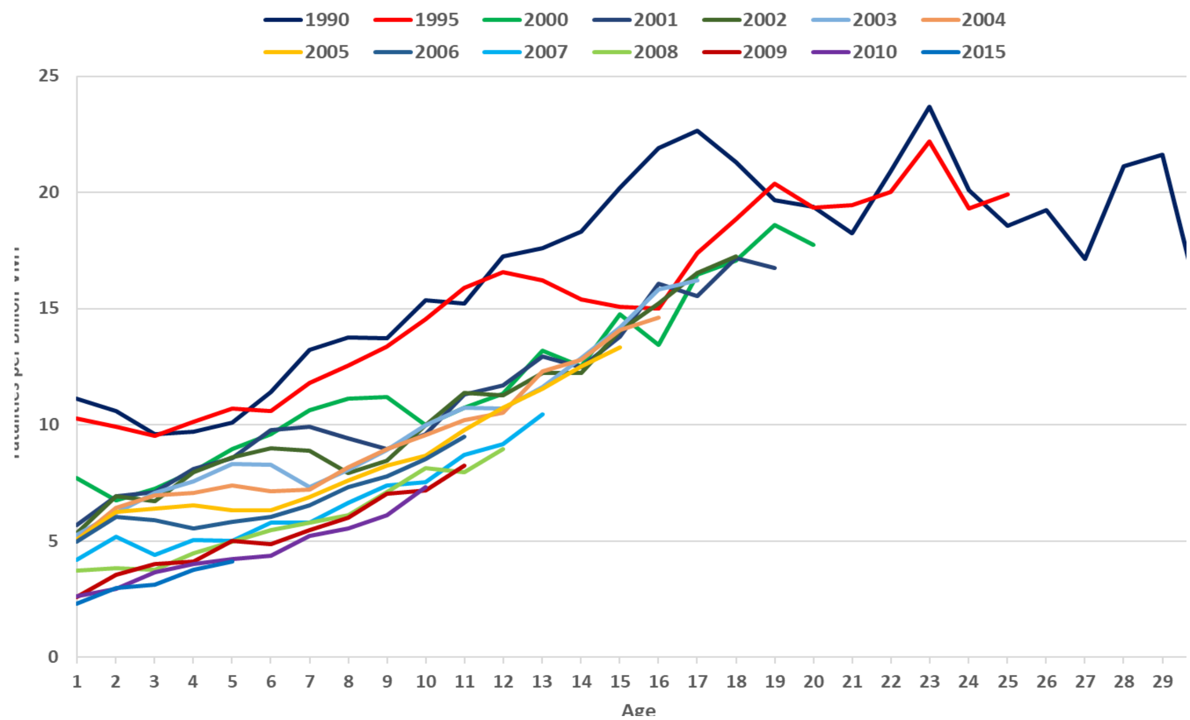


Figure 7-2 – Fatality Rates by Age for Selected Model Years

[827] Fatalities occurring among occupants of light-duty vehicles of different model years in use during each calendar year were tabulated from NHTSA's Fatal Accident Reporting System (FARS, https://www.nhtsa.gov/research-data/fatality-analysis-reporting-system-fars. (Accessed: February 14, 2022).). Fatality rates for each model year and age were estimated by calculating age as equal to (calendar year – model year) and dividing the count of fatalities for each model year and age by the number of miles that vehicles produced during that model year and remaining in use during that calendar year are estimated to be driven. The numbers of non-fatal injuries and vehicles involved in property damage-only crashes were tabulated from NHTSA's National Automotive Sampling System General Estimates System (NASS GES, https://www.nhtsa.gov/national-automotive-sampling-system/nass-general-estimates-system (Accessed: February 14, 2022)), and were converted to rates per billion miles driven using the same procedure for calculating fatality rates. Non-fatal injury and property damage only crash rates show patterns of variation over historical model years and age that are similar to those for fatalities shown in Figure 7-2.

[828] https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/811825. (Accessed: February 14, 2022).

7.1.4 Safer New Cars: The Cohort Effect

Figure 7-3 isolates the fatality rates for recent model years during the first years after each one is initially produced and sold, and enters the fleet.[829] It clearly illustrates the gradual decline in new vehicles' fatality rates over successive model years, but it also shows that this decline has proceeded in distinct steps rather than continuously. As the figure suggests, some of the largest improvements in new cars and light truck safety have coincided with the implementation of NHTSA safety regulations, including those requiring front-seat air bags (2000), side air bags (2006-08), and TPMS (2008). To reflect the historical pattern of safety improvements shown in Figure 7-3, we group successive model years that had similar fatality rates when new into a smaller number of cohorts, based on visual examination of the figure and the effective dates of NHTSA safety regulations. Grouping model years in this way also enables more reliable identification of the effect of vehicle age, since it allows some independent variation in vehicles' ages within model year cohorts during any calendar year, rather than having age be uniquely determined by the combination of calendar year and model year.

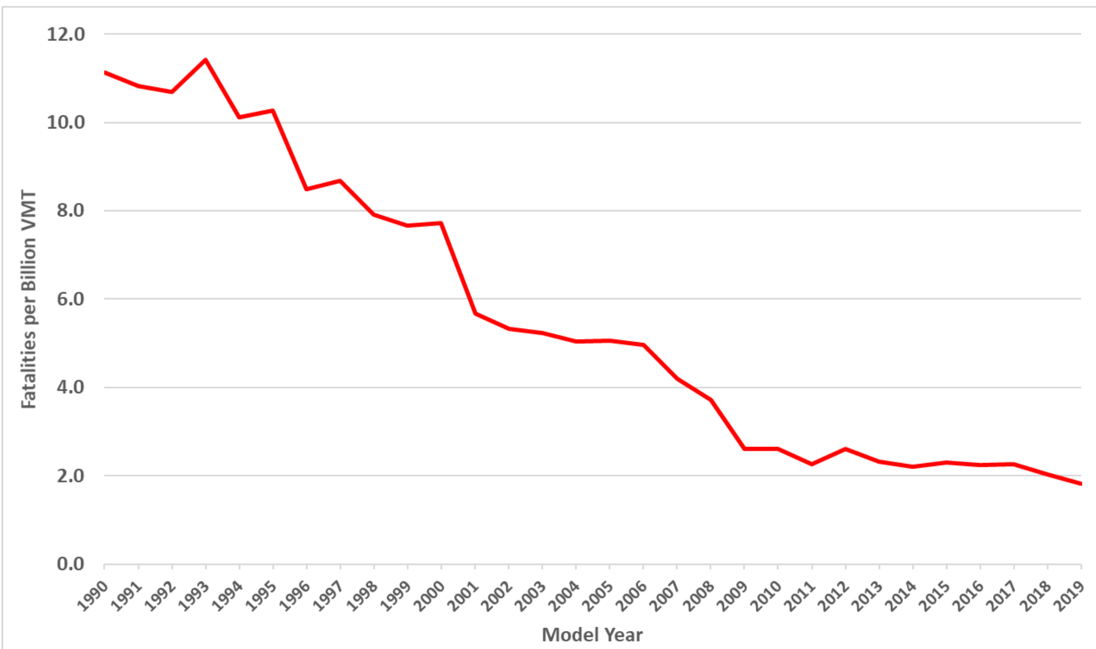


Figure 7-3 – Fatality Rates for New Light-Duty Vehicles

7.1.5 Factors that Affect Safety Over Time: Period Effects

As indicated previously, period effects are factors that vary over time and modify the gradual evolution in safety that results from the introduction of new, safer model year cohorts into the fleet and the effect of increasing age on their safety. Period effects can influence the safety of all model years making up the fleet during the years when they occur, although they do not necessarily have the same effect on each model year's safety. One important example is the

[829] Vehicles from each successive new model year are produced and sold over a period spanning well over a single calendar year, so we use their average fatality rate for the first two years they are represented in the fleet to be sure of including most or all vehicles from each model year.

changing demographic composition of the driver population to include more older drivers and women; this trend improves overall safety because younger male drivers have historically been involved in more frequent crashes. Another period effect on safety is the gradual shift of driving from rural to urban and suburban areas, since road conditions in the latter tend to be safer and travel speeds lower, thus reducing the frequency and severity of crashes.

Other important period influences on safety include driver behavior, since factors like the use of lap and shoulder belts – which has increased steadily since they were introduced but appears to be reaching a plateau – significantly reduce the severity of injuries vehicle occupants suffer in crashes. Other aspects of driver behavior such as driving under the influence of alcohol (which continues to decline) and using electronic devices such as smart phones that distract drivers' attention (which is increasing rapidly, particularly among younger drivers) are both linked to more frequent involvement in crashes. Still other period effects include gradual improvements in road design that reduce crash rates, such as wider travel lanes, more gradual curves, and fewer roadside obstructions. Faster response to crash situations by emergency vehicles and personnel, together with improved effectiveness of emergency medical treatment, also appear to have reduced the consequences of injuries to occupants of vehicles involved in crashes.

7.1.6 Measuring Safety

The agency developed separate statistical models to project future rates of fatalities, non-fatal injuries, and light-duty vehicles' involvement in property damage-only crashes per billion vehicle-miles of travel. Fatality rates were calculated by dividing fatalities to occupants of vehicles from each model year in use during a calendar year by the total number of miles those vehicles were estimated to be driven. As discussed in detail in Chapter 4.3, the number of vehicle-miles (VMT) driven was estimated by multiplying the number of vehicles originally produced during each model year that remain use in a subsequent calendar year by the average number of miles that vehicles of their age are driven annually.[830] This produces fatality rates by calendar year and model year for each calendar year from 1990-2019; the model years included range from 1975 (the earliest for which reliable registration data were available) to 2019 (the newest model year in the fleet during calendar year 2019). A similar process was used to calculate non-fatal injuries to light-duty vehicle occupants per billion miles driven, and the number of cars and light trucks involved in property damage-only crashes per billion miles driven.

7.1.7 Model Specification and Estimation

Defining a model year's age as the number of calendar years since its introduction (age = calendar year – model year) transforms the fatality, non-fatal injury, and property damage rates from unique combinations of calendar year and model year to combinations of calendar year and age. Viewed from this perspective, each model year's safety is measured at different ages throughout its lifetime. Combining these data for a succession of model years makes it possible to isolate model year and age-specific effects on overall safety. However, a model year's fatality rate during any subsequent calendar year will also reflect period-specific influences that are

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[830] A model year's age during a past calendar year is equal to the difference between that calendar year and that model year. For example, vehicles produced during model year 2000 were age 10 during calendar year 2010, since 2010-2000 = 10.

unique to that calendar year. Because each model year has a unique age during the calendar year when that specific combination of period effects prevailed, however, it is impossible to disentangle aging and period effects on any model year's safety.[831]

Common approaches to overcoming this problem include constraining the effects of multiple cohorts, ages, or time periods to be identical, specifying the model to be non-linear in age or other parameters, and using measures that vary over calendar years (instead of a simple count of calendar years elapsed) to capture period effects. We use a combination of these approaches; as noted previously, we first group successive model years with similar fatality rates in their first year of use into "safety cohorts." This introduces some independent variation between model year and age, because during any calendar year each of the model years grouped together in a safety cohort have different ages, which facilitates measuring independent cohort and aging effects. Next, we include both age and its squared value as explanatory variables, in order to capture the leveling-off of fatality rates as model years approach age 20 as shown in Figure 7-2.

We attempted to use various measures likely to affect all vehicles' safety to capture period effects, including the fraction of drivers using lap and shoulder belts, the fraction driving under the influence of alcohol, the fraction using hand-held electronic devices while driving, the proportion of licensed drivers who are male and under the age of 25 (historically the riskiest cohort of drivers), and the fraction of light-duty vehicle travel in rural areas.[832] A major complication with these measures is that they are closely correlated over the period we analyzed, which makes it difficult to disentangle their separate effects. Table 7-1 shows the pairwise correlations among these period-effect measures, and as it illustrates, many of these are extremely high. Thus, even after controlling for the effects of model year and age, it is extremely difficult to isolate the independent contributions of these individual factors.

We use model years from 1975 through 2019 as a panel whose members are observed at different ages ranging from their first year in use (age=1) to an upper limit of 40 and employ fixed effects to represent individual model years.[833] Because the estimation period is shorter than 40 years, no single model year can be observed throughout its entire lifetime, but multiple model years are observed at every age over the entire range, so the effect of age should be measured reliably. As discussed previously, we group successive model years with similar fatality rates during their first year in use into "safety regimes," and constrain the fixed effects for the model years making up each regime to be identical. This provides some variation in the age of vehicles making up each regime during any calendar year, which improves the models' ability to measure the independent effects of age and period variables. We group 30 model years used in the models for fatality rates into 9 safety regimes, with some regimes corresponding to

[831] Viewed another way, defining age = calendar year – model year means that there can be independent variation in only two of the three variables (since they uniquely determine the third), so it is impossible to identify their three separate effects on safety.
[832] We were unable to obtain useful measures of roadway design parameters or road conditions that would be expected to affect safety. Such measures tend to be reported for individual road and highway segments or routes, making it difficult to combine these data into aggregate measures that describe overall driving conditions likely to affect safety and how those conditions vary by calendar year. Nor could we identify satisfactory measures of incident response time or the effectiveness of emergency medical treatment in reducing the consequences of injuries occurring in motor vehicle crashes.
[833] For an introduction to this method, see Wooldridge, Jeffrey M. (2009), Introductory Econometrics: A Modern Approach, 4th ed., South-Western Cengage Learning. Chapters 13 and 14.

only a single model year and others including as many as 8 consecutive model years. For the non-fatal injury and property damage crash models, we group the 26 model years included in the sample into 5 safety regimes, each including 2 to 9 consecutive model years.

Table 7-1 – Correlations Between Time-Varying Measures Affecting Safety

Variable	Unemployment Rate	% of Licensed Drivers Male 16-24	% of VMT in Rural Areas	% of Occupants Wearing Lap and Shoulder Belts	% of Fatal Crashes Involving Drunk Driver	% of Drivers Using Hand-Held Devices
Unemployment Rate	1.00					
% of Licensed Drivers Male 16-24	0.11	1.00				
% of VMT in Rural Areas	-0.05	0.89	1.00			
% of Occupants Wearing Lap and Shoulder Belts	0.06	-0.94	-0.91	1.00		
% of Fatal Crashes Involving Drunk Driver	0.26	0.88	0.65	-0.75	1.00	
% of Drivers Using Hand-Held Devices	-0.24	0.44	0.59	-0.66	0.32	1.00

To address the difficulty presented by close correlation of the period effect measures, some model specifications substitute a linear time trend – a variable that takes the value of one in the first calendar year and increases by one in each successive calendar year – to capture the effect of their joint movement on safety. Measuring the model's dependent variables as the natural logarithm of the relevant rate (fatalities, non-fatal injuries, or involvement in property damage crashes) for each model year and age offers the advantage that a linear time trend implies a constant *percentage* decline in fatality rates each year, and this specification provides a close fit to the observed historical pattern of safety improvements. We also experimented with more complex specifications to test whether the rate of improvement in fleet-wide safety has been constant over time, including using a non-linear function of time and testing for more abrupt changes in the rate of improvement in safety during the analysis period.[834] Finally, after noting that the linear time trend did not fully capture the effects on fleet-wide safety associated with the economic recessions in 1991, 2001-2, and 2008-11, we supplemented the time trend with indicator (or "dummy") variables to capture temporary departures from the longer-term trend during those years.

With minor variations, we used this same model specification to analyze trends in non-fatal injuries per billion miles driven by cars and light trucks, and in the number of those vehicles involved in property damage only crashes per billion miles. The data used to estimate these models spanned a slightly shorter period (1990-2015), which was limited by the fact that NHTSA implemented a new crash sampling system starting in 2016, and the difficulty of using it together with the system it replaced to generate a continuous history of non-fatal and property damage crash estimates. As indicated previously, the groupings of model years into safety regimes used in these models also differed slightly from that used in the fatality rate model. Based on examination of non-fatal injury and property damage rates for new cars and light trucks, model years were grouped into 5 regimes, ranging from 2 to 9 consecutive model years, in contrast to the 9 regimes used in the fatality model.

7.1.8 Estimation Results

The estimation period for the fatality rate model spans 40 calendar years (1990-2019), while that for the non-fatal injury and property damage rate models include 36 years (1990-2015). This means that only a single model year (1990) is observed over its entire 40-year service lifetime for the fatality model, while no model year is observed throughout its entire service life for the non-fatal injury and property damage models. On average, individual model years are observed for 13-14 years, with older model years observed only during the later years of their service lives, while the most recent model years are of course observed only at the very early ages of their expected lifetimes.[835] We test several different specifications for each model, and evaluate them to determine which version is likely to provide the most reliable forecasts of safety for the future period spanned by the agency's evaluation of potential CAFE standards, which extends through 2050.

7.1.9 Fatality Rate Model

Table 7-2 summarizes estimation results for the fatality rate models. As it indicates, the fixed effects for safety regimes show the expected monotonic decline over progressively more recent model years, with surprisingly consistent reductions in new car and light truck fatality rates occurring with each move from one regime to the next. The largest reductions appear to occur in model years 2003, 2010, and 2018, although only the last of those is significantly larger than the reductions associated with the transitions between previous cohorts. The values of the diagnostic

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[834] Because the model's dependent variable is the natural logarithm of model year and age-specific fatality rates, using a linear time trend corresponds to assuming a constant *percentage* decline in fatality rates each year (rather than a constant *absolute* decline each year), and this pattern appeared to provide the best fit to the observed historical pattern of safety improvements.

[835] Although the typical observation period is considerably shorter than the maximum number of years that a model year remains in the vehicle fleet, it is only slightly shorter than the "expected" lifetime of a model year, or the length of time that a typical car or light truck remains in use after it is produced and initially sold.

statistic rho reported in the last line of the table, which measures the proportion of the total variation in fatality rates that is accounted for by differences in the models' fixed effects – indicate that the largest share represents persistent variation across model years as they age. Overall, the models replicate historical variation in fatality rates both among model years (as measured by the values of "Within R-squared") and over time ("Between R-squared") quite well.

As the results for Models 1 and 2 show, the combination of model-year fixed effects and age explain much of the variation in fatality rates over time and among model years over their lifetimes. Linear, squared, and cubed values of age all show statistically significant effects, but the effect of age cubed is empirically small and does not add measurably to the models' explanatory power, so subsequent results rely on the simpler specification that includes only age and age squared to capture the patterns shown previously in Figure 7-2.

Although not shown in the table, we experimented with interactions between model year and age to test whether the form of the aging effect on safety has changed significantly for more recent model years. Using this approach, we found statistically significant differences in the effect of age on safety across model year cohorts, with the aging effect appearing to become less pronounced for more recent model years. Because we have only observed the safety of the most recent model year grouping (which includes cars and light trucks from model years 2010 through 2019) up-to age 10, we were unable to use the estimated coefficients on the age variables for this cohort to develop reliable projections of these vehicles' safety performance throughout their entire lifetimes. Since these projections are also used to forecast the safety of future model years throughout their lifetimes, the dearth of long-term data for this age cohort required us to rely on estimates of the aging effect derived from all model years included in the analysis, rather than just the most recent ones.

Table 7-2 – Estimation Results for Fatality Rate Models

Explanatory Variables	Estimated Coefficients (Standard Errors in Parentheses; *** p<0.01, ** p<0.05, * p<0.1)											
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Constant	2.005***	2.079***	2.134***	2.699***	1.555***	2.378***	0.563	-1.011	2.077***	2.063***	2.154***	2.169***
	(0.015)	(0.020)	(0.019)	(0.080)	(0.171)	(0.317)	(0.442)	(0.710)	(0.016)	(0.014)	(0.025)	(0.030)
Model Years 1998-2002	-0.194 ***	-0.194 ***	-0.194 ***	-0.124 ***	-0.109 ***	-0.0693 ***	-0.0405 ***	-0.0371 **	-0.0563 ***	-0.0595 ***	-0.0576 ***	-0.0586 ***
	(0.012)	(0.012)	(0.011)	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)	(0.018)	(0.015)	(0.015)	(0.015)
Model Years 2003-05	-0.360 ***	-0.351 ***	-0.356 ***	-0.246 ***	-0.225 ***	-0.154 ***	-0.106 ***	-0.0992 ***	-0.135 ***	-0.139***	-0.141***	-0.143***
	(0.016)	(0.016)	(0.015)	(0.021)	(0.020)	(0.022)	(0.023)	(0.023)	(0.028)	(0.024)	(0.023)	(0.023)
Model Year 2006	-0.501 ***	-0.489 ***	-0.493 ***	-0.366 ***	-0.337 ***	-0.249 ***	-0.190 ***	-0.183 ***	-0.233 ***	-0.235***	-0.240***	-0.242***
	(0.028)	(0.027)	(0.025)	(0.030)	(0.028)	(0.030)	(0.030)	(0.030)	(0.038)	(0.032)	(0.032)	(0.032)
Model Year 2007	-0.632 ***	-0.619 ***	-0.620 ***	-0.485 ***	-0.450 ***	-0.354 ***	-0.290 ***	-0.281 ***	-0.342 ***	-0.339***	-0.345***	-0.346***
	(0.029)	(0.028)	(0.026)	(0.031)	(0.030)	(0.032)	(0.032)	(0.032)	(0.041)	(0.034)	(0.034)	(0.033)
Model Years 2008-09	-0.750 ***	-0.736 ***	-0.740 ***	-0.591 ***	-0.549 ***	-0.441 ***	-0.371 ***	-0.362 ***	-0.428 ***	-0.432***	-0.438***	-0.440***
	(0.023)	(0.022)	(0.020)	(0.028)	(0.027)	(0.031)	(0.032)	(0.032)	(0.040)	(0.034)	(0.033)	(0.033)
Model Year 2010	-0.896 ***	-0.882 ***	-0.897 ***	-0.734 ***	-0.688 ***	-0.570 ***	-0.492 ***	-0.482 ***	-0.541 ***	-0.568***	-0.574***	-0.577***
	(0.033)	(0.032)	(0.030)	(0.036)	(0.035)	(0.037)	(0.039)	(0.038)	(0.049)	(0.041)	(0.040)	(0.040)
Model Years 2011-17	-1.018 ***	-1.013 ***	-1.043 ***	-0.846 ***	-0.792 ***	-0.649 ***	-0.555 ***	-0.545 ***	-0.592 ***	-0.621***	-0.635***	-0.638***
	(0.019)	(0.018)	(0.017)	(0.032)	(0.031)	(0.038)	(0.040)	(0.039)	(0.049)	(0.041)	(0.040)	(0.040)
Model Years 2018--19	-1.316 ***	-1.355 ***	-1.359 ***	-1.111 ***	-1.038 ***	-0.851 ***	-0.727 ***	-0.721 ***	-0.775 ***	-0.804***	-0.829***	-0.832***
	(0.057)	(0.055)	(0.052)	(0.060)	(0.057)	(0.060)	(0.062)	(0.061)	(0.078)	(0.065)	(0.064)	(0.064)
Vehicle Age	0.0901 ***	0.0601 ***	0.0924 ***	0.106***	0.109***	0.122***	0.127***	0.128***	0.114***	0.115***	0.117***	0.117***
	(0.002)	(0.006)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Vehicle Age^2	-0.00193 ***	0.000753	-0.00203 ***	-0.00217 ***	-0.00219 ***	-0.00242 ***	-0.00242 ***	-0.00243 ***	-0.00203 ***	-0.00213 ***	-0.00222 ***	-0.00222 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Vehicle Age^3		-6.42e-05 ***										

Explanatory Variables	Estimated Coefficients (Standard Errors in Parentheses; *** p<0.01, ** p<0.05, * p<0.1)											
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**	**Model 12**
		(0.000)										
Unemployment Rate			-2.327 ***	-2.025 ***	-2.936 ***	-3.241 ***	-3.396 ***	-3.568 ***				
			(0.242)	(0.232)	(0.251)	(0.243)	(0.235)	(0.241)				
% Using Lap/Shoulder Belts				-0.933 ***	-0.736 ***	-1.801 ***	-0.903 ***	0.0826				
				(0.129)	(0.125)	(0.242)	(0.282)	(0.448)				
% Fatalities Involving Drunk Driver					3.240***	3.065***	0.16	1.16				
					(0.435)	(0.659)	(0.815)	(0.882)				
% Using Hand-Held Electronic Devices						-0.0467 ***	-0.0342 ***	-0.0294 ***				
						(0.007)	(0.007)	(0.007)				
% Drivers Male <25 Years							29.33***	27.63***				
							(5.171)	(5.160)				
% Rural Travel								1.642***				
								(0.583)				
Trend									-0.0217 ***	-0.0203 ***	-0.0337 ***	-0.0327 ***
									(0.002)	(0.002)	(0.004)	(0.004)
Trend^2											0.000373 ***	
											(0.000)	
Trend Shift												-0.00176
												(0.002)
Trend Shift x Trend												0.000387 ***
												(0.000)
Calendar Year 1991										0.191***	0.122**	0.107*
										(0.053)	(0.054)	(0.055)
Calendar Year 2001										0.0667	0.00872	-0.00495
										(0.044)	(0.044)	(0.046)
Calendar Year 2007										0.0469**	0.0673***	0.0650***
										(0.018)	(0.018)	(0.018)
Calendar Year 2008										-0.0166	0.00386	0.00198
										(0.018)	(0.018)	(0.018)

Explanatory Variables	Estimated Coefficients (Standard Errors in Parentheses; *** p<0.01, ** p<0.05, * p<0.1)											
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Calendar Year 2009										-0.170***	-0.150***	-0.151***
										(0.017)	(0.018)	(0.017)
Calendar Year 2010										-0.153***	-0.134***	-0.135***
										(0.017)	(0.017)	(0.017)
Observations	448	448	448	448	448	393	393	393	448	448	448	448
R-squared within (1)	0.89	0.90	0.91	0.92	0.93	0.93	0.93	0.93	0.91	0.94	0.94	0.94
R-squared between (2)	0.97	0.99	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
R-squared overall (3)	0.67	0.67	0.66	0.81	0.84	0.92	0.94	0.94	0.91	0.91	0.90	0.90
Corr (u_i, Xb) (4)	0.43	0.44	0.42	0.56	0.60	0.74	0.75	0.75	0.68	0.67	0.66	0.66
sigma_u (5)	0.42	0.42	0.43	0.36	0.34	0.28	0.25	0.24	0.26	0.27	0.28	0.28
sigma_e (6)	0.10	0.09	0.09	0.08	0.08	0.07	0.07	0.07	0.09	0.07	0.07	0.07
rho (7)	0.95	0.95	0.96	0.95	0.95	0.94	0.93	0.93	0.90	0.93	0.94	0.94

(1) Indicates proportion of variance among individual model year cohorts model accounts for.

(2) Indicates proportion of variance for all model year cohorts over time model accounts for.

(3) Indicates proportion of total variance among individual model year cohorts and over time model accounts for.

(4) Correlation between model error term and explanatory variables included in model.

(5) Standard deviation of residual terms for individual model year cohorts across time periods.

(6) Standard deviation of overall model error term.

(7) Proportion of total variance accounted for by differences among model year cohorts.

The results for Models 3 through 8 reported in Table 7-2 illustrate the challenge of incorporating the various period effect measures caused by their close correlations. Increases in the unemployment rate, which are primarily associated with the recessions occurring in 1991-92, 2001-02, and 2008-10, have the expected effect of reducing fatality rates, which is well-documented in previous research. Not surprisingly, Models 4 through 8 show that increasing use of lap and shoulder belts over time has made a major contribution to the decline in fatality rates, although growth in their use has slowed in recent years and appears to be approaching a plateau (near 90 percent). Driving under the influence of alcohol is strongly associated with higher fatality rates in Models 5 to 8, although the apparent strength of this result may largely reflect the fact that it is measured as the fraction of fatalities occurring in crashes where at least one driver showed a high alcohol blood level, so some “reverse causality” undoubtedly contributes to this result.

Models 6 to 8 in Table 7-2 appear to show that drivers’ use of hand-held electronic devices *reduces* fatality rates, but this result strongly contradicts the seemingly persuasive argument that their use distracts drivers visually, cognitively, and manually, so it must be regarded skeptically. The fact that including this measure significantly affects the estimated effect of seat belt use also suggests that its counter-intuitive estimated effect may stem from their relatively close correlation (-0.66, shown previously in Table 7-1). The estimated positive coefficients on variables measuring the fraction of licensed drivers who are young (under age 25) males and the fraction of car and light truck travel in rural areas shown for Models 7 and 8 in Table 7-2 suggest that declines over time in both of these measures have also contributed significantly to the observed decline in fatality rates. Again, however, the close correlation of these measures with seat belt use and driving under the influence of alcohol (as well as with each other; see Table 7-1) and the fact that introducing them into the model causes such pronounced changes in the estimated coefficients on those variables makes the strength of their apparent effect on fatalities suspect.

As an alternative to relying on these period effect variables, Models 9 to 12 in Table 7-2 substitute a linear time trend in an effort to capture their combined effect. As indicated previously, this implies a constant annual *percent* decline in fatality rates, which means that the magnitude of the annual reduction in fatality rates due to the combination of period effects has declined over time. The coefficient estimates on the time trend variable in Models 9 through 12 imply a 2-3 percent annual decline in fatality rates for occupants of cars and light trucks of all model years and ages included in the sample, over and above the effect of sustained improvements in the safety of new models entering the fleet each year. Models 10 to 12 supplement the time trend with indicator variables for recession years, to account for the fact that higher unemployment or other economic stresses during those years may have changed the composition of drivers on the road in ways that resulted in safer travel. As the estimated coefficients on these variables show, fatality rates declined more rapidly than the historical downward trend would have predicted in 2009 and 2010, although there was little or no evidence that this occurred in 1992 or 2008, and the results suggest that declines in fatalities during 1991 and 2007 were actually slower than would have been predicted by the historical trend alone.

Finally, Models 11 and 12 include basic tests for whether the downward historical trend in fatality rates has slowed over time. Model 11 tests for gradual slowing in the rate by including the squared value of the time trend; the positive coefficient on the squared value suggests a slowing trend, but its value is so small relative to that of the coefficient on the time trend itself that this slowing has barely been perceptible.[836] Model 12 tests for whether there was a perceptible slowing of the downward trend in fatalities beginning in the year 2007, as visual examination of the historical trend in the fleet-wide fatality rate suggests. As with the previous test, the positive coefficient on the Trend Shift variable in Model 12 suggests some slowing of the historical decline, but it again appears to be so slight as to be almost imperceptible.[837] On balance, we conclude that after accounting for the gradual improvement in new car safety and the association between age and diminished safety, a constant annual percentage decline explains historical variation in fatality rates as well as do more complex trends.

7.1.10 Non-Fatal Injury Rates

Table 7-3 reports estimation results for a similar set of models to explain the historical decline in non-fatal injuries sustained by occupants of automobiles and light-duty trucks. As with the fatality rate model, the dependent variable in all of the model specifications summarized in the table is the natural logarithm of non-fatal injuries per billion miles traveled by cars and light trucks, and this rate varies across model years in any calendar year as well as over the calendar years for which any model year is represented in the data sample. The non-fatal injury rate models use a much coarser grouping of model years into safety regimes than did the fatality rate model, with the 26 model years included in the sample grouped into only 5 regimes. Nevertheless, Table 7-3 shows that the fixed effects associated with the safety regimes show the same monotonic decline over successive model years, again with fairly consistent reductions in non-fatal injury rates as the regimes change with model years 1998, 2001, 2007, and 2009. The largest reductions appear to occur in model years 1998 and 2001, with slightly smaller declines occurring in 2007 and 2009.

As with fatality rates, the results for Models 1 and 2 reported in Table 7-3 show that model-year fixed effects and age alone explain much of the variation in fatality rates over time and among model years, and the effect of age cubed is empirically small and does not increase the models' explanatory power. The estimated effects of the period variables on non-fatal injury rates also parallel those observed for fatality rates, with a few notable exceptions, and once again illustrate the difficulty of incorporating multiple period effect measures. Increases in the unemployment rate again have the expected effect of reducing injury rates, while increasing use of lap and shoulder restraints again appears to have significantly reduced the rate of non-fatal injuries to car and light truck occupants. In Models 5 and 6, driving under the influence of alcohol appears to be significantly associated with *lower* injury rates, but this effect disappears in subsequent models and in any case is again suspect for the reasons discussed previously.

Table 7-3 shows that drivers' use of hand-held electronic devices has no apparent effect on non-fatal injury rates, although this result may again stem partly from its correlation with the measure of lap and shoulder belt use. The estimated negative coefficients on the fraction of licensed drivers who are young males – which suggest that their representation in the driver population reduces the rate of non-fatal injuries – are implausible, and the magnitude of the coefficient in

[836] For example, including this additional variable in Model 11 reduces the estimated annual decline in fatality rates from -3.4 to -3.3 percent.
[837] The results for Model 12 suggest that the annual decline in fatality rates slowed from 3.3 to 3.2 percent beginning in 2007.

Model 8 also makes it extremely suspect. The estimated effect of the shift in car and light truck travel from rural to urban areas has the expected direction (it reduces the rate of non-fatal injuries), but its magnitude is suspiciously large and including it removes all of the explanatory power from the seat belt use measure; both results seem likely to reflect the extremely close correlation between these two measures (-0.91, as shown in Table 7-3), rather than their true effects.

Table 7-3 – Estimation Results for Non-Fatal Injury Rate Models

Explanatory Variables	Estimated Coefficients (Standard Errors in Parentheses; *** p<0.01, ** p<0.05, * p<0.1)											
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Constant	6.846***	6.909 ***	6.902 ***	7.755***	8.214***	8.381 ***	8.905***	6.019***	6.890***	6.882***	7.067***	6.935***
	(0.019)	(0.026)	(0.025)	(0.095)	(0.206)	(0.403)	(0.685)	(0.918)	(0.021)	(0.019)	(0.031)	(0.033)
Model Years 1998-2000	-0.195 ***	-0.195 ***	-0.189 ***	-0.0900 ***	-0.0944 ***	-0.0813 ***	-0.0866 ***	-0.0823 ***	-0.124 ***	-0.124***	-0.119***	-0.112***
	(0.017)	(0.016)	(0.017)	(0.018)	(0.018)	(0.019)	(0.020)	(0.020)	(0.023)	(0.019)	(0.017)	(0.017)
Model Years 2001-2006	-0.351 ***	-0.341 ***	-0.335 ***	-0.165 ***	-0.171 ***	-0.150 ***	-0.160 ***	-0.150 ***	-0.226 ***	-0.215***	-0.221***	-0.209***
	(0.015)	(0.015)	(0.016)	(0.023)	(0.023)	(0.027)	(0.029)	(0.028)	(0.032)	(0.026)	(0.025)	(0.024)
Model Years 2007-2008	-0.465 ***	-0.453 ***	-0.437 ***	-0.207 ***	-0.220 ***	-0.192 ***	-0.207 ***	-0.194 ***	-0.286 ***	-0.271***	-0.289***	-0.277***
	(0.028)	(0.028)	(0.029)	(0.036)	(0.036)	(0.041)	(0.044)	(0.043)	(0.049)	(0.041)	(0.038)	(0.036)
Model Years 2009-2015	-0.511 ***	-0.508 ***	-0.491 ***	-0.212 ***	-0.229 ***	-0.200 ***	-0.218 ***	-0.206 ***	-0.290 ***	-0.320***	-0.348***	-0.334***
	(0.025)	(0.025)	(0.026)	(0.038)	(0.038)	(0.047)	(0.050)	(0.049)	(0.056)	(0.046)	(0.043)	(0.041)
Vehicle Age	0.0487 ***	0.0195 **	0.0499 ***	0.0729 ***	0.0715 ***	0.0847 ***	0.0837 ***	0.0845 ***	0.0629 ***	0.0657***	0.0706***	0.0722***
	(0.004)	(0.009)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
Vehicle Age^2	-0.00193 ***	0.00104	-0.00192 ***	-0.00222 ***	-0.00220 ***	-0.00267 ***	-0.00266 ***	-0.00267 ***	-0.00202 ***	-0.00214 ***	-0.00239 ***	-0.00242 ***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Vehicle Age^3		-8.14e-05 ***										
		(0.000)										
Unemployment Rate			-1.183 ***	-0.991 ***	-0.698**	-1.010 ***	-1.049 ***	-2.112 ***				
			(0.361)	(0.323)	(0.341)	(0.335)	(0.337)	(0.401)				
% Using Lap/ Shoulder Belts				-1.410 ***	-1.486 ***	-1.240 ***	-1.498 ***	0.71				
				(0.152)	(0.154)	(0.312)	(0.414)	(0.630)				
% Non-Fatal Injuries in					-1.296**	-2.722 ***	-1.95	0.889				

Explanatory Variables	Estimated Coefficients (Standard Errors in Parentheses; *** p<0.01, ** p<0.05, * p<0.1)											
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Crashes Involving Drunk Driver					(0.517)	(0.902)	(1.217)	(1.331)				
% Using Hand-Held Electronic Devices						0.00915	0.00542	0.0149				
						(0.009)	(0.010)	(0.009)				
% Drivers Male <25 years							-8.16	-27.34***				
							(8.629)	(9.344)				
% Rural Travel								4.358***				
								(0.961)				
Trend									-0.0130***	-0.0115***	-0.0419***	-0.0155***
									(0.003)	(0.002)	(0.005)	(0.004)
Trend^2											0.000952***	
											(0.000)	
Trend Shift												-0.0165***
												(0.002)
Trend Shift x Trend												0.000737***
												(0.000)
Calendar Year 1991										0.0417	-0.0931	-0.0124
										(0.060)	(0.059)	(0.058)
Calendar Year 2001										-0.0695	-0.181***	-0.122**
										(0.049)	(0.049)	(0.048)
Calendar Year 2007										-0.0852***	-0.0493**	-0.0431**
										(0.021)	(0.020)	(0.019)
Calendar year 2008										-0.0979***	-0.0651***	-0.0616***
										(0.020)	(0.019)	(0.019)

Explanatory Variables	Estimated Coefficients (Standard Errors in Parentheses; *** p<0.01, ** p<0.05, * p<0.1)											
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**	**Model 12**
Calendar Year 2009										-0.215***	-0.187***	-0.185***
										(0.020)	(0.019)	(0.018)
Calendar Year 2010										-0.117***	-0.0952 ***	-0.0958 ***
										(0.019)	(0.018)	(0.017)
Observations	336	336	336	336	336	281	281	281	336	336	336	336
R-squared within (1)	0.37	0.39	0.39	0.52	0.53	0.62	0.62	0.64	0.41	0.61	0.66	0.69
R-squared between (2)	0.57	0.67	0.74	0.99	0.99	0.99	0.99	0.99	0.95	0.98	0.99	0.99
R-squared overall (3)	0.18	0.22	0.26	0.79	0.79	0.83	0.82	0.84	0.68	0.73	0.72	0.75
Corr (u_i, Xb) (4)	0.10	0.14	0.19	0.74	0.73	0.73	0.72	0.73	0.66	0.61	0.57	0.59
sigma_u (5)	0.21	0.21	0.20	0.09	0.10	0.08	0.09	0.09	0.12	0.13	0.14	0.13
sigma_e (6)	0.10	0.10	0.10	0.09	0.09	0.08	0.08	0.08	0.10	0.08	0.08	0.07
rho (7)	0.81	0.81	0.79	0.50	0.54	0.51	0.54	0.53	0.60	0.71	0.77	0.77
Footnotes: See Table 7-2 – Estimation Results for Fatality Rate Models.												

Substituting the time trend measure for the period effect variables in the models for non-fatal injuries reveals a considerably slower rate of decline (1.1-1.6 percent annually, except for the anomalously large decline suggested by Model 11) than was the case with fatalities. Again, including indicator variables for recession years improves the model's fit to the data slightly, and the transient effects of higher unemployment and other economic stresses during those years weaken the downward trend in non-fatal injuries slightly. As with the fatality rate models, Models 11 and 12 in Table 7-3 show some slowing in the downward trend in non-fatal injury rates, although the apparent increase in the strength of the downward trend suggested by Model 11 seems suspect. In any case, both models show only very slight weakening in the downward historical trend, slowing it by only 0.1 to 0.2 percent per year.

7.1.11 Property Damage Rates

Table 7-4 shows the results of estimating similar models for crashes that cause only property damage to vehicles or the immediate surroundings. Here, the dependent variable is the natural logarithm of the number of vehicles involved in property damage only crashes per billion vehicle-miles driven by cars and light trucks, and this measure again varies across the model years (and thus vehicles of different ages) making up the fleet during each calendar year, as well as over successive calendar years (and thus ages) for each model year. The models for property damage group model years into the same 5 clusters as did those for non-fatal injuries the fatality rate model, but Table 7-4 shows that there is not the same orderly downward progression the fixed effects associated with model year groups as was evident in the models for fatality and non-fatal injury rates. In several specifications, property damage crash rates for model years 2007-08 seem to be slightly *higher* when they were newly introduced than those for the immediately preceding group of model years, although in each of those cases crash involvement rates once again decline significantly for model years 2009 and later.

As with fatality and non-fatal injury rates, Table 7-4 shows that model-year fixed effects and age alone explain much of the variation in property damage rates, while the effect of age cubed is empirically small and does not significantly improve the models' ability to explain historical variation in the data. The estimated effects of the period variables on the rate of property damage crashes are inconsistent across models and difficult to interpret; for example, while the estimated coefficient on the unemployment rate consistently shows the anticipated negative sign, its magnitude is extremely sensitive to the combination of other period effect variables that are included. The effect of the drunk driving measure varies in *both* direction and magnitude depending on the other variables used in combination with it, and there is little evidence that drivers' use of hand-held electronic devices affects property damage crash rates significantly. The effects of the fraction of licensed drivers who are young males and the proportion of vehicle use in rural areas have the expected directions, although the strength of the former again seems unexpectedly large in relation to the other period effect measures.

The results for Models 8 through 11 in Table 7-4 provide only limited evidence that the same downward trend that was observed for fatality and non-fatal injury rates also applies in the case of property damage crashes. One possible explanation for this result is that crashes resulting in significant property damage, but no injuries have actually become more common over time as vehicles have become increasingly complex in design and more costly to repair. Only Models 10 and 11 in Table 7-4, the two specifications that allow for a weakening in the trend over time, show the expected downward trend over time in the rate of cars' and light trucks' involvement in property damage crashes. Its apparent strength in Model 10 – which allows the trend to slow gradually over time – is not only large by comparison to those estimated for fatal and injury crashes, but also and well over twice that in Model 11, which allows the trend to become less steep starting in 2010. In both cases, however, the trend moderates only very minimally over time, the same result that was observed in the models for fatality and non-fatal injury rates.

Table 7-4 – Estimation Results for Property Damage-Only Crash Involvement Rates

Explanatory Variables	Estimated Coefficients (Standard Errors in Parentheses; *** p<0.01, ** p<0.05, * p<0.1)										
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**
Constant	7.822***	7.858***	7.861***	7.801***	8.230***	9.302***	9.360 ***	7.813 ***	7.796 ***	8.044***	7.963***
	(0.014)	(0.019)	(0.019)	(0.138)	(0.206)	(0.244)	(0.242)	(0.016)	(0.015)	(0.022)	(0.023)
Model Years 1998-2000	-0.0420 ***	-0.0422 ***	-0.0380 ***	-0.0366 ***	0.0184	-0.0326 **	-0.0257*	-0.0562 ***	-0.0578 ***	-0.0510 ***	-0.0478 ***
	(0.013)	(0.012)	(0.012)	(0.013)	(0.012)	(0.013)	(0.013)	(0.017)	(0.015)	(0.012)	(0.012)
Model Years 2001-2006	-0.0793 ***	-0.0740 ***	-0.0687 ***	-0.0665 ***	0.0105	-0.0842 ***	-0.0703 ***	-0.104 ***	-0.103 ***	-0.110 ***	-0.106***
	(0.012)	(0.012)	(0.012)	(0.013)	(0.014)	(0.019)	(0.019)	(0.025)	(0.022)	(0.017)	(0.017)
Model Years 2007-2008	-0.0610 ***	-0.0541 **	-0.0410*	-0.0373	0.0623 ***	-0.0756 ***	-0.0567*	-0.0970 **	-0.0909 ***	-0.115 ***	-0.111***
	(0.021)	(0.021)	(0.022)	(0.024)	(0.023)	(0.029)	(0.029)	(0.038)	(0.033)	(0.026)	(0.026)
Model Years 2009-2015	-0.0930 ***	-0.0911 ***	-0.0786 ***	-0.0738 ***	0.0374	-0.134 ***	-0.112 ***	-0.137 ***	-0.162 ***	-0.198 ***	-0.194***
	(0.019)	(0.019)	(0.019)	(0.022)	(0.024)	(0.033)	(0.033)	(0.043)	(0.038)	(0.030)	(0.029)
Vehicle Age	0.0379 ***	0.0212 ***	0.0387 ***	0.0391 ***	0.0602 ***	0.0495 ***	0.0512 ***	0.0351 ***	0.0369 ***	0.0434 ***	0.0441 ***
	(0.003)	(0.007)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)
Vehicle Age^2	-0.00142 ***	0.00028	-0.00142 ***	-0.00142 ***	-0.00201 ***	-0.00196 ***	-0.00197 ***	-0.00141 ***	-0.00150 ***	-0.00183 ***	-0.00185 ***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Vehicle Age^3		-4.67e-05 ***									
		(0.000)									
Unemployment Rate			-0.831 ***	-0.873 ***	-1.241 ***	-1.549 ***	-1.827 ***				
			(0.270)	(0.286)	(0.241)	(0.227)	(0.243)				
% of Vehicles Damaged in Crashes Involving Drunk Driver				0.189	-1.746 ***	1.767**	3.126***				
				(0.430)	(0.641)	(0.775)	(0.898)				
% Using Hand-Held Electronic Devices					0.00754	0.0101**	0.00293				
					(0.005)	(0.005)	(0.005)				

Explanatory Variables	Estimated Coefficients (Standard Errors in Parentheses; *** p<0.01, ** p<0.05, * p<0.1)										
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**
% Drivers Male <25 years						-30.54 ***	-44.27 ***				
						(4.362)	(6.413)				
% Rural Travel							1.210***				
							(0.419)				
Trend								0.00261	0.00426 **	-0.0363 ***	-0.0146 ***
								(0.002)	(0.002)	(0.003)	(0.003)
Trend^2										0.00127 ***	
										(0.000)	
Trend Shift											-0.0149 ***
											(0.001)
Trend Shift x Trend											0.00112 ***
											(0.000)
Calendar Year 1991									0.103**	-0.0775*	-0.0363
									(0.049)	(0.041)	(0.041)
Calendar Year 2001									0.00881	-0.140***	-0.114***
									(0.040)	(0.034)	(0.034)
Calendar Year 2007									-0.0348 **	0.0132	0.0142
									(0.017)	(0.014)	(0.014)
Calendar Year 2008									-0.0305*	0.0134	0.0131
									(0.017)	(0.014)	(0.013)
Calendar Year 2009									-0.144 ***	-0.107***	-0.108***
									(0.016)	(0.013)	(0.013)
Calendar Year 2010									-0.0910 ***	-0.0622 ***	-0.0641 ***
									(0.016)	(0.013)	(0.012)
Observations	336	336	336	336	281	281	281	336	336	336	336
R-squared within (1)	0.40	0.41	0.42	0.42	0.66	0.71	0.72	0.40	0.56	0.72	0.74

Explanatory Variables	Estimated Coefficients (Standard Errors in Parentheses; *** p<0.01, ** p<0.05, * p<0.1)										
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**
R-squared between (2)	0.79	0.83	0.85	0.86	0.94	0.73	0.88	0.33	0.07	0.87	0.87
R-squared overall (3)	0.41	0.43	0.45	0.46	0.71	0.62	0.68	0.31	0.41	0.47	0.50
Corr (u_i, Xb) (4)	0.14	0.16	0.20	0.21	-0.50	0.06	0.15	-0.06	-0.08	-0.15	-0.13
sigma_u (5)	0.04	0.03	0.03	0.03	0.02	0.05	0.04	0.05	0.06	0.07	0.07
sigma_e (6)	0.08	0.08	0.08	0.08	0.06	0.06	0.06	0.08	0.07	0.05	0.05
rho (7)	0.18	0.17	0.14	0.13	0.14	0.46	0.38	0.32	0.44	0.66	0.67
Footnotes: See Table 7-2 – Estimation Results for Fatality Rate Models.											

7.1.12 Using the Models to Forecast

To simplify forecasting baseline future rates for fatalities, non-fatal injuries, and involvement in property damage only crashes, we utilize the versions of each model that include fixed effects for safety regimes, vehicle age and its squared value, the time trend measure (including any significant change in the trend), and indicator variables for recession years. Specifically, we use model 10 from Table 7-1 and Table 7-3, and model 11 from Table 7-4.

Starting with the relevant rate for the latest model year when it was new (e.g., the fatality rate for model year 2019 during calendar year 2019, when most vehicles from that model year were sold and placed into service), we apply estimates of the shares of new vehicles produced during future model years that will be equipped with various crash avoidance technologies and the effectiveness of each of those technologies in reducing crashes (fatal, non-fatal, or property damage, as appropriate). The nature of these technologies, projections of the shares of new cars and light trucks that will be equipped with each of them, and estimates of the effectiveness of those technologies in preventing these three different types of crashes are discussed in the following section. This generates forecasts of fatality, non-fatal injury, and property damage crash involvement rates for future model years during their initial year of use, which for simplicity is assumed to be the same calendar year.

During each future calendar year, the appropriate new model year is assumed to be incorporated into the fleet, with its forecast rate (of fatalities per billion miles, for example). At the same time, the rate for each earlier model year making up the fleet during that calendar year is increased to reflect the aging effect implied by the coefficients on the variables age and age-squared in the relevant model. Any remaining vehicles originally produced during the model year that would have reached age 41 in a future calendar year are assumed to be retired from service or driven so little that they contribute negligibly to overall safety. Finally, the rates (again, fatality, non-fatal injury, or property damage) for these earlier model years are also adjusted downward to reflect continuation of their historical downward trends, which were estimated as part of the models discussed previously.

This produces estimates of fatality, non-fatal injury, and property damage crash involvement rates for each model year making up the fleet during each future calendar year, and the process is continued until calendar year 2050. Multiplying these rates by the estimated number of miles driven by cars and light trucks of each model year in use during a future calendar year produces baseline estimates of total fatalities, non-fatal injuries, and cars and light trucks involved in property damage-only crashes.

Figure 7-3 illustrates the recent history and baseline forecast of the overall fatality rate for occupants of cars and light trucks. The sharp rise in the fatality rate for 2020 reflects the steep drop in car and light truck VMT during that year due to the COVID-19 pandemic and accompanying restrictions on activity, as well as an increase in fatalities that is not yet fully explained, but which may be due to riskier driving on less congested roadways.[838] These rates are also used as the basis for estimating changes in safety resulting from reductions in the mass

[838] *See*, *e.g.*, https://www.nhtsa.gov/press-releases/2020-fatality-data-show-increased-traffic-fatalities-during-pandemic. (Accessed: February 14, 2022).

of new vehicles, additional rebound-effect driving, and changes in the numbers of cars and light trucks from different model years making up each calendar year's fleet. The underlying causes and methods for estimating each of those three sources of changes in safety are discussed in detail in various subsections of this chapter.

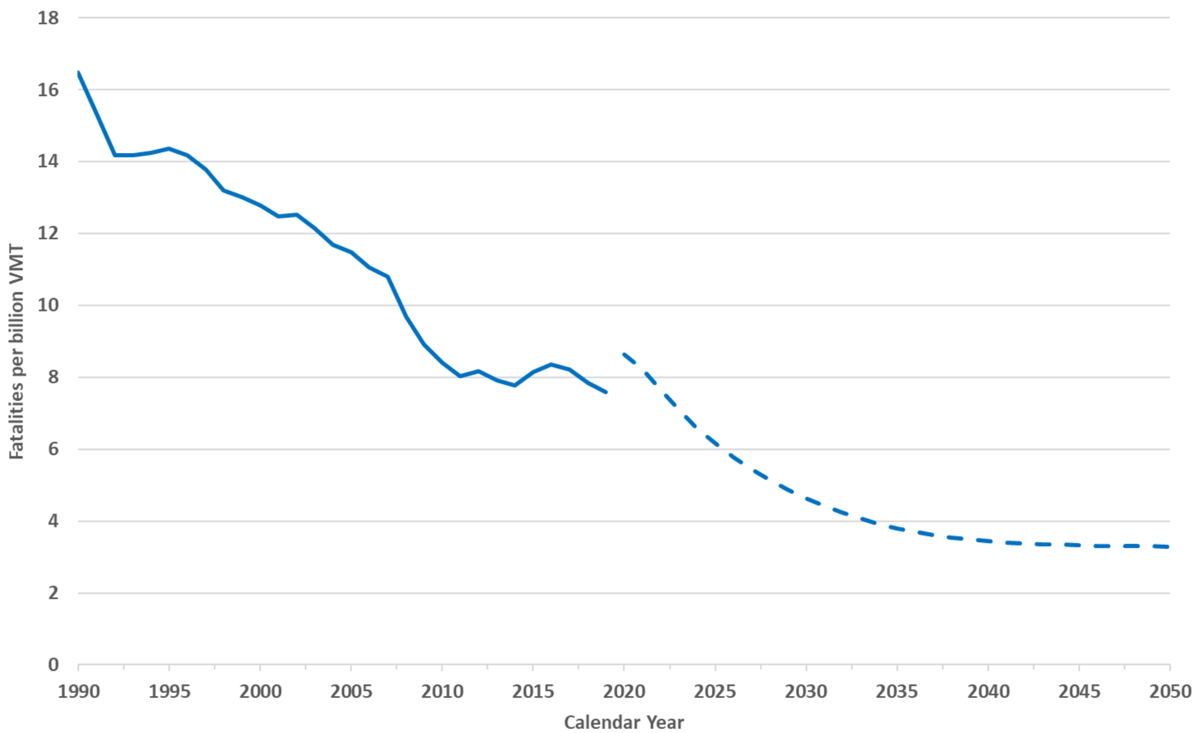

Figure 7-4 – Recent and Projected Future Fatality Rates for Cars and Light Trucks

Note: The abrupt rise in the fatality rate for 2020 shown in this figure reflects the large drop in car and light truck VMT during that year due to the COVID-19 pandemic and accompanying restrictions on activity, as well as a rise in fatalities.

7.1.13 Future Safety Trends Predicted by Advanced Safety Technologies

The baseline model described above uses trends observed over several decades to make a coarse projection of future safety rates. To augment these projections with knowledge about forthcoming safety improvements, the agency applied detailed empirical estimates of the market uptake and improving effectiveness of crash avoidance technologies to estimate their effect on the fleet-wide fatality rate, including explicitly incorporating both the direct effect of those technologies on the crash involvement rates of new vehicles equipped with them, as well as the "spillover" effect of those technologies on improving the safety of occupants of vehicles that are not equipped with these technologies.

The development of advanced crash avoidance technologies in recent years indicates some level of safety improvement is almost certain to occur going forward. Moreover, autonomous vehicles offer the possibility of significantly reducing the effect of human perception, judgment or error in crash causation, a contributing factor in roughly 94 percent of all crashes. However, there is insufficient information and certainty regarding autonomous vehicles eventual impact to include them in this analysis.

Advanced technologies that are currently deployed or in development include:

1. **Forward Collision Warning (FCW)** systems passively assist drivers in avoiding or mitigating the impact of rear-end collisions (i.e., a vehicle striking the rear portion of a vehicle traveling in the same direction directly in front of it). FCW uses forward-looking vehicle detection capability, such as RADAR, LIDAR (laser), camera, etc., to detect other vehicles ahead and use the information from these sensors to warn the driver and to prevent crashes. FCW systems provide an audible, visual, or haptic warning, or any combination thereof, to alert the driver of an FCW-equipped vehicle of a potential collision with another vehicle or vehicles in the anticipated forward pathway of the vehicle.

2. **Crash Imminent Braking (CIB)** systems actively assist the drivers by mitigating the impact of rear-end collisions. These safety systems have forward-looking vehicle detection capability provided by sensing technologies such as RADAR, LIDAR, video camera, etc. CIB systems mitigate crash severity by automatically applying the vehicle's brakes shortly before the expected impact (i.e., without requiring the driver to apply force to the brake pedal).

3. **Dynamic Brake Support (DBS)** is a technology that actively increases the amount of braking provided to the driver during a rear-end crash avoidance maneuver. If the driver has applied force to the brake pedal, DBS uses forward-looking sensor data provided by technologies such as RADAR, LIDAR, video cameras, etc. to assess the potential for a rear-end crash. Should DBS ascertain a crash is likely (i.e., the sensor data indicate the driver has not applied enough braking to avoid the crash), DBS automatically intervenes. Although the manner in which DBS has been implemented differs among vehicle manufacturers, the objective of the interventions is largely the same - to supplement the driver's commanded brake input by increasing the output of the foundation brake system. In some situations, the increased braking provided by DBS may allow the driver to avoid a crash. In other cases, DBS interventions mitigate crash severity.

4. **Pedestrian Automatic Emergency Breaking (PAEB)** systems provide automatic braking for vehicles when pedestrians are in the forward path of travel and the driver has taken insufficient action to avoid an imminent crash. Like CIB, PAEB safety systems use information from forward-looking sensors to automatically apply or supplement the brakes in certain driving situations in which the system determines a pedestrian is in imminent danger of being hit by the vehicle.

5. **Rear Automatic Braking** features have the ability to sense the presence of objects behind a reversing vehicle, alert the driver of the presence of the object(s) via auditory and visual alerts, and automatically engage the available braking system(s) to stop the vehicle.

6. **Semi-automatic Headlamp Beam Switching** devices provide either automatic or manual control of headlamp beam switching at the option of the driver. When the control is automatic, headlamps switch from the upper beam to the lower beam when illuminated by headlamps on an approaching vehicle and switch back to the upper beam when the road ahead is dark. When the control is manual, the driver may obtain either beam manually regardless of the conditions ahead of the vehicle.

7. **Lane Departure Warning (LDW)** is a driver assistance system that monitors lane markings on the road and alerts the driver when their vehicle is about to drift beyond a delineated edge line of their current travel lane.

8. **Lane Keep Assist (LKA)** utilizes LDW sensors to monitor lane markings but, in addition to warning the driver, provides gentle steering adjustments to prevent drivers from unintentionally drifting out of their lane.

9. **Lane Centering** keeps the vehicle centered in its lane and typically comes with steering assist to help the vehicle take gentle turns at highway speeds. These systems also work together with adaptive cruise control and lane keeping assist to give the car semi-autonomous capability.

10. **Blind Spot Detection (BSD)** systems use digital camera imaging technology or radar sensor technology to detect one or more vehicles in either of the adjacent lanes that may not be apparent to the driver. The system warns the driver of an approaching vehicle's presence to help facilitate safe lane changes.

11. **Lane Change Alert (LCA)** systems use digital camera imaging technology or radar sensor technology to detect vehicles either in, or rapidly approaching in adjacent lanes that may not be apparent to the driver. The system warns the driver of an approaching vehicle's presence to help facilitate safe lane changes.

7.1.13.1 Crash Avoidance Technologies

Beginning with the 2020 CAFE final rule, NHTSA augmented the sales-scrappage safety analysis with recent research into the effectiveness of specific advanced crash avoidance safety technologies (also known as ADAS or advanced driver assistance systems) that are expected to drive future safety improvement to estimate the impacts of crash avoidance technologies. The analysis analyzes six crash avoidance technologies that are currently being produced and commercially deployed in the new vehicle fleet. These FCW, Automatic Emergency Braking (AEB),[839] LDW, LKA, BSD, and LCA. These are the principal technologies that are being developed and adopted in new vehicle fleets and will likely drive vehicle-based safety improvements for the coming decade. These technologies are being installed in more and more new vehicles; in fact, manufacturers recently reported that they voluntarily installed AEB systems in more than 70 percent of their new vehicles sold in the year ending August 31,

[839] AEB is a combination of CIB, DBS, and PEAB.

2019.[840] NHTSA notes that the terminology and the detailed characteristics of these systems may differ across manufacturers, but the basic system functions are generally similar.

These 6 technologies address three basic crash scenarios through warnings to the driver or alternately, through dynamic vehicle control:

1. Forward collisions, typically involving a crash into the rear of a stopped vehicle;
2. Lane departure crashes, typically involving inadvertent drifting across or into another traffic lane; and
3. Blind spot crashes, typically involving intentional lane changes into unseen vehicles driving in or approaching the driver's blind spot.

Unlike traditional safety features where the bulk of the safety improvements were attributable to improved protection when a crash occurs (crash worthiness), the impact of advanced crash avoidance technologies (ADAS or advanced driver assistance systems) will have on fatality and injury rates is a direct function of their effectiveness in preventing or reducing the severity of the crashes they are designed to mitigate. This effectiveness is typically measured using real world data comparing vehicles with these technologies to similar vehicles without them. While these technologies are actively being deployed in new vehicles, their penetration in the larger on-road vehicle fleet has been at a low but increasing level. This limits the precision of statistical regression analyses, at least until the technologies become more common in the on-road fleet.

NHTSA's approach to measuring these impacts is to derive effectiveness rates for these advanced crash-avoidance technologies from safety technology literature. NHTSA then applies these effectiveness rates to specific crash target populations for which the crash avoidance technology is designed to mitigate and adjusted to reflect the current pace of adoption of the technology, including the public commitment by manufactures to install these technologies. The products of these factors, combined across all 6 advanced technologies, produce a fatality rate reduction percentage that is applied to the fatality rate trend model discussed above, which projects both vehicle and non-vehicle safety trends. The combined model produces a projection of impacts of changes in vehicle safety technology as well as behavioral and infrastructural trends.

7.1.13.2 Technology Effectiveness Rates

7.1.13.2.1 Forward Crash Collision Technologies

For forward collisions, manufacturers are currently equipping vehicles with FCW, which warns drivers of impending collisions, as well as AEB, which incorporates the sensor systems from FCW together with dynamic brake support (DBS) and crash imminent braking (CIB) to help

[840] NHTSA Announces Update to Historic AEB Commitment by 20 Automakers, NHTSA press release December 17, 2019. https://www.nhtsa.gov/press-releases/nhtsa-announces-update-historic-aeb-commitment-20-automakers. (Accessed: February 14, 2022).

avoid crashes or mitigate their severity. Manufacturers have committed voluntarily to install some form of AEB on all light vehicles by the 2023 model year (September 2022).[841]

Table 7-5 summarizes studies which have measured effectiveness for various forms of FCW and AEB over the past 13 years. Most studies focused on crash reduction rather than injury reduction. This is a function of limited injury data in the on-road fleet, especially during the early years of deployment of these technologies. In addition, it reflects engineering limitations in the technologies themselves. Initial designs of AEB systems were basically incapable of detecting stationary objects at speeds higher than 30 mph, making them potentially ineffective in higher speed crashes that are more likely to result in fatalities or serious injury. For example, Wiacek et al. (2-15) conducted a review of rear-end crashes involving a fatal occupant in the 2003-2012 NASS-CDS data-bases to determine the factors that contribute to fatal rear-end crashes.[842] They found that the speed of the striking vehicle was the primary factor in 71 percent of the cases they examined. The average Delta-v of the striking vehicle in these cases was 46 km/h (28.5 mph), implying pre-crash travel speeds in excess of this speed. While Table 7-5 includes studies going back to 2005, the agency focus' discussion on more recent studies conducted after 2012 in order to reflect more current safety systems and vehicle designs.

Table 7-5 – Summary of AEB Technology Effectiveness Estimates

Authors	AEB Type	Crashes	Fatalities	Injury Reduction		All Injuries
				Serious	Minor	
Sugimoto & Sauer (2005)[843]	CMBS	38%	44%			
Page et al. (2005)[844]	EBA		7.50%			11%
Najm et al. (2005)[845]	ACAS[846]	6-15%				
Breuer et al. (2007)[847]	BAS+[848]	44%				
Kuehn et al. (2009)[849]	CMBS	40.80%				

[841] *See* https://www.nhtsa.gov/press-releases/nhtsa-iihs-announcement-aeb. (Accessed: February 14, 2022). Note that the agreement calls for CIB, but systems installed by manufacturers include various combinations of technologies that make up AEB.

[842] Wiacek, C., Bean, J., Sharma, D., *Real World Analysis of Fatal Rear-End Crashes*, National Highway Traffic Safety Administration, 24th Enhanced Safety of Vehicles Conference, 150270, 2015.

[843] Sugimoto, Y., and Sauer, C., (2005). Effectiveness Estimation Method for Advanced Driver Assistance System and its Application to Collision Mitigation Brake systems, paper number 05-148, 19th International Technical Conference on the Enhanced safety of Vehicles (ESV), Washington D.C., June 6-9, 2005.

[844] Page, Y., Foret-Bruno, J., & Cuny, S. (2005). Are expected and observed effectiveness of emergency brake assist in preventing road injury accidents consistent? 19th ESV Conference, Washington DC.

[845] Najm, W.G., Stearns, M.D., Howarth, H., Koopman, J. & Hitz, J., (2006). Evaluation of an Automotive Rear-End Collision Avoidance System (technical report DOT HS 810 569), Cambridge, MA: John A. Volpe National Transportation System Center, U.S. Department of Transportation.

[846] Automotive Collision Avoidance System (ACAS).

[847] Breuer, JJ., Faulhaber, A., Frank, P. and Gleissner, S. (2007). Real world Safety Benefits of Brake Assistance Systems, Proceedings of the 20th International Technical Conference of the Enhanced Safety of Vehicles (ESV) in Lyon, France June 18-21, 2007. https://trid.trb.org/view/1364815

[848] Brake Assistance Systems (BAS).

[849] Keuhn, M., Hummel, T., and Bende J., Benefit estimation of advanced driver assistance systems for cars derived from real-world accidents, Paper No. 09-0317, 21st International Technical Conference on the Enhanced Safety of Vehicles (ESV) – International Congress Centre, Stuttgart, Germany, June 15-18, 2009.

Authors	AEB Type	Crashes	Fatalities	Injury Reduction		All Injuries
				Serious	Minor	
Grover et al. (2008)[850]	AEB	30%				
Kisano &Gabler (2015)[851]	AEB	0-67%	2-69%	2-69%		
HLDI (2011)[852]	AEB	22-27%				51%
Doecke et al. (2012)[853]	AEB	25-28%				
Chauvel et al. (2013)[854]	PAEB	4.30%	15%	37%		
Fildes et al. (2015)[855]	AEB	38%				
Cicchino (2017)[856]	FCW	27%				20%
	Low AEB	43%				45%
	High AEB	50%				56%
Kusano & Gabler (2012)[857]	FCW	3.20%	29%	29%		
	AEB	7.70%	50%	50%		
Leslie et al. (2019)[858]	FCW	21%				
	AEB	46%				

Doecke et al. (2012) created simulations of 103 real world crashes and applied AEB system models with differing specifications to determine the change in impact speed that various AEB interventions might produce. Their modeling found significant rear-end crash speed reductions with various AEB performance assumptions. In addition, they estimated a 29 percent reduction in rear-end crashes and that 25 percent of crashes over 10 km/h were reduced to 10 km/h or less.

Cicchino (2017) analyzed the effectiveness of a variety of forward collision mitigation systems including both FCW and AEB systems. Cicchino used a Poisson regression to compare rates of police-reported crashes per insured vehicle year between vehicles with these systems and the

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[850] Grover, C., Knight, I., Okoro, F., Simmons I., Couper, G., Massie, P., and Smith, B. (2008). Automated Emergency Brake Systems: Technical requirements, Costs and Benefits, PPR227, TRL Limited, DG Enterprise, European Commission, April 2008.

[851] Kusano, K.G., and Gabler, H.C. (2015). Comparison of Expected Crash Injury and Injury Reduction from Production Forward Collision and Lane Departure Warning Systems, Traffic Injury Prevention 2015; Suppl. 2: S109-14. https://www.tandfonline.com/doi/full/10.1080/15389588.2015.1063619?scroll=top&needAccess=true

[852] HLDI (2011). Volvo's City Safety prevents low-speed crashes and cuts insurance costs, Status Report, Vol. 46, No. 6, July 19,2011.

[853] Docke, S.D., Anderson, R.W.G., Mackenzie, J.R.R., Ponte, G. (2012). The potential of autonomous emergency braking systems to mitigate passenger vehicle crashes. Australian Road Safety Research Policing and Education Conference, October 4-6, 2012, Wellington, New Zealand.

[854] Chauvel, C., Page, Y., Files, B.N., and Lahausse, J. (2013). Automatic emergency braking for pedestrian's effective target population and expected safety benefits, Paper No. 13-0008, 23rd International Technical Conference on the Enhanced Safety of Vehicles (ESV), Seoul, Republic of Korea, May 27-30, 2013.

[855] Fildes B., Keall M., Bos A., Lie A., Page, Y., Pastor, C., Pennisi, L., Rizzi, M., Thomas, P., and Tingvall, C. Effectiveness of Low Speed Autonomous Emergency Braking in Real-World Rear-End Crashes. Accident Analysis and Prevention, AAP-D-14-00692R2.

[856] Cicchino, J.B. (2017). Effectiveness of forward collision warning and autonomous emergency braking systems in reducing front-to-rear crash rates. Accident Analysis and Prevention, V. 99, Part A, February 2017, pp. 142–52.

[857] Kusano, K.D., and Gabler H.C. (2012). Safety Benefits of Forward Collision Warning, Brake Assist, and Autonomous Braking Systems in Rear-End Collisions, Intelligent Transportation Systems, IEEE Transactions, Volume 13 (4).

[858] Leslie, A, Kiefer, R., Meitzner, M, and Flannagan, C. (2019). Analysis of the Field Effectiveness of General Motors Production Active Safety and Advanced headlighting Systems. University of Michigan Transportation Research Institute, UMTRI-2019-6, September 2019.

same models that did not elect to install them. The analysis was based on crashes occurring during 2010 to 2014 in 22 States and controlled for other factors that affected crash risk. Cicchino found that FCW reduced all rear-end striking crashes by 27 percent and rear-end striking injury crashes by 20 percent, and that AEB functional at high speeds reduced these crashes by 50 and 56 percent, respectively. She also found that low speed AEB without driver warning reduced all crashes by 43 percent and injury crashes by 45 percent. She also found that even low-speed AEB could impact crashes at higher speed limits. Reductions were found of 53 percent, 59 percent, and 58 percent for all rear-end striking crash rates, rear-end striking injury crash rates, and rear-end third party injury crash rates, respectively, at speed limits of 40-45 mph. For speed limits of 35 mph or less, reductions of 40 percent, 40 percent, and 43 percent were found. For speed limits of 50 mph or greater, reductions of 31 percent, 30 percent, and 28 percent, were found. Further, Cicchino (2016) found significant reductions (30 percent) in rear-end injury crashes even in crashes on roadways where speed limits exceeded 50 mph.

Kusano and Gabler (2012) examined the effectiveness of various levels of forward collision technologies including FCW and AEB based on simulations of 1,396 real world rear end crashes from 1993-2008 NASS CDS databases. The authors developed a probability-based framework to account for variable driver responses to the warning systems. Kusano and Gabler found FCW systems could reduce rear-end crashes by 3.2 percent and driver injuries in rear-end crashes by 29 percent. They also found that full AEB systems with FCW, pre-crash brake assist, and autonomous pre-crash braking could reduce rear-end crashes by 7.7 percent and reduce moderate to fatal driver injuries in rear-end crashes by 50 percent.

Fildes et al. (2015) performed meta-analyses to evaluate the effectiveness of low-speed AEB technology in passenger vehicles based on real-world crash experience across six different predominantly European countries. Data from these countries was pooled into a standard analysis format and induced exposure methods were used to control for extraneous effects. The study found a 38 percent overall reduction in rear-end crashes for vehicles with AEB compared to similar vehicles without this technology. The study also found no statistical evidence for any difference in effectiveness between urban roads with speed limits less than or equal to 60 km/h, and rural roads with speed limits greater than 60 km/h. Fildes et al. (2015) found no statistical difference in the performance of AEBs on lower speed urban or higher speed rural roadways.

Kusano and Gabler (2015) simulated rear-end crashes based on a sample of 1,042 crashes in the 2012 NASS-CDS. Modelling was based on 54 model year 2010-2014 vehicles that were evaluated in NHTSA’s New Car Assessment Program (NCAP). Kusano and Gabler found FCW systems could prevent 0-67 percent of rear-end crashes and 2-69 percent of serious to fatal driver injuries.

Leslie et al. (2019) analyzed the relative crash performance of 123,377 General Motors (GM) MY 2013 to 2017 vehicles linked to State police-reported crashes by VIN. GM provided VIN-linked safety content information for these vehicles to enable precise identification of safety technology content. The authors analyzed the effectiveness of a variety of crash avoidance technologies including both FCW and AEB separately. They estimated effectiveness comparing system-relevant crashes to baseline (control group) crashes using a quasi-induced exposure method in which rear-end struck crashes are used as the control group. Leslie et al. found that

FCW reduced rear-end striking crashes of all severities by 21 percent, and that AEB (which includes FCW) reduced these crashes by 46 percent.[859]

For this analysis, NHTSA based its projections on Leslie et al. because they are the most recent study, and thus reflect the most current versions of these systems in the largest number of vehicles, and also because they arguably have the most precise identification of the presence of the specific technologies in the vehicle fleet. Furthermore, Leslie et al. was the only study to report estimates for each of the six crash avoidance technologies analyzed for the final rule, hence providing a certain level of consistency amongst estimates. NHTSA recognizes that there is uncertainty in estimates of these technologies' effectiveness, especially at this early stage of deployment. For this reason, the agency examines a range of effectiveness rates to estimate boundary outcomes in a sensitivity analysis.

Leslie et al. measured effectiveness against all categories of crashes but did not specify effectiveness against crashes that result in fatalities or injuries. NHTSA examined a range of effectiveness rates against fatal crashes using a central case based on boundary assumptions of no effectiveness and full effectiveness across all crash types. Our central case is thus a simple average of these two extremes. Sensitivity cases were based on the 95th percent confidence intervals calculated from this central case. Leslie et al. found effectiveness rates of 21 percent for FCW and 46 percent for AEB. Our central fatality effectiveness estimates will thus be 10.5 percent for FCW and 23 percent for AEB. The calculated 95th percentile confidence limits range is 8.11 to 12.58 percent effective for FCW and 20.85 to 25.27 for AEB. We note that our central estimate is conservative compared to averages of those studies that did specifically examine fatality impacts; that is, the analysis assumes reduced future fatalities less than most of, or the average of, those studies, and thus minimizes the estimate of fatality impacts under alternatives to the current standards. Furthermore, we note that the estimates against fatal crashes is higher in the recent studies in Table 7-5, which reflects our understanding that earlier iterations of AEB and FCW may have been less effective against crashes that result in fatalities than newer and improved versions.[860]

[859] NHTSA notes that UMTRI, the sponsoring organization for the Leslie et al. study, published a previous version of this same study utilizing the same methods in March of 2018 (Flannagan, C. and Leslie, A, Crash Avoidance Technology Evaluation Using Real-World crashes, University of Michigan Transportation Research Institute, March 22, 2018). The agency focused on the more recent 2019 study because its sample size is significantly larger, and it represents more recent model year vehicles. The revised (2019) study uses the same basic techniques but incorporated a larger database of system-relevant and control cases (123,377 cases in the 2019 study vs. 35,401 in the 2018 study). Relative to the Flannagan and Leslie (2018) findings, the results of the 2019 study varied by technology. The revised study found effectiveness rates of 21 percent for FCW and 46 percent for AEB, compared to 16 and 45 percent in the 2018 study. The revised study found effectiveness rates of 10 percent for LDW and 20 percent for LKA, compared to 3 and 30 percent for these technologies in the 2018 study. The revised study found effectiveness rates of 3 percent for BSD and 26-37 percent for LCA systems, compared to 8 percent and 19-32 percent for these technologies in the 2018 study. Thus, some system effectiveness estimates increased while others decreased.

[860] As an example of improvements, NHTSA notes that the Mercedes system described in their 2015 owner's manual specified that for stationary objects the system would only work in crashes below 31 mph, but that in their manual for the 2019 model, the systems are specified to work in these crashes up to 50 mph.

7.1.13.2.2 Lane Departure Crash Technologies

For lane departure crashes, manufacturers are currently equipping vehicles with lane departure warning (LDW), which monitors lane markings on the road and alerts the driver when their vehicle is about to drift beyond a delineated edge line of their current travel lane, as well as lane keep assist (LKA), which provides gentle steering adjustments to help drivers avoid unintentional lane crossing. Table 7-6 summarizes studies which have measured effectiveness for LDW and LKA.

Table 7-6 – Summary of LDW Technology Effectiveness Estimates

Authors	LDW Type	Crash Reduction	Fatalities	Injury Reduction		All Injuries
				Serious	Minor	
Cicchino (2018)[861]	LDW	11%				21%
Sternlund, Strandroth, et al. (2017)[862]	LDW/LKA					6-30%
Leslie et al. (2019)[863]	LDW	10%				
	LKA	20%				
Kusano & Gabler (2015)[864]	LDW	11-23%	13-22%	13-22%		
Kusano, Gorman, et al. (2014)[865]	LDW	29%		24%		

Cicchino (2018) examined crash involvement rates per insured vehicle year for vehicles that offered LDW as an option and compared crash rates for those that had the option installed to those that did not. The study focused on single-vehicle, sideswipe, and head-on crashes as the relevant target population for LDW effectiveness rates. The study examined 5,433 relevant crashes of all severities found in 2009-2015 police-reported data from 25 States. The study was limited to crashes on roadways with 40 mph or greater speed limits not covered in ice or snow since lower travel speeds would be more likely to fall outside of the LDW systems' minimum operational threshold. Cicchino found an overall reduction in relevant crashes of 11 percent for vehicles that were equipped with LDW. She also found a 21 percent reduction in injury crashes. The result for all crashes was statistically significant, while that for injury crashes approached significance ($p<0.07$). Cicchino did not separately analyze LKA systems.

Sternlund et al. (2017) studied single vehicle and head-on injury crash involvements relevant to LDW and LKA in Volvos on Swedish roadways. They used rear-end crashes as a control and compared the ratio of these two crash groups in vehicles that had elected to install LDW or LKA

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[861] Cicchino, J.B. (2018). Effects of lane departure warning on police-reported crash rates, Journal of Safety Research 66 (2018), pp.61-70. National Safety Council and Elsevier Ltd., May, 2018. https://pubmed.ncbi.nlm.nih.gov/30121111/

[862] Sternlund, S., Strandroth, J., Rizzi, M., Lie, A., and Tingvall, C. (2017). The effectiveness of lane departure warning systems – A reduction in real-world passenger car injury crashes. Traffic Injury Prevention V. 18 Issue 2 Jan 2017. https://pubmed.ncbi.nlm.nih.gov/27624313/

[863] Leslie et al. (2019), op. cit.

[864] Kusano and Gabler (2015), op. cit.

[865] Kusano, K., Gorman, T.I., Sherony, R., and Gabler, H.C. Potential occupant injury reduction in the U.S. vehicle fleet for lane departure warning-equipped vehicles in single-vehicle crashes. Traffic Injury Prevention 2014 Suppl 1:S157-64. https://pubmed.ncbi.nlm.nih.gov/25307382/

to the ratio in vehicles that did not have this content. Studied crashes were limited to roadways with speeds of 70-120 kph and not covered with ice or snow. Sternlund et al. found that LDW/LKA systems reduced single vehicle and head-on injury crashes in their crash population by 53 percent, with a lower limit of 11 percent, which they determined corresponded to a reduction of 30 percent (lower limit of 6 percent) across all speed limits and road surface assumptions.

Leslie et al. (2019) analyzed the relative crash performance of 123,377 General Motors (GM) MY 2013 to 2017 vehicles linked to state police-reported crashes by VIN. GM provided VIN-linked safety content information for these vehicles to enable precise identification of safety technology content. The authors analyzed the effectiveness of a variety of crash avoidance technologies including both LDW and LKA separately. They estimated effectiveness comparing system-relevant crashes to baseline (control group) crashes using a quasi-induced exposure method in which rear-end struck crashes are used as the control group. Leslie et al. found that LDW reduced lane departure crashes of all severities by 10 percent, and that LKA (which includes LDW) reduced these crashes by 20 percent.

Kusano et al. (2014) developed a comprehensive crash and injury simulation model to estimate the potential safety impacts of LDW. The model simulated results from 481 single-vehicle collisions documented in the NASS-CDS database for the year 2012. Each crash was simulated as it actually occurred and again as it would occur had the vehicles been equipped with LDW. Crashes were simulated multiple times to account for variation in driver reaction, roadway, and vehicle conditions. Kusano et al. found that LDW could reduce all roadway departure crashes caused by the driver drifting from his or her lane by 28.9 percent, resulting in 24.3 percent fewer serious injuries.

Kusano and Gabler (2015), simulated single-vehicle roadway departure crashes based on a sample of 478 crashes in the 2012 NASS-CDS. Modelling was based on 54 model year 2010-2014 vehicles that were evaluated in NHTSA's New Car Assessment Program (NCAP). Kusano and Gabler found LDW systems could prevent 11-23 percent of drift-out-of-lane crashes and 13-22 percent of serious to fatally injured drivers.

As noted previously for frontal crash technologies, we will base our projections on Leslie et al. because they are the most recent study, thereby reflecting the most current versions of these systems in the largest number of vehicles, and because they arguably have the most precise identification of the presence of the specific technologies in the vehicle fleet. However, unlike forward crash technologies, lane change technologies are operational at travel speeds where fatalities are likely to occur. Both LDW and LKA typically operate at speeds above roughly 35 mph. For this reason, and because the research noted in Table 7-6 indicates similar effectiveness against fatalities, injuries, and crashes, we believe it is reasonable to assume the Leslie et al. crash reduction estimates are generally applicable to all crash severities, including fatal crashes. Our central effectiveness estimates are thus 10 percent for LDW and 20 percent for LKA. For sensitivity analysis, we adopt the 95 percent confidence intervals from Leslie et al. For LKA this range is 14.95-25.15 percent. For LDW, the upper range was 4.95-13.93 percent.

7.1.13.2.3 Blind Spot Crash Technologies

To address blind spot crashes, manufacturers are currently equipping vehicles with BSD, which detects vehicles in either of the adjacent lanes that may not be apparent to the driver. The system warns the driver of an approaching vehicle's presence to help facilitate safe lane changes and avoid crashes. A more advanced version of this, LCA, also detects vehicles that are rapidly approaching the driver's blind spot. Table 7-7 summarizes studies which have measured effectiveness for BSD and LCA.

Table 7-7 – Summary of BSD Technology Effectiveness Estimates

Authors	BSD Type	Crash Reduction	Injury Reduction
Cicchino (2017b)[866]	BSD	14%	23%
Leslie et al. (2019)[867]	BSD	3%	
	LCA	26%	
Isaksson-Hellman & Lindman (2018)[868]	LCA	30%*	31%**
* reduction in claim costs across all lane change crashes			
** reduction in severe crashes with repair costs greater than $1250			

Cicchino (2017) used Poisson regression to compare crash involvement rates per insured vehicle year in police-reported lane-change crashes in 26 U.S. States during 2009-2015 between vehicles with blind spot monitoring and the same vehicle models without the optional system, controlling for other factors that can affect crash risk. Systems designs across the 10 different manufacturers included in the study varied regarding the extent to which the size of the adjacent lane zone that they covered exceeded the blind spot area, speed differentials at which vehicles could be detected, and their ability to detect rapidly approaching vehicles, but these different systems were not examined separately. The study examined 4,620 lane change crashes, including 568 injury crashes. Cicchino found an overall reduction of 14 percent in blind spot related crashes of all severities, with a non-significant 23 percent reduction in injury crashes.

Leslie et al. (2019) analyzed the relative crash performance of 123,377 2013-2017 General Motors (GM) vehicles linked to State police-reported crashes by VIN. GM provided VIN-linked safety content information for these vehicles to enable precise identification of safety technology content. The authors analyzed the effectiveness of a variety of crash avoidance technologies including both BSD and LCA separately. They estimated effectiveness comparing system-relevant crashes to baseline (control group) crashes using a quasi-induced exposure method in which rear-end struck crashes are used as the control group. Flannagan and Leslie found that BSD reduced lane departure crashes of all severities by 3 percent (non-significant), and that LCA (which includes BSD) reduced these crashes by 26 percent.

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[866] Cicchino, J.B. (2017b). Effects of blind spot monitoring systems on police-reported lane-change crashes. Insurance Institute for Highway Safety, August 2017.
[867] Leslie et al. (2019), op. cit.
[868] Isaksson-Hellman, I., Lindman, M., An evaluation of the real-world safety effect of a lane change driver support system and characteristics of lane change crashes based on insurance claims. Traffic Injury Prevention, February 28, 2018: 19 (supp. 1). https://pubmed.ncbi.nlm.nih.gov/29584482/

Isaksson-Hellman and Lindman (2018) evaluated the effect of the Volvo Blind Spot Information System (BLIS) on lane change crashes. Volvo's BLIS functions as an LCA, detecting vehicles approaching the blind spot as well as those already in it. The authors analyzed crash rate differences in lane change situations for cars with and without the BLIS system based on a population of 380,000 insured vehicle years. The authors found the BLIS system did not significantly reduce the overall number of lane change crashes of all severities, but they did find a significant 31 percent reduction in crashes with a repair cost exceeding $1250, and a 30 percent lower claim cost across all lane change crashes, indicating a reduced crash severity effect.

Like lane change technologies, blind spot technologies are operational at travel speeds where fatalities are likely to occur. NHTSA therefore assumes the Leslie et al. crash reduction estimates are generally applicable to all crash severities, including fatal crashes. Our central effectiveness estimates are thus 3 percent for BSD and 26 percent for LCA. For sensitivity analysis, we adopt the 95 percent confidence intervals from Leslie et al. For LCA this range is 16.59-33.74 percent. For BSD, the upper range was 14.72 percent, but the findings were not statistically significant. The agency therefore limited the range to 0-14.72 percent. Table 7-8 summarizes the effectiveness rates calculated in Leslie et al. and used in this analysis. Differences between the rates listed as "Used in CAFE Fatality Analysis" and those computed from Leslie et al. are explained in the above discussion.

Table 7-8 – Summary of Advanced Technology Effectiveness Rates for Central and Sensitivity Cases

Tech.	UMTRI September 2019 Report					Used in CAFE Fatality Analysis		
	Estimate	Std. Error	Central	Low	High	Central	Low	High
FCW	-0.2334	0.0288	21	16.22	25.16	10.5	8.11	12.58
AEB	-0.6218	0.0419	46	41.71	50.54	23	20.85	25.27
LDW	-0.1004	0.0253	10	4.95	13.93	10	4.95	13.93
LKA	-0.2258	0.0326	20	14.95	25.15	20	14.95	25.15
BSD	-0.0297	0.0661	3	-10.50	14.72	3	0.00	14.72
LCA	-0.2965	0.0587	26	16.59	33.74	26	16.59	33.74

7.1.13.3 Target Populations for Crash Avoidance Technologies

The impact these technologies will have on safety is a function of both their effectiveness rate and the portion of occupant fatalities that occur under circumstances that are relevant to the technologies function. NHTSA based target population estimates on a recent study that examined these portions specifically for a variety of crash avoidance technologies. Wang (2019)[869] documented target populations for five groups of collision avoidance technologies in passenger vehicles including forward collisions, lane keeping, blind zone detection, forward pedestrian impact, and backing collision avoidance. The first three of these affect the light vehicle occupant target population examined in this analysis. Wang separately examined crash populations stratified by severity including fatal injuries, non-fatal injuries, and property damaged only (PDO) vehicles. Wang based her analysis on 2011-2015 data from NHTSA's

[869] https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812653. (Accessed: February 14, 2022).

Fatality Analysis Reporting System (FARS), National Automotive Sampling System (NASS), and General Estimates System (GES). FARS data were the basis for fatal crashes while nonfatal injuries and PDOs were derived from the NASS and GES.

Wang followed the pre-crash typology concept initially developed by Volpe.[870] Under this concept, crashes are categorized into mutually exclusive and distinct scenarios based on vehicle movements and critical events occurring just prior to the crash. Table 7-9 summarizes the portion of total annual crashes and injuries for each crash severity category that is relevant to the three crash scenarios examined.

Table 7-9 – Summary of Target Crash Proportions by Technology Group

Safety System Crash Type	Crashes	Fatalities	MAIS 1-5 Injuries	PDOVs
Frontal Crashes	29.4%	3.8%	31.5%	36.3%
Lane Departure Crashes	19.4%	44.3%	17.1%	11.9%
Blind Spot Crashes	8.7%	1.6%	6.7%	11.8%

The relevant proportions vary significantly depending on the severity of the crash. The rear-end crashes that are addressed by FCW and AEB technologies tend to be low-speed crashes and thus account for a larger portion of non-fatal injury and PDO crashes than for fatalities. Only 4 percent of fatal crashes occur in front-to-rear crashes, but over 30 percent of nonfatal crashes are this type. By contrast, fatal crashes are highly likely to involve inadvertent lane departure, 44 percent of all light vehicle occupant fatalities occur in crashes that involve lane departure, but only 17 percent of non-fatal injuries and 12 percent of PDOs involve this crash scenario. Blind spot crashes account for only about 2 percent of fatalities, 7 percent of MAIS1-5 injuries, and 12 percent of PDOs.

The target population of this analysis is occupants of light-duty vehicles subject to CAFE. We chose occupants of light-duty vehicles rather than a more inclusive group such as all road users—which would include pedestrians, bicyclists, and occupants of heavier vehicles—because the agency has been collecting data and developing statistical models for in-vehicle occupants for decades. The agency sought comment in the proposal on whether all road users should be included in the fatality model. While we are not including all road users in the safety model for this final rule, we will consider including them in future iterations of the model. The values in Table 7-5 are portions of all crashes that occur annually. These include crashes of motor vehicles not subject to the current CAFE rulemaking such as medium and large trucks, buses, motorcycles, bicycles, etc. To adjust for this, the values in Wang are normalized to represent their portion of all light passenger vehicle (PV) crashes, rather than all crashes of any type. Wang provides total PV fatalities consistent with her technology numbers which are used as a baseline for this process. Based on 2011-2015 FARS data, Wang found an average of 29,170 PV occupant fatalities occurred annually.

[870] Najm, W. G., Smith, J., & Yanagisawa, M. (2007, April). *Pre-crash scenario typology for crash avoidance research* (Report No. DOT HS 810 767). Washington, DC: National Highway Traffic Safety Administration.

A second adjustment to Wang's results was made to make them compatible with the effectiveness estimates found in Leslie et al. In her target population estimate for lane departure warning, Wang included both head-on collisions and rollovers, but Leslie et al. did not. The Leslie et al. effectiveness rate is thus applicable to a smaller target population than that examined by Wang. To make these numbers more compatible, counts for these crash types were removed from Wang's lane departure totals.

Electronic Stability Control (ESC) has been standard equipment in all light vehicles in the United States since the 2012 model year. ESC is highly effective in reducing roadway departure and traction loss crashes, and although it will be present in all future model year vehicles, it was present in only about 30 percent of the 2011-2015 on-road fleet examined by Wang. To reflect the impact of ESC on future on-road fleets therefore, NHTSA further adjusted Wang's numbers to reflect a 100 percent ESC presence in the on-road fleet. NHTSA allocated the reduced roadway departure fatalities to the LDW target population, and the reduced traction loss fatalities to the AEB target population. This has the effect of reducing the total fatalities in both groups as well as in the total projected fatalities baseline.

Table 7-10 summarizes the revised incidence counts and re-calculated proportions of total PV occupant crash /injury. Revised totals are derived from original totals referenced in Table 1-3 in Wang (2019).

Table 7-10 – Adjusted Target Crash Counts and Proportions

Crash Type	Crashes	Fatalities	MAIS 1-5	PDOVs
Frontal Crashes	1,703,541	1,048	883,386	2,641,884
% All PV Occupant Crashes	30.2%	4.0%	32.4%	36.8%
Lane Departure Crashes	1,126,397	9,428	479,939	863,213
% All PV Occupant Crashes	20.0%	35.8%	17.6%	12.0%
Blind Spot Crashes	503,070	542	188,304	860,726
% All PV Occupant Crashes	8.9%	2.1%	6.9%	12.0%
Total, all Tech Groups	3,333,008	11,017	1,551,629	4,365,823
% All PV Occupant Crashes	59.1%	41.8%	56.8%	60.9%
All Crashes	5,640,000	26,364	2,730,000	7,170,000

7.1.13.4 Fleet Penetration Schedules

The third element of the rule's safety projections is the fleet technology penetration schedules. Advanced safety technologies (ADAS) will only influence the safety of future MY fleets to the extent that they are installed and used in those fleets. These technologies are already being installed on some vehicles to varying degrees, but the agency expects that over time, they will become standard equipment due to some combination of market pressure and/or safety regulation. NHTSA adopts this assumption based on the history of most previous vehicle safety technologies, which are now standard equipment on all new vehicles sold in the United States.

The pace of technology adoption is estimated based on a variety of factors, but the most fundamental is the current pace of adoption in recent years. These published data were obtained from Ward's Automotive Reports for each technology.[871] Since these technologies are relatively recent, only a few years of data—typically 2 or 3 years—were available from which to derive a trend. This makes these projections uncertain, but under these circumstances, a continuation of the known trend is the baseline assumption, which we modify only when there is a rationale to justify it.

The technologies are examined in pairs reflecting their mutual target populations. Both FCW and AEB affect the same target population—frontal collisions. Both systems have been installed in some current MY vehicles, but their relative paces are expected to diverge significantly due to a formal agreement brokered by NHTSA and IIHS involving nearly all auto manufacturers, to have AEB installed in 100 percent of their vehicles by September 2022 (MY 2023).[872] Wards first published installation rates for FCW and AEB for the 2016 model year and as of this analysis the 2017 MY is the latest data they have published. We thus have data indicating that FCW was installed in 17.6 percent of MY 2016 vehicles and 30.5 percent of MY 2017 vehicles. AEB was installed in 12.0 percent of MY 2016 vehicles and 27.0 percent of MY 2017 vehicles. More recent reports submitted by manufacturers to the Federal Register indicate that installation rates accelerated in MY 2018 and 2019 vehicles. Four manufacturers, Tesla, Volvo, Audi, and Mercedes have already met their voluntary commitment of 100 percent installation 3 years ahead of schedule. During the period, September 1, 2018, through August 31, 2019, 12 of the 20 manufacturers equipped more than 75 percent of their new passenger vehicles with AEB, and overall manufacturers equipped more than 9.5 million new passenger vehicles with AEB.[873]

Because of the NHTSA/IIHS agreement, NHTSA assumed that some form of AEB will be in 100 percent of light vehicles by MY 2023. To derive installation rates for MYs 2020 through 2022, NHTSA interpolated between the MY 2019 rate of 58.3 percent and the MY 2023 rate of 100 percent. To derive a MY 2015 estimate, NHTSA modelled the results for MYs 2016-2023 and calculated a value for year x=0, essentially extending the model results back one year on the same trendline.

For FCW, NHTSA used the same interpolation/modeling method as was used for AEB to derive an initial baseline trend. However, while both systems are available on some portion of the current MY fleet, the agency anticipates that by MY 2023, all vehicles will have AEB systems that essentially encompass both FCW and AEB functions. NHTSA therefore projects a gradual increase in both systems until the sum of both systems penetration rates exceeds 100 percent. At

[871] Derived from Ward's Automotive Yearbooks, 2014 through 2018, % Factory Installed Electronic ADAS Equipment tables, weighting domestic and imported passenger cars and light trucks by sales volume.
[872] https://www.nhtsa.gov/press-releases/nhtsa-iihs-announcement-aeb. (Accessed: February 14, 2022).
[873] NHTSA Announces Update to Historic AEB Commitment by 20 Automakers. December 17, 2019. https://www.nhtsa.gov/press-releases/nhtsa-announces-update-historic-aeb-commitment-20-automakers. (Accessed: February 14, 2022).

that point, the agency projects a gradual decrease in FCW only installations until FCW only systems are completely replaced by AEB systems in MY 2023.

For LDW, Wards penetration data were available as far back as MY 2013, giving a total of 7 data points through MY 2019. The projection for LDW was derived by modelling these data points. The data indicate a near linear trend and our initial projections of future years were derived directly from this model. Wards did not report any of the more advanced LKA systems until MY 2016, leaving only 4 data points through 2019. NHTSA modelled a simple trendline through these data points to estimate the pace of future LKA installations. As with Frontal crashes, the agency assumes a gradual phase-in of the most effective technology, LKA, will eventually replace the lesser technology, LDW, and NHTSA allows gradual increases in both systems penetration until their sum exceeds 100 percent, at which point LDW penetration begins to decline to zero while LKA penetration climbs to 100 percent.

For blind spot crashes, Wards data were available for MYs 2013-2017 for BSD, but no data were available to distinguish LCA systems. LCA systems were available as optional equipment on at least 10 MY 2016 vehicles.[874] In addition, Flannagan and Leslie found numerous cases in State databases involving vehicles with LCA. Because LCA data are not specifically identified, NHTSA will estimate its frequency based on the samples found in Flannagan & Leslie. In that study, 62 percent of vehicles with blind spot technologies had BSD alone, while 38 percent had LCA (which includes BSD). NHTSA employs this ratio to establish the relative frequency of these technologies in our projections. As with frontal and lane change technologies, the agency assumes a gradual phase-in of the most effective technology, LCA, will eventually replace the lesser technology, BSD, and the agency allows gradual increases in both systems penetration until their sum exceeds 100 percent, at which point BSD penetration begins to decline to zero while LCA penetration climbs to 100 percent.

7.1.13.5 Impact Calculations

Table 7-11, Table 7-12, and Table 7-13 summarize the resulting estimates of impacts on fatality rates for frontal crash technologies, lane change technologies, and blind spot technologies respectively for MYs 2015-2035. All previously discussed inputs are shown in the tables. The effect of each technology is the product of its effectiveness, its percent installation in the MY fleet, and the portion of the total light vehicle occupant target population that each technology might address. Since installation rates for each technology apply to different portions of the vehicle fleet (i.e., vehicles have either the more basic or more advanced version of the technology), the effect of the two technologies combined is a simple sum of the two effects. Similarly, because each crash type addresses a unique target population, there is no overlap among the three crash types and the sum of the normalized crash impacts across all three crash types represents the total impact on fatality rates from these 6 technologies for each model year. These cumulative results are shown in the last column of Table 7-13. As technologies phase in to newer MY fleets,[875] their impact on the light vehicle occupant fatality rate increases

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[874] https://www.autobytel.com/car-buying-guides/features/10-cars-with-lane-change-assist-using-cameras-or-sensors-130847. (Accessed: February 14, 2022).

[875] While it is technically possible to retrofit these systems into the on-road fleet, such retrofits would be significantly more expensive than OEM installations. NHTSA thus assumes all on-road fleet penetration of these technologies will come through new vehicle sales.

proportionally to roughly 8.5 percent before levelling off. That is, eventually, by approximately MY 2026, these technologies are ultimately expected to reduce fatalities and fatality rates for new vehicles by 8.6 percent from their initial baseline levels.

Table 7-11 – Phased Impact of Crashworthiness Technologies on Fatality Rates, Forward Collision Crashes

MY	Forward Collision Warning		Automatic Emergency Braking		% T.P.	Weighted Effectiveness
	FCW Eff.	% Inst.	AEB Eff.	% Inst.		
2015	10.5%	0.047	23.0%	0.011	4.0%	0.000292
2016	10.5%	0.176	23.0%	0.120	4.0%	0.001831
2017	10.5%	0.305	23.0%	0.270	4.0%	0.00374
2018	10.5%	0.466	23.0%	0.445	4.0%	0.006011
2019	10.5%	0.417	23.0%	0.583	4.0%	0.007068
2020	10.5%	0.313	23.0%	0.687	4.0%	0.007585
2021	10.5%	0.209	23.0%	0.792	4.0%	0.008103
2022	10.5%	0.104	23.0%	0.896	4.0%	0.008625
2023	10.5%	0	23.0%	1	4.0%	0.009139
2024	10.5%	0	23.0%	1	4.0%	0.009139
2025	10.5%	0	23.0%	1	4.0%	0.009139
2026	10.5%	0	23.0%	1	4.0%	0.009139
2027	10.5%	0	23.0%	1	4.0%	0.009139
2028	10.5%	0	23.0%	1	4.0%	0.009139
2029	10.5%	0	23.0%	1	4.0%	0.009139
2030	10.5%	0	23.0%	1	4.0%	0.009139
2031	10.5%	0	23.0%	1	4.0%	0.009139
2032	10.5%	0	23.0%	1	4.0%	0.009139
2033	10.5%	0	23.0%	1	4.0%	0.009139
2034	10.5%	0	23.0%	1	4.0%	0.009139
2035	10.5%	0	23.0%	1	4.0%	0.009139

Table 7-12 – Phased Impact of Crashworthiness Technologies on Fatality Rates, Lane Departure Crashes

MY	Lane Departure Warning		Lane Keep Assist		% T.P.	Weighted Effectiveness
	LDW Eff.	% Inst.	LKA Eff.	% Inst.		
2015	10.0%	0.177	20.0%	0.000	35.8%	0.006329
2016	10.0%	0.198	20.0%	0.088	35.8%	0.013374
2017	10.0%	0.280	20.0%	0.205	35.8%	0.024674
2018	10.0%	0.382	20.0%	0.320	35.8%	0.036546
2019	10.0%	0.479	20.0%	0.442	35.8%	0.04874
2020	10.0%	0.442	20.0%	0.558	35.8%	0.055717
2021	10.0%	0.324	20.0%	0.676	35.8%	0.059925
2022	10.0%	0.207	20.0%	0.794	35.8%	0.064134
2023	10.0%	0.089	20.0%	0.911	35.8%	0.068343
2024	10.0%	0	20.0%	1	35.8%	0.071519
2025	10.0%	0	20.0%	1	35.8%	0.071519
2026	10.0%	0	20.0%	1	35.8%	0.071519
2027	10.0%	0	20.0%	1	35.8%	0.071519
2028	10.0%	0	20.0%	1	35.8%	0.071519

2029	10.0%	0	20.0%	1	35.8%	0.071519
2030	10.0%	0	20.0%	1	35.8%	0.071519
2031	10.0%	0	20.0%	1	35.8%	0.071519
2032	10.0%	0	20.0%	1	35.8%	0.071519
2033	10.0%	0	20.0%	1	35.8%	0.071519
2034	10.0%	0	20.0%	1	35.8%	0.071519
2035	10.0%	0	20.0%	1	35.8%	0.071519

Table 7-13 – Phased Impact of Crashworthiness Technologies on Fatality Rates, Blind Spot Crashes and Combined Total – All Three Crash Types

MY	Blind Spot Detection		Lane Change Assist		% T.P.	Weighted Effectiveness	Three Techs Avg Eff. Impact
	BSD Eff.	% Inst.	LCA Eff.	% Inst.			
2015	3.0%	0.082	26.0%	0.123	2.1%	0.000711	0.007332
2016	3.0%	0.124	26.0%	0.186	2.1%	0.001073	0.016278
2017	3.0%	0.155	26.0%	0.233	2.1%	0.001342	0.029756
2018	3.0%	0.191	26.0%	0.287	2.1%	0.001654	0.044211
2019	3.0%	0.222	26.0%	0.333	2.1%	0.001915	0.057723
2020	3.0%	0.252	26.0%	0.376	2.1%	0.002165	0.065467
2021	3.0%	0.283	26.0%	0.424	2.1%	0.002442	0.07047
2022	3.0%	0.314	26.0%	0.472	2.1%	0.002718	0.075473
2023	3.0%	0.345	26.0%	0.520	2.1%	0.002994	0.080476
2024	3.0%	0.376	26.0%	0.568	2.1%	0.00327	0.083938
2025	3.0%	0.384	26.0%	0.617	2.1%	0.003532	0.084189
2026	3.0%	0.335	26.0%	0.665	2.1%	0.003759	0.084417
2027	3.0%	0.287	26.0%	0.713	2.1%	0.003987	0.084644
2028	3.0%	0.239	26.0%	0.761	2.1%	0.004214	0.084871
2029	3.0%	0.101	26.0%	0.809	2.1%	0.004442	0.085099
2030	3.0%	0.143	26.0%	0.857	2.1%	0.004669	0.085326
2031	3.0%	0.095	26.0%	0.905	2.1%	0.004896	0.085554
2032	3.0%	0.047	26.0%	0.953	2.1%	0.005124	0.085781
2033	3.0%	0	26.0%	1	2.1%	0.005345	0.086002
2034	3.0%	0	26.0%	1	2.1%	0.005345	0.086002
2035	3.0%	0	26.0%	1	2.1%	0.005345	0.086002

7.1.13.6 Impact of Advanced Technologies on Older Vehicles' Fatality Rates

The users of older vehicles will also benefit from crash avoidance technologies on newer vehicles when those technologies prevent multi-vehicle crashes with older vehicles. Crash avoidance technologies prevent crashes from happening and thus benefit both the vehicle with the technology and any other vehicles that it might have collided with. However, the scope of these impacts on older vehicle's fatality rates are somewhat limited due to several factors:

- Single vehicle crashes, which make up about half of all fatal crashes, will not be affected. Only multi-vehicle crashes involving a newer vehicle with the advanced technology and an older vehicle will be affected. Multi-vehicle crashes account for roughly half of all light vehicle occupant fatalities.

- For a new safety technology to benefit an older vehicle in a multi-vehicle crash, the vehicle with the technology must have been in a position to control or prevent the crash. For example, in front-to-rear crashes which can be addressed by FCW and AEB, the older vehicle would only benefit if it was the vehicle struck from behind. If the struck vehicle were the newer vehicle, its AEB technology would not prevent the crash. Logically this would occur in roughly half of two-vehicle crashes and a third of all three-vehicle crashes. Since most multi-vehicle crashes involve only two vehicles, roughly half of all multi-vehicle crashes might qualify.

- The benefits experienced by older vehicles are proportional to the probability that the vehicles they collide with are newer vehicles with advanced crash avoidance technology. We estimate that the probability that this would occur is a function of the relative exposure of vehicles by age, measured by the portion of total VMT driven by vehicles of that age. Based on VMT schedules (see CY 2016 example in Table 7-14) new (current MY) vehicles account for about 9.6 percent of annual fleet VMT. The relevant portion would increase over time as additional MY vehicles are produced with advanced technologies. However, the portion of older vehicle crashes that might be affected by newer technologies is initially very small—only about 2 percent (.5*.5*.096) of older vehicles involved in crashes might benefit from advanced crash avoidance technologies in other vehicles in the first year.

Table 7-14 – Registrations, Total VMT, and Proportions of Total VMT by Vehicle Age

Registrations, Total VMT, And Proportions of Total VMT By Vehicle Age				
Model Year	**Age**	**CY 2016 Registrations**	**VMT (thousand)**	**% Total VMT**
1977	39	286,019	927,877	0.000329
1978	38	332,760	1,247,190	0.000443
1979	37	375,561	1,556,553	0.000553
1980	36	205,942	903,948	0.000321
1981	35	208,192	1,010,499	0.000359
1982	34	213,697	1,130,039	0.000401
1983	33	265,583	1,496,439	0.000531
1984	32	408,058	2,428,835	0.000862
1985	31	477,178	2,993,451	0.001063
1986	30	605,932	3,991,280	0.001417
1987	29	644,568	4,396,414	0.001561
1988	28	629,179	4,431,880	0.001574
1989	27	747,740	5,475,868	0.001944
1990	26	755,244	5,685,511	0.002019
1991	25	899,252	6,991,287	0.002483
1992	24	1,005,716	8,055,442	0.00286
1993	23	1,308,396	10,784,619	0.003829

Registrations, Total VMT, And Proportions of Total VMT By Vehicle Age				
Model Year	**Age**	**CY 2016 Registrations**	**VMT (thousand)**	**% Total VMT**
1994	22	1,738,409	14,739,099	0.005234
1995	21	2,212,145	19,191,169	0.006815
1996	20	2,364,368	21,059,984	0.007478
1997	19	3,401,992	31,134,256	0.011055
1998	18	4,079,728	38,358,375	0.013621
1999	17	5,377,629	52,039,074	0.018478
2000	16	6,826,267	67,907,099	0.024113
2001	15	7,475,530	76,512,692	0.027169
2002	14	8,912,404	94,016,400	0.033384
2003	13	9,825,521	106,764,943	0.037911
2004	12	10,806,847	121,080,704	0.042994
2005	11	11,649,021	134,404,144	0.047725
2006	10	11,699,430	138,962,811	0.049344
2007	9	12,519,932	153,300,527	0.054435
2008	8	11,781,605	148,871,424	0.052862
2009	7	8,171,782	106,120,610	0.037682
2010	6	9,944,848	133,696,015	0.047474
2011	5	10,967,994	152,795,831	0.054256
2012	4	12,409,627	177,760,326	0.06312
2013	3	14,197,792	210,386,962	0.074706
2014	2	14,726,690	226,423,858	0.0804
2015	1	16,208,153	257,415,893	0.091405
2016	0	16,338,755	269,760,666	0.095789
Total		223,005,486	2,816,209,994	1

To reflect this safety benefit for older vehicles, NHTSA calculated a revised fatality rate for each older MY vehicle on the road based on its interaction with each new MY starting with MY 2021 vehicles based on the following relationship:

Revised fatality rate = Fm-((x-y)mnp)+F(1-m)

Where:

F = initial fatality rate for each MY
x = baseline MY fatality rate
y = current MY fatality rate
m = proportion of occupant fatalities that occur in multi-vehicle crashes (52 percent)
n = probability that crash is with a new MY vehicle containing advanced technologies
p = probability that new vehicle is “striking” vehicle

The initial fatality rate for each vehicle MY (F) was derived by combining fatality counts from NHTSA’s Fatality Analysis Reporting System (FARS) with VMT data from IHS/Polk.

The baseline MY fatality rate (x) represents the baseline rate over which the impact of new crash avoidance technologies should be measured. It establishes the baseline rate for each MY that will be compared to the most current MY rate to determine the change in fatality rate (FR) for each MY. The relative effectiveness of new crash-avoidance technologies in modifying the fatality rate of older model vehicles is measured differently depending on the age of the older vehicle. The fatality rate is a historical measure that reflects safety differences due to both crashworthiness technologies such as air bags and crash avoidance technologies such as electronic stability control, but up through MY 2017, crashworthiness standards are the predominate cause of these differences.

The most recent significant crashworthiness safety standard, which upgraded roof strength standards, was effective in all new passenger vehicles in MY 2017. Crashworthiness standards would not have secondary benefits for older MY vehicles. Post MY 2017, NHTSA believes crash avoidance technologies will drive safety improvements. To isolate the added crash avoidance safety expected in newer vehicles, the marginal impact of the difference between the MY 2017 fatality rate and the most current MY fatality rate represents the added marginal effectiveness of new crash-avoidance technologies of each subsequent MY for MYs 2017 and earlier. Beginning with MY 2018, the difference between the older MY fatality rate and most current MY rate determines the potential safety benefit for the older vehicles.

The current MY fatality rate (y), represents the projected fatality rate of future MY vehicles after adjustment for the impacts of the advanced crash avoidance technologies and projected improvements in non-technology factors examined in this analysis. This process was discussed in detail in the previous section.

The proportion of passenger vehicle occupant fatalities that occur in multi-vehicle crashes (m), was derived from an analysis of occupants of fatal passenger vehicle crashes from 2002-2017 FARS. The analysis indicated that 47.8 percent of fatal crash occupants were in single vehicle crashes, 40.2 percent were in two vehicle crashes, and 12 percent were in crashes involving 3 or more vehicles. Overall, 52.2 percent were in multi-vehicle crashes.

The portion of older vehicle crashes involving newer vehicles containing advanced crash avoidance technologies (n), is assumed to be equal to the cumulative risk exposure of vehicles that have these technologies. This exposure is measured by the product of annual VMT by vehicle age and registrations of vehicles of that age. The CAFE Model calculates this dynamically, but as an example, based on 2016 registration data (see Table 7-14), the most current model year would represent 9.6 percent of all VMT in a calendar year, implying a 9.6 percent probability that the vehicle encountered would be from the most current MY. This percentage would increase for each calendar year as more model year vehicles adopt advanced crashworthiness technologies. NHTSA notes that other factors such as uneven concentrations of newer vs. older vehicles or improved crash avoidance in the younger vehicles already on the road that are the basis for our VMT proportion table might disrupt this assumption, but it is likely that this would only serve to slow the probability of these encounters, making this a conservative assumption in that it maximizes the probability that older vehicles might benefit from newer technologies.

The probability that the vehicle with advanced crash avoidance technology is the controlling or striking vehicle (p), was calculated using the relative frequency of fatal crash occupants in multi-vehicle crashes. As noted previously, 40.2 percent were in two vehicle crashes, and 12 percent were in crashes involving 3 or more vehicles. NHTSA assumes a probability of 50 percent for two vehicle crashes and 33 percent for crashes with 3 or more vehicles. Weighted together we estimate a 46.1 percent probability that, given a multi-vehicle crash involving a vehicle with advanced technologies and an older vehicle without them, the newer vehicle will be the striking vehicle or in a position where its crash avoidance technologies might influence the outcome of the crash with the older vehicle.

This process is illustrated in Table 7-15 below for adjustments due to improvements in MY 2021 vehicles back through MY 1995. In Table 7-15 the actual model year fatality rate is shown in the second column. As noted above, the base fatality rate, shown in column 3, is the MY 2017 rate for all MYs prior to 2018, after which it becomes the actual MY rate. Column 4 shows the difference between the fatality rate for MY 2021 and the base rate for each MY. Column 5 shows the resulting revised fatality rate that would be used for each older MY, and columns 6 and 7 list the change in that rate. The various factors noted in the above formula are applied in column 5. The results indicate a 0.006 decrease in pre-2018 MY vehicles fatality rates, with declining impacts going forward to MY 2021. In subsequent years, this impact would grow to reflect the both the increased probability that an older vehicle would be involved in crashes with vehicles equipped with advanced technology, as well as the increased technology levels in progressively newer vehicles.[876] The actual impacts are dynamically calculated within the CAFE Model using updated inputs applicable to this final rule and reflect revised fatality rate trends going forward and cover even older model years.

Table 7-15 – Example Adjustment to Fatality Rates of Older Vehicles to Reflect Impact of Advanced Crash Avoidance Technologies in Newer Vehicles

Model Year	MY Fatality Rate	Base Fatality Rate	Difference Base FR - New MY FR	Revised Fatality Rate	% Change	Difference
1995	17.979	8.628	0.269	17.973	0.00034	-0.0062
1996	16.519	8.628	0.269	16.513	0.00038	-0.0062
1997	15.789	8.628	0.269	15.783	0.00039	-0.0062
1998	14.709	8.628	0.269	14.703	0.00042	-0.0062
1999	13.679	8.628	0.269	13.673	0.00045	-0.0062
2000	12.909	8.628	0.269	12.903	0.00048	-0.0062
2001	12.259	8.628	0.269	12.253	0.00051	-0.0062
2002	11.489	8.628	0.269	11.483	0.00054	-0.0062
2003	10.889	8.628	0.269	10.883	0.00057	-0.0062
2004	10.349	8.628	0.269	10.343	0.00060	-0.0062
2005	9.679	8.628	0.269	9.673	0.00064	-0.0062
2006	9.349	8.628	0.269	9.343	0.00066	-0.0062

[876] Table 7-15 was created using inputs from the 2020 CAFE rule NPRM and is provided for explanatory purposes only.

Model Year	MY Fatality Rate	Base Fatality Rate	Difference Base FR - New MY FR	Revised Fatality Rate	% Change	Difference
2007	9.284	8.628	0.269	9.278	0.00067	-0.0062
2008	9.220	8.628	0.269	9.214	0.00067	-0.0062
2009	9.155	8.628	0.269	9.149	0.00068	-0.0062
2010	9.090	8.628	0.269	9.084	0.00068	-0.0062
2011	9.024	8.628	0.269	9.018	0.00069	-0.0062
2012	8.959	8.628	0.269	8.953	0.00069	-0.0062
2013	8.893	8.628	0.269	8.887	0.00070	-0.0062
2014	8.827	8.628	0.269	8.821	0.00070	-0.0062
2015	8.761	8.628	0.269	8.755	0.00071	-0.0062
2016	8.694	8.628	0.269	8.688	0.00071	-0.0062
2017	8.628	8.628	0.269	8.622	0.00072	-0.0062
2018	8.561	8.561	0.202	8.556	0.00054	-0.00466
2019	8.494	8.494	0.135	8.491	0.00037	-0.00311
2020	8.426	8.426	0.068	8.425	0.00018	-0.00156
2021	8.359	8.359	0.000	8.359	0	0

7.2 Impact of Weight Reduction on Safety

Vehicle mass reduction can be one of the more cost-effective means of improving fuel economy, particularly for makes and models not already built with much high-strength steel or aluminum closures or low-mass components. Manufacturers have stated that they will continue to reduce vehicle mass to meet more stringent standards, and therefore, this expectation is incorporated into the modeling analysis supporting the standards. Newer vehicles incorporate design and hardware improvements that may mitigate some of the direct safety effects to occupants associated with light-weighting.

Historically, as shown in FARS data analyzed by NHTSA,[877] mass reduction concentrated among the heaviest vehicles (chiefly, the largest LTVs, CUVs and minivans) has been estimated

[877] *See* Kahane, C. J. (1997). Relationships Between Vehicle Size and Fatality Risk in Model Year 1985- 93 Passenger Cars and Light Trucks, NHTSA Technical Report. DOT HS 808 570. Washington, DC: National Highway Traffic Safety Administration, http://wwwnrd.nhtsa.dot.gov/Pubs/808570.PDF; Kahane, C. J. (2003). Vehicle Weight, Fatality Risk and Crash Compatibility of Model Year 1991-99 Passenger Cars and Light Trucks, NHTSA Technical Report. DOT HS 809 662. Washington, DC: National Highway Traffic Safety Administration, http://wwwnrd.nhtsa.dot.gov/Pubs/809662.PDF; Kahane, C. J. (2010). "Relationships Between Fatality Risk, Mass, and Footprint in Model Year 1991-1999 and Other Passenger Cars and LTVs," Final Regulatory Impact Analysis: Corporate Average Fuel Economy for MY 2012-MY 2016 Passenger Cars and Light Trucks. Washington, DC: National Highway Traffic Safety Administration, pp. 464–542, http://www.nhtsa.dot.gov/staticfiles/DOT/NHTSA/Rulemaking/Rules/Associated%20Files/CAF E_2012-2016_FRIA_04012010.pdf Kahane, C.J. (2012). Relationships Between Fatality Risk, Mass, and Footprint in Model Year 2000-2007 Passenger Cars and LTVs: Final Report, NHTSA Technical Report. Washington, DC: National Highway Traffic Safety Administration, Report No. DOT-HS-811-665; Puckett, S.M. and Kindelberger, J.C. (2016, June). Relationships between Fatality Risk, Mass, and Footprint in Model Year 2003-2010 Passenger Cars and LTVs – Preliminary Report. (Docket No. NHTSA2016-0068). Washington, DC: National Highway Traffic Safety Administration.

to reduce overall fatalities, while mass reduction concentrated among the lightest vehicles (chiefly, smaller passenger cars) has been estimated to increase overall fatalities. Past NHTSA analyses have consistently indicated that increasing the disparity of the masses of vehicles is harmful to safety. In collisions among vehicles, mass reduction in heavier vehicles alone is more beneficial to the occupants of lighter vehicles than it is harmful to the occupants of the heavier vehicles. Mass reduction in lighter vehicles alone is more harmful to the occupants of lighter vehicles than it is beneficial to the occupants of the heavier vehicles. Reducing mass simultaneously across multiple vehicles can have a range of net effects; for example, proportional mass reduction across the vehicle fleet would be expected to have a roughly neutral effect on societal fatality rates for two-vehicle crashes. This highlights the role of mass disparity in societal fatality risk: as the overall vehicle fleet moves closer together is in terms of mass (or, as measured in our analysis, curb weight), the impacts of changes in vehicle mass on fatality risk decrease for crashes involving two or more vehicles. However, even if manufacturers were capable of coordinating and reducing mass equally across the new vehicle fleet, new vehicles would encounter vehicles with different masses within the existing fleet. Further, many fatalities and injuries occur in single vehicle crashes and collisions between light-duty vehicles and cyclists or pedestrians and these must also be taken into account in representing the effects of mass reduction on societal fatality rates.

In response to questions of whether designs and materials of more recent model year vehicles may have weakened the historical statistical relationships between mass, size, and safety, NHTSA updated its public database for statistical analysis consisting of crash data. The database incorporates the full range of real-world crash types. NHTSA also sponsored a study conducted by George Washington University (GWU) to develop a fleet simulation model and study the impact and relationship of light-weighted vehicle design with crash injuries and fatalities. That study is discussed in detail in Chapter 7.2.5. The GWU study found results that are directionally consistent with NHTSA's statistical analyses of vehicle mass and fatality risk.

As described below, NHTSA's current analysis did not find a statistically significant relationship between mass and safety. This may reflect the effects of a decreased sample size (the current study was based on 32 percent fewer fatal cases than the Kahane 2012 study) as well as possible mitigating effects from newer safety technologies or vehicle designs. While not finding statistical significance, NHTSA's current study did find results that are directionally consistent with previous NHTSA studies and the GWU fleet simulation. The common pattern across all studies is that changes in mass disparity are associated with changes in motor vehicle safety: increased disparity increases fatality risk, while decreased disparity decreases risk. The agency will continue to conduct research on the impacts of mass disparity on vehicle safety in an effort to identify the impacts of evolving vehicle fleets.

The CAFE standards detailed here are "footprint-based," with footprint being defined as a measure of a vehicle's size, roughly equal to the wheelbase times the average of the front and rear track widths. Manufacturers are less likely than they were in the past to reduce vehicle footprint to reduce mass for increased fuel economy. Indeed, as reflected in shifts from smaller passenger cars to larger trucks, SUVs, and CUVs (see Chapter 1.2.8 and FRIA Chapter 3.2 Simulating Manufacturers' Potential Responses to the Alternatives) the average footprint of light-duty vehicles has increased slightly and gradually since the adoption of footprint-based standards. Footprint-based standards create a disincentive for manufacturers to produce smaller-footprint vehicles. This is because, as footprint decreases, the corresponding fuel economy target becomes more stringent. The agency believes that the shape of the footprint curves themselves is such that the curves should neither encourage manufacturers to increase the footprint of their fleets, nor to decrease it. Several technologies, such as substitution of light, high-strength materials for conventional materials during vehicle redesigns, have the potential to reduce weight and conserve fuel while maintaining a vehicle's footprint.

For the rulemaking analysis, the CAFE Model tracks the amount of mass reduction applied to each vehicle model, and then applies estimated changes in societal fatality risk per 100 pounds of mass reduction determined through the statistical analysis of FARS crash data. 100-pound mass reductions have been considered in NHTSA analyses as a matter of convention; the implications of the analysis would not change meaningfully either for focal vehicle classes or for the fleet at large (i.e., in terms of mass disparity) if different magnitudes of mass reduction were considered. This process allows the CAFE Model to tally changes in fatalities attributed to mass reduction across all the analyzed future model years. In turn, the CAFE Model is able to provide an overall impact of the final standards and alternatives on fatalities attributed to changes in mass disparity resulting from mass reduction. The projections of societal effects of mass reduction from the CAFE Model are subject to uncertainty in the paths that manufacturers will follow in applying mass reduction to the fleet. That is, there is uncertainty in which vehicle models will undergo mass reduction. Rather, the model is calibrated to incorporate the best available information on the application, and safety effects, of mass reduction.

7.2.1 Historical Analyses of Vehicle Mass and Safety

The methodology used for the statistical analysis of historical crash data has evolved over many years. The methodology used for this final rule is carried forward from the 2020 CAFE rule, and reflects learnings and refinements from: NHTSA studies in 2003, 2010, 2011, 2012, and 2016; independent peer review of 23 studies by the University of Michigan Transportation Research Institute (UMTRI); two public workshops hosted by NHTSA; interagency collaboration among NHTSA, DOE and EPA; and comments to CAFE and GHG rulemakings in 2010, 2012, the 2016 Draft TAR, and the 2020 rulemaking. As explained in greater detail below, the methodology used for the statistical analysis of historical crash data for this final rule is the best and most up-to-date available.

Over the course of refining the methodology and the corresponding data per stakeholder feedback and internal review, NHTSA has confirmed the central relationship that mass reduction is most likely to reduce societal fatalities when concentrated among the heaviest vehicles. For crashes involving two or more vehicles, this relationship manifests itself within the vehicle fleet in terms of the dispersion of vehicle mass (or curb weights): All else being equal, as disparities in mass among vehicles increase, fatalities increase as well. That is, mass reduction concentrated among the lightest vehicles would increase the dispersion of mass (i.e., the heaviest vehicles become even heavier than the lightest vehicles), while mass reduction concentrated among the heaviest vehicles would decrease the dispersion of mass (i.e., the lightest vehicles grow closer in mass to the heaviest vehicles).

Representing the overall relationship of mass reduction and safety within the CAFE Model (e.g., through model coefficients placing a detrimental effect on mass reduction in the lightest vehicles and a beneficial effect on mass reduction in the heaviest vehicles) enables the model to project effects of mass reduction in individual vehicle models on societal fatalities. The model achieves this by incorporating the corresponding effects of vehicle-model-specific mass reduction on the dispersion of mass for multi-vehicle crashes and effects of mass reduction on other types of crashes across the vehicle fleet.[878] Projected levels of mass reduction are internal to the CAFE Model and represent plausible paths forward for manufacturers to meet fuel economy targets in an economical manner, rather than specific predictions on mass reduction paths. Thus, there is some uncertainty introduced by the use of CAFE Model estimates as predictions of future changes in the distribution of vehicle mass. Consistency in the directionality and magnitude of the central point estimates across NHTSA's analyses has increased NHTSA's confidence that reducing the dispersion of mass across the vehicle fleet would reduce societal fatalities.

Researchers have been using statistical analysis to examine the relationship of vehicle mass and safety in historical crash data for many years and continue to refine their techniques. In the MY 2012-2016 final rule, NHTSA stated we would conduct further study and research into the interaction of mass, size, and safety to assist future rulemakings and start to work collaboratively by developing an interagency working group between NHTSA, EPA, DOE, and CARB to evaluate all aspects of mass, size, and safety. The team would seek to coordinate government-supported studies and independent research to the greatest extent possible to ensure the work is complementary to previous and ongoing research and to guide further research in this area.

Subsequent to the publication of the MY 2012-2016 rule, NHTSA identified three specific areas to direct research in preparation for future CAFE rulemakings. First, NHTSA would contract with an independent institution to review the statistical methods NHTSA and DRI used to analyze historical data related to mass, size, and safety, and to provide recommendations on whether existing or other methods should be used for future statistical analysis of historical data.

In 2010, NHTSA published the results of the contractor's review in a research report (hereinafter 2010 Kahane report). The 2010 Kahane report considered the potential near multicollinearity in the historical data and suggested methods to overcome it in a logistical regression analysis. The 2010 Kahane report was also peer reviewed by two other experts in the safety field - Farmer (Insurance Institute for Highway Safety) and Lie (Swedish Transport Administration) prior to publication.

Second, NHTSA and EPA, in consultation with DOE, would update the MY 1991–1999 database, used to calculate the mass safety coefficients, with newer vehicle data and create a common database that could be made publicly available to address concerns that differences in data were leading to different results in statistical analyses by different researchers. The database contains FARS and State-level crash data, to enable the estimation of changes in fatality risk as a function of vehicle curb weight across recent light-duty vehicle models. The FARS component of the database essentially forms the numerator of fatality risk calculations (i.e., societal fatalities), while the State component of the database forms the denominator (i.e., VMT

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[878] There are nine types of crashes specified in the mass-safety analysis: three types of single-vehicle crashes, five types of two-vehicle crashes; and one classification of all other crashes. Single-vehicle crashes include first-event rollovers, collisions with fixed objects, and collisions with pedestrians, bicycles and motorcycles. Two-vehicle crashes include collisions with: heavy-duty vehicles; cars, CUVs, or minivans, truck-based LTVs. All other fatal crash types include collisions involving more than two vehicles, animals, trains and other crash types.

by vehicle model). The FARS component of the database represents a census of fatalities associated with vehicle models in the sample; the State component of the database represents a random sample of vehicle exposure (i.e., induced exposure, comprised of crashes where drivers are assumed to be not at fault), yielding estimates of distributions of key contextual factors, such as driver age, driver sex, and vehicle location. Combining these data within a logistic regression yields a range of estimated fatality risks (i.e., fatalities per VMT) for each vehicle model, which vary with respect to vehicle curb weight, footprint, and contextual effects. This enables the logistic regression to isolate effects associated with curb weight, yielding the estimates of primary interest for the analysis summarized in this section.

And third, NHTSA sought to identify vehicles using newer material substitution and smart design and to assess if there were sufficient crash data involving those vehicles for statistical analysis to assess if modern mass reduction methods affected the historical relationship between vehicle mass, size, and safety. If sufficient data existed, statistical analysis would be conducted to compare the relationship among mass, size, and safety of these smart design vehicles to vehicles of similar size and mass with more traditional designs.

By the time of the MY 2017-2025 final rule, significant progress had been made on these tasks. The independent review then-recent statistical analyses of the relationship between vehicle mass, size, and crash fatality rates had been completed by UMTRI. Led by Dr. Green, UMTRI evaluated more than 20 academic papers, including studies done by NHTSA's Kahane, Wenzel of the U.S. Department of Energy's Lawrence Berkeley National Laboratory, Dynamic Research, Inc., and others. UMTRI's basic findings will be discussed below.

To support rulemaking efforts, NHTSA created a common, updated database for statistical analysis consisting of crash data of model years 2000-2007 vehicles in calendar years 2002-2008, as compared to the database used in prior NHTSA analyses, which was based on model years 1991–1999 vehicles in calendar years 1995-2000. The new database was the most up-to-date possible, given the processing lead time for crash data and the need for enough crash cases to permit statistically meaningful analyses. NHTSA made the preliminary version of the new database, which was the basis for NHTSA's 2011 preliminary report (hereinafter 2011 Kahane report), available to the public in May 2011, and an updated version in April 2012 (used in NHTSA's 2012 final report, hereinafter 2012 Kahane report), enabling other researchers to analyze the same data and hopefully minimize discrepancies in results because of inconsistencies across databases. NHTSA updated the crash and exposure databases for the 2016 Draft TAR analysis and has added a new variable denoting status as a medium- or heavy-duty truck to the database accompanying the NPRM and this final rule.

NHTSA was aware of several studies that had been initiated using the 2011 version or the 2012 version of NHTSA's newly established safety database. In addition to new Kahane studies, other recent and on-going studies included two by Wenzel at Lawrence Berkeley National Laboratory (LBNL) under contract with the U.S. DOE and one by DRI contracted by ICCT. These studies took somewhat different approaches to examining the statistical relationship between fatality risk, vehicle mass, and size. In addition to a detailed assessment of the 2011 Kahane report, Wenzel considered the effect of mass and footprint reduction on casualty risk per crash, using data from 13 states. Casualty risk includes fatalities and serious or incapacitating injuries. Both LBNL studies were peer reviewed and subsequently revised and updated. DRI used models separating the effect of mass reduction on two components of fatality risk - crash avoidance and crashworthiness. The LBNL and DRI studies were available in the docket for the 2012 final rule.

For the 2020 CAFE rule, the crash and exposure databases were updated again; these databases were used to support this final rule as well. The databases were updated to include crash data for MY 2004-2011 vehicles during CY 2006-2012; for ensuing rulemakings, NHTSA intends to once again update the databases with more recent model years and calendar years, where feasible. As in previous analyses, NHTSA has made the databases available to the public on its website.[879]

NHTSA has continued to sponsor new studies and research to inform the current CAFE rulemaking. In addition, the National Academies of Science/National Academies of Sciences, Medicine, and Medicine (NAS/NASEM) published reports that include discussions of relationships between vehicle mass and societal fatality risk.[880] The 2015 NAS report summarizes results from studies by NHTSA, DRI, and LBNL, confirming the general relationships between vehicle mass disparity and societal fatality risk (i.e., mass reduction in the lightest vehicles is detrimental, mass reduction on in the heaviest vehicles is beneficial) and noting that future changes in technology and fleet composition could lead to different conclusions. The 2021 NASEM report highlights the role that mass disparity among the vehicle fleet plays in societal fatality risk, with greater mass disparity associated with greater societal fatality risk. The NASEM report clarifies that the path of mass disparity is unknown (i.e., general trends and the application of mass reduction technologies could increase or decrease mass disparity). The NASEM report qualifies the general conclusions associated with mass disparity, noting that new vehicle designs, continued effects associated with footprint-based fuel economy standards, changes in demand across vehicle classes, and increased demand for vehicles with (heavier) electrified powertrains could yield different safety relationships from those identified in relevant studies. Throughout the rulemaking process, NHTSA's goal is to publish as much of the agency's research as possible. In establishing standards, all available data, studies, and objective information without regard to whether they were sponsored by NHTSA, will be considered.

Undertaking these tasks has helped come closer to resolving ongoing debates in statistical analysis research of historical crash data and has informed NHTSA analysis supporting this final rule. It is intended that these conclusions will continue to be applied going forward in future rulemakings, and it is believed the research will assist the public discussion of the issues.

[879] Visit https://www.nhtsa.gov/content/nhtsa-ftp/191, (Accessed: February 14, 2022), for access to the databases and other files and documentation associated with CAFE rulemaking.
[880] National Research Council. 2015. Cost, Effectiveness, and Deployment of Fuel Economy Technologies for Light-Duty Vehicles. Washington, DC: The National Academies Press. https://doi.org/10.17226/21744, (Accessed: February 14, 2022) and National Academies of Sciences, Medicine, and Engineering. 2021. Assessment of Technologies for Improving Light-Duty Fuel Economy 2025-2035. Washington, DC: The National Academies Press. https://doi.org/10.17226/26092. (Accessed: February 14, 2022).

7.2.1.1 2011 NHTSA Workshop on Vehicle Mass, Size, and Safety

On February 25, 2011, NHTSA hosted a workshop on mass reduction, vehicle size, and fleet safety at the Headquarters of the U.S. Department of Transportation in Washington, D.C. The purpose of the workshop was to provide a broad understanding of current research in the field and provide stakeholders and the public with an opportunity to weigh in on this issue. NHTSA also created a public docket to receive comments from interested parties who were unable to attend.

Speakers included Kahane of NHTSA, Wenzel of LBNL, Van Auken of DRI, Padmanaban of JP Research, Inc., Lund of the Insurance Institute for Highway Safety, Green of UMTRI, Summers of NHTSA, Peterson of Lotus Engineering, Kamiji of Honda, German of ICCT, Schmidt of the Alliance of Automobile Manufacturers, Nusholtz of Chrysler, and Field of the Massachusetts Institute of Technology.

The wide participation in the workshop allowed the agency to hear from a broad range of experts and stakeholders. Contributions were particularly relevant to the analysis of effects of mass reduction for the MY 2017-2025 final rule. Presentations were divided into two sessions addressing two expansive sets of issues - statistical evidence of the roles of mass and size on safety, and engineering realities regarding structural crashworthiness, occupant injury, and advanced vehicle design. Some main points from the workshop were:

- Statistical studies of crash data attempting to identify relative recent historical effects of vehicle mass and size on fleet safety show complicated relationships with many confounding influences in data.
- Analyses must control for individual technologies with significant safety effects (e.g., Electronic Stability Control, airbags).
- Physics of a two-vehicle crash require the lighter vehicle experience a greater change in velocity, which, all else being equal, often leads to disproportionately more injury risk.
- The separation of key parameters is a challenge to analyses, as vehicle size has historically been highly correlated with vehicle mass.
- No consensus on whether smaller, lighter vehicles maneuver better, and thus avoid more crashes, than larger, heavier vehicles.
- Kahane's results from his 2010 report found a scenario, which took some mass out of heavier vehicles but little or no mass out of the lightest vehicles, did not affect safety in absolute terms, and noted if analyses were able to consider the mass of both vehicles in a two-vehicle crash, results may be more indicative of future crashes.

7.2.1.2 UMTRI Report

NHTSA contracted with UMTRI to conduct an independent review of a set of statistical analyses of relationships between vehicle curb weight, footprint variables (track width, wheelbase), and fatality rates from vehicle crashes. The purpose of this review was to examine analysis methods, data sources, and assumptions of statistical studies, with the objective of identifying reasons for any differences in results. Another objective was to examine the suitability of various methods for estimating fatality risks of future vehicles.

UMTRI reviewed a set of papers, reports, and manuscripts provided by NHTSA (listed in Appendix A of UMTRI's report[881]) examining statistical relationships between fatality or casualty rates and vehicle properties such as curb weight, track width, wheelbase, and other variables.

Fundamentally, the UMTRI team concluded the database created by Kahane appeared to be an impressive collection of files from appropriate sources and the best ones available for answering the research questions considered in this study; the disaggregate logistic regression model used by NHTSA in its 2003 report (hereinafter 2003 Kahane report) seemed to be the most appropriate model, valid for the analysis in the context that it was used - finding general associations between fatality risk and mass, and general directions of reported associations were correct.

7.2.1.3 2012 LBNL Reports

In its 2012 "Phase 1" report, LBNL replicated the 2012 NHTSA baseline results and conducted 19 alternative regression models to test the sensitivity of the NHTSA baseline model to changes in the measure of risk, variables included, and data used. In its report, LBNL pointed out that other vehicle attributes, driver characteristics, and crash circumstances were associated with much larger changes in risk than mass reduction. LBNL also demonstrated there was little correlation between mass and fatality risk by vehicle model, even after accounting for all other vehicle attributes, driver characteristics, and crash circumstances.

In its 2012 "Phase 2" report, LBNL used data from police reported crashes in the 13 states to study casualty (fatality plus severe injury) risk per VMT, and to divide risk per VMT into its two components - crash frequency (crashes per VMT) and crashworthiness/crash compatibility (risk per crash). LBNL found mass reduction was associated with increases in crash frequency and decreases in fatality or serious injury risk per crash. Preliminary versions LBNL's Phase 1 and Phase 2 reports were reviewed by external reviewers, and comments were incorporated into final versions published in 2012.[882]

7.2.1.4 2012 DRI Reports

DRI published three preliminary reports in 2012. DRI's preliminary Phase I report updated its analysis of data from 1995 to 2000 and was able to replicate results from the 2003 Kahane report. DRI's preliminary Phase II report replicated the 2012 rulemaking baseline results and used a simultaneous two-stage model to estimate separate effects of mass reduction on crash

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[881] Green, P.E., Kostyniuk, L.P., Gordon, T.J., and M.P. Reed. (2011). *Independent Review Statistical Analyses of Relationship between Vehicle Curb Weight, Track Width, Wheelbase and Fatality Rates*. Report for U.S. Department of Transportation, Report No. UMTRI-2011-12. Available in the docket to the MY 2017-2025 rulemaking at regulations.gov, or at https://deepblue.lib.umich.edu/bitstream/handle/2027.42/85162/102752.pdf?sequence=1&isAllowed=y. (Accessed: February 14, 2022).

[882] See Wenzel, T.P. (2012). An Analysis of the Relationship between Casualty Risk Per Crash and Vehicle Mass and Footprint for Model Year 2000-2007 Light-Duty Vehicles – Final Report. Lawrence Berkeley National Laboratory Report No. LBNL-5697E and Wenzel T.P. (2012). Assessment of NHTSA's Report "Relationships Between Fatality Risk, Mass, and Footprint in Model Year 2000-2007 Passenger Cars and LTVs" – Final Report. Lawrence Berkeley National Laboratory Report No. LBNL-5698E.

frequency and fatality risk per crash. Results from DRI's two-stage model were comparable to LBNL's Phase 2 analysis - mass reduction was associated with increases in crash frequency and decreases in risk per crash. DRI's preliminary summary report showed the effect of two alternative regression models - using stopped rather than non-culpable vehicles as the basis for the induced exposure database and replacing vehicle footprint with its component's wheelbase and track width. Under these two alternatives, mass reduction was estimated to have less harmful (e.g., for the lightest passenger cars) or more beneficial (e.g., for the heaviest LTVs) impacts on societal fatality risk. The three preliminary DRI reports were peer-reviewed with comments incorporated into the final versions published in 2013.

Results from LBNL's Phase 2 and DRI's Phase II reports implied the increase in fatality risk per VMT from mass reduction in lighter cars estimated by the NHTSA baseline model was because of increasing crash frequency and not increasing fatality risk once a crash had occurred, as mass was reduced. In the 2012 Kahane report, NHTSA argued effects of crash frequency could not be separated from risk per crash because of reporting bias in state crash data, such as lack of a crash severity measure, and possible bias because of underreporting of less severe crashes in certain states. This is a complex issue, in which it is possible for crashes to be reported at variable rates across vehicle type, vehicle size, or vehicle weight. That is, if underreporting were solely random, it may be feasible to draw unbiased inferences with respect to crash risk and crash severity independently. However, if underreporting is not random (e.g., crashes involving smaller, lighter, or older, less valuable vehicles may be less likely to meet State reporting thresholds), factors leading to variable reporting rates would be conflated with representations of crash frequency.

7.2.1.5 2013 NHTSA Workshop on Vehicle Mass, Size, and Safety

On May 13-14, 2013, NHTSA hosted a follow-on symposium to continue exploring relevant issues and concerns with mass, size, and potential safety tradeoffs, bringing together experts in the field to discuss questions to address CAFE standards for model years 2022-2025. The first day of the two-day symposium focused on engineering, while the second day investigated various methodologies for assessing statistical evidence of roles of vehicle mass and size on occupant safety.

Speakers for the second day, focusing on the subject matter of this chapter, included Kahane of NHTSA, Nolan of the Insurance Institute for Highway, Nusholtz of Chrysler, Van Auken of Dynamic Research Incorporated, and Wenzel of Lawrence Berkeley National Laboratory. Summaries of the topics follow:

- Kahane gave an overview of statistical studies designed to determine the incremental change in societal risk as vehicle mass of a particular vehicle is modified while keeping its footprint (the product of wheelbase and track width) constant. The physics of crashes, in particular conservation of momentum and equal and opposite forces, imply mass reduction in the heaviest vehicles and/or mass increase in the lightest vehicles can reduce societal risk in two-vehicle crashes. It is, therefore, reasonable that reducing disparities in mass ratio in the vehicle fleet (such as by reducing the mass of heavy vehicles by a larger percentage than that of light vehicles) should reduce societal harm. This trend was noticed in data for model year 2000-2007 vehicles but only statistically significant for the lightest group of vehicles. This is similar to results found for model year 1991-1999 vehicles in a 2003 study. Kahane acknowledged numerous confounding factors such as maneuverability of different vehicle classes (although data indicated smaller cars were more likely to be involved in crashes), driver attributes and vulnerabilities, advances in restraint safety systems and vehicle structures, and electronic stability control.

- Wenzel replicated Kahane's results using the same data and methods but came to slightly different conclusions. Wenzel demonstrated that the effect of mass or footprint reduction estimated on societal risk is much smaller than the effect estimated for other vehicle attributes, driver characteristics, or crash circumstances. Wenzel plotted actual fatality risk versus weight by vehicle make and model and estimated predicted risk by make and model after accounting for all control variables used in NHTSA's baseline model except for mass and footprint. The remaining, or residual risk, not explained by the control variables has no correlation with vehicle weight. Wenzel presented results of the 19 alternative regression models he conducted to test the sensitivity of results from NHTSA's baseline model. He also presented results from LBNL's Phase 2 analysis, which examined the effect of mass or footprint reduction on the two components of risk per VMT - crashes per VMT (crash frequency), and risk per crash (crashworthiness). His analysis of casualty risk using crash data from 13 states and his replication of the DRI two-state simultaneous regression model indicate mass reduction is associated with an increase in crash frequency but a decrease in risk per crash.

- Van Auken also replicated Kahane's results from the NHTSA baseline model and presented results from three sensitivity regression models. Replacing footprint with its components wheelbase and track width reduces the estimated increase in risk from mass reduction in cars and suggests reduction in light trucks decreases societal risk. Using stopped rather than non-culpable vehicles to derive the induced exposure dataset also reduces the estimated increase in risk from mass reduction in lighter-than-average cars and light trucks and estimates mass reduction in heavier cars and trucks decreases societal risk. Adding these changes to the NHTSA baseline model greatly reduces the estimated increase in risk from mass reduction in the lightest cars and is associated with decreases in risk for all other vehicle types. Van Auken described in more detail his two-stage simultaneous regression model, which allows risk per vehicle mile of travel to be decomposed into crashes per VMT (crash frequency) and risk per crash (crashworthiness/ crash compatibility). As with Wenzel's analysis, Van Auken found mass reduction is associated with an increase in crash frequency but with a decrease in risk per crash. Once again, resulting trends were similar to those from Kahane and Wenzel. Van Auken explored the issue of inducing the exposure of vehicles via crash statistics in which relative exposure was measured by non-culpable vehicles in the crash database versus by its subset of stopped vehicles in the data and also investigated the effect of substituting footprint for track width and wheelbase as size variables in the regression.

- Nusholtz of Chrysler presented an analysis of the sensitivity of the fleet-wide fatality risk to changes in vehicle mass and size. He noted the difficulty in finding a definitive metric for "size." He dismissed some assertions of mass having negligible (or purely negative) effects on safety as leading to absurd conclusions in the extreme. He extended the methods of Joksch (1993) and Evans (1992) to estimate risk as a function of readily measurable vehicle attributes and reported crash characteristics. He used crash physics (closing speed, estimates of inelastic stiffness, and energy absorption) to estimate changes in fleet risk as a function of changes in these parameters. He observed mass is a dominant factor but believed crush space could begin to dominate if vehicles could be made larger. Nusholtz concurred removing more mass from larger vehicles could reduce risk but is not convinced such a strategy will be sufficient to meet fuel economy goals. He regards safety implications of mass reduction to be transition issues of greater importance so long as legacy heavier vehicles are used in significant numbers.

- Nolan analyzed historical trends in the fleet. While median vehicle mass has increased, safety technologies have enhanced the safety of current small cars to the level only achieved by larger cars in the past. In particular, electronic stability control has reduced the relative importance of some severe crash modes. While acknowledging that smaller vehicles will always be at a disadvantage, there is hope further technological advances such as crash avoidance systems hold promise in advancing safety. Fleet safety would be enhanced if these technologies could quickly penetrate across the fleet to small cars as well as large ones.

- Nusholtz presented the results of an attempt to separate the effect of mass on crash outcome as distinct from the likelihood of the crash itself. It was acknowledged mass can affect both. Nusholtz emphasized crash parameters (e.g., closing speed) necessarily dominate. Kahane suggested reporting rates might be sufficiently different to affect results. Nusholtz cautioned physics and statistics must be considered but, in a way, connecting them to reality rather than abstractions. Nusholtz noted assessments of that effect are difficult because determining when and why a crash did not occur is problematic against the backdrop of confounding information.

7.2.1.6 Subsequent Analyses by LBNL

As part of its review of the 2012 DRI studies, LBNL recreated DRI's two-stage simultaneous regression model, which estimated the effect of mass or footprint reduction on the two components of fatality risk per VMT - number of crashes per VMT and risk of fatality per crash. LBNL first replicated DRI's methodology of taking a random "decimated" sample of crash data from 10 states for induced exposure records. Although LBNL was not able to exactly recreate DRI's results, its results were comparable to DRI's, and LBNL's Phase 2, analysis. That is, mass reduction is associated with - (1) increases in crash frequency for all vehicle types; and (2) with decreases in fatalities per crash for all vehicle types except heavier cars. LBNL then re-ran the two-stage regression model using all crash data from the 13 states NHTSA used in their baseline model and obtained similar results.

The LBNL Phase 2 study and DRI Phase II study had two unexpected results - mass reduction is associated with increased crash frequency but decreased risk per crash, and signs on some of the control variables are in the unexpected direction. Mass reduction could feasibly reduce crash risk due to increased maneuverability and braking capability; the converse result may reflect driver behavior (e.g., riskier maneuvers under higher power-to-weight ratios) or important structural changes under light-weighting. Examples of unexpected signs for control variables include - side airbags in light trucks and CUVs/minivans were estimated to reduce crash frequency; the crash avoidance technologies electronic stability control (ESC) and antilock braking systems (ABS) were estimated to reduce risk once a crash had occurred; and all-wheel-drive and brand new vehicles were estimated to increase risk once a crash had occurred. In addition, male drivers were estimated to have essentially no effect on crash frequency but were associated with a statistically significant increase in fatality risk once a crash had occurred. In addition, driving at night, on high-speed or rural roads, was associated with higher increases in risk per crash than on crash frequency.

A possible explanation for these unexpected results is that important control variables were not included in regression models. For example, crashes involving male drivers, in vehicles equipped with AWD, or occurring at night on rural or high-speed roads, may not be more frequent but are rather more severe than other crashes, leading to greater fatality or casualty risk. Drivers who select vehicles with certain safety features may tend to drive more carefully, resulting in vehicle safety features designed to improve crashworthiness or compatibility, such as side airbags, and are associated with lower crash frequency.

LBNL made several attempts to create a regression model that "corrected" for these unexpected results. LBNL first examined results of three vehicle braking and handling tests conducted by Consumer Reports - the maximum speed achieved during the avoidance maneuver test, acceleration time from 45 to 60 mph, and dry braking distance.

When these three test results were added to the LBNL baseline regression model of the number of crashes per mile of vehicle travel in cars, none of the three handling/braking variables had the expected effect on crash frequency. In other words, an increase in maximum maneuver speed, the time to reach 60 miles per hour, or braking distance on dry pavement in cars, either separately or combined, was associated with a decrease in the likelihood of a crash, of any type or with a stationary object. Adding one or all of the three handling/braking variables had relatively little effect on the estimated relationship between mass or footprint reduction in cars and crash frequency, either in all types of crashes or only in crashes with stationary objects.

LBNL next tested the sensitivity of the relationship between mass or footprint reduction and crash frequency by adding five additional variables to the regression models - initial vehicle price, average household income, bad driver rating, alcohol/drug use, and seat belt use. An increase in vehicle price, household income, or belt use was associated with a decrease in crash frequency, while an increase in alcohol/drug use was associated with an increase in crash frequency, for all three vehicle types; a poor bad driver rating increases crash frequency in cars, but unexpectedly decreases crash frequency in light trucks and CUVs/minivans. Including these five variables, either individually or including all in the same regression model, did not change general results of the baseline LBNL regression model - mass reduction is associated with an increase in crash frequency in all three types of vehicles, while footprint reduction is associated with an increase in crash frequency in cars and light trucks but with a decrease in crash frequency in CUVs/ minivans. The variable with the biggest effect was initial vehicle purchase price, which dramatically reduced the estimated increase in crash frequency in heavier-than-average cars (and in heavier-than-average light trucks, and all CUVs/minivans). These results suggest other, subtler, differences in vehicles and their drivers account for the unexpected finding that lighter vehicles have higher crash frequencies than heavier vehicles for all three types of vehicles.

In the 2012 Kahane report NHTSA suggested two possible explanations for unexpected results in the LBNL Phase 2 analysis and the DRI and LBNL two-stage regression models – the analyses did not account for the severity of the crash, and there was possible bias in the crashes reported to police in different states, with less severe crashes being under-reported for certain vehicle types. LBNL analyzed the first of Kahane's explanations for the unexpected result of mass reduction being associated with decreased risk per crash, by re-running the baseline Phase 2 regressions after excluding the least-severe crashes from the state crash databases objects. Only vehicles described as "disabled" or as having "severe" damage were included, while vehicles driven away from the crash site or that had functional, none, or unknown damage were excluded. Excluding non-severe crashes had little effect on the relationship between mass reduction and crash frequency; in either LBNL's Phase 2 baseline model or the two-stage simultaneous model - mass reduction was associated with an increase in crash frequency and a decrease in risk per crash. Excluding the non-severe crashes also did not change unexpected results for other control variables - most of the side airbag variables and the crash compatibility variables in light trucks, continued to be associated with an increase in crash frequency, while antilock braking systems, electronic stability control, AWD, male drivers, young drivers, and driving at night, in rural counties, and on high-speed roads continued to be associated with an increase in risk per crash.

DOE contracted with Wenzel of LBNL to conduct an assessment of NHTSA's updated 2016 study of the effect of mass and footprint reductions on U.S. fatality risk per VMT (LBNL 2016 "Phase 1" preliminary report), and to provide an analysis of the effect of mass and footprint reduction on casualty risk per police-reported crash, using independent data from 13 states (LBNL 2016 "Phase 2" preliminary report).

The 2016 LBNL Phase 1 report replicated the analysis in NHTSA's 2016 report (hereinafter, 2016 Puckett and Kindelberger report), using the same data and methods, and in many cases using the same SAS programs, to confirm NHTSA's results. The LBNL report confirmed NHTSA's 2016 finding, holding footprint constant, each 100-lbs of mass reduction is associated with a 1.49 percent increase in fatality risk per VMT for cars weighing less than 3,197 pounds, a 0.50 percent increase for cars weighing more than 3,197 pounds, a 0.10 percent decrease in risk for light trucks weighing less than 4,947 pounds, a 0.71 percent decrease in risk for light trucks weighing more than 4,947 pounds, and a 0.99 percent decrease in risk for CUVs/minivans.

Wenzel tested the sensitivity of model estimates to changes in the measure of risk as well as control variables and data used in the regression models. Wenzel concluded there is a wide range in fatality risk by vehicle model for models possessing comparable mass or footprint, even after accounting for differences in drivers' age and gender, safety features installed, and crash times and locations.

The 2016 LBNL Phase 1 report notes many of the control variables NHTSA includes in its logistic regressions are statistically significant and have a much larger estimated effect on fatality risk than vehicle mass. For example, installing torso side airbags, electronic stability control, or an antilock braking system in a car was estimated to reduce fatality risk by at least 7 percent; cars driven by men were estimated to have a 40 percent higher fatality risk than cars driven by women; and cars driven at night, on rural roads, or on roads with a speed limit higher than 55 mph were estimated to have a fatality risk over 100 times higher than cars driven during the daytime on low-speed non-rural roads. The report concluded that, while the estimated effect of mass reduction may result in a statistically-significant increase in risk in certain cases, the increase is small and is overwhelmed by other known vehicle, driver, and crash factors.

7.2.1.7 Presentation to NAS Subcommittee

Kahane, Wenzel, Ridella, Thomas of Honda, and Nolan of IIHS, were invited to the June 2013 NAS subcommittee on light-duty fuel economy to present results from their 2012 analyses. At the meeting, committee members raised several questions about the studies; presenters responded to these questions at the meeting, as well as in two emails in August 2013 and December 2014.

7.2.1.8 2015 National Academy of Sciences Report

In 2015, the National Academy of Sciences published the report "Cost, Effectiveness and Deployment of Fuel Economy Technologies for Light-Duty Vehicles." The report is the result of the work of the Committee on Assessment of Technologies for Improving the Fuel Economy of Light-Duty Vehicles, Phase 2, established upon the request of NHTSA to help inform the midterm review. The committee was asked to assess the CAFE standard program and the analysis leading to the setting of standards, as well as to provide its opinion on costs and fuel consumption improvements of a variety of technologies likely to be implemented in the light-duty fleet between now and 2030.

The Committee found the estimates of mass reductions to be conservative for cars; the Committee projected mass reductions between 5 percent (for small and large cars) and 6.5 percent (for midsize cars) larger than the projections. The Committee acknowledged the possibility of negative safety effects during the transition period because of variances in how reductions occurred. Because of this, the Committee recommended NHTSA consider and, if necessary, take steps to mitigate this possibility.

7.2.1.9 National Bureau of Economic Research (NBER) Working Paper

In a NBER working paper, Bento et al. (2017) present an analysis of relationships among traffic fatalities, CAFE standards, and distributions of MY 1989-2005 light-duty vehicle curb weights. Consistent with NHTSA's mass-size-safety analyses, Bento et al. concluded decreases in the dispersion of curb weights have a positive effect on safety. A central conclusion in Bento et al. is the monetized value of the net safety improvements achieved under CAFE exceed costs of meeting CAFE standards (i.e., CAFE offers a positive net societal benefit independent of fuel-related impacts). However, NHTSA identified factors in the analysis limiting the inference that can be drawn with respect to CAFE rulemaking going forward. The temporal range of the analysis does not include current footprint-based standards that incentivize light-weighting existing models rather than switching to lighter models. The statistical approach in the analysis did not account for the rebound effect or effects of CAFE on vehicle sales (which affect per-mile fatality risk), and Bento et al. also represented annual CAFE compliance costs at a level substantially less than expected to comply with standards.

7.2.2 Recent NHTSA Analysis Supporting CAFE Rulemaking

As mentioned previously, NHTSA and EPA's 2012 joint final rule for MY 2017 and beyond set "footprint-based" standards, with footprint being defined as roughly equal to the wheelbase multiplied by the average of the front and rear track widths. Basing standards on vehicle footprint is intended to discourage manufacturers from downsizing their vehicles because fuel economy targets are contingent on the vehicles size—the smaller the vehicle's footprint, the higher (more stringent) MPG target. However, mass reduction that maintains a vehicle's footprint does not create an additional MPG burden as downsizing and is a viable compliance mechanism. Several technologies, such as substitution of light, high-strength materials for conventional materials during vehicle redesigns, have the potential to reduce weight and conserve fuel while maintaining a vehicle's footprint.

NHTSA considers the likely effect of mass reduction on safety. The relationship between a vehicle's mass, size, and fatality risk is complex, and it varies in different types of crashes. As summarized above, NHTSA, along with others, have been examining this relationship for over a decade. The safety chapter of NHTSA's April 2012 final regulatory impact analysis (FRIA) of CAFE standards for MY 2017-2021 passenger cars and light trucks included a statistical analysis of relationships between fatality risk, mass, and footprint in MY 2000-2007 passenger cars and LTVs (light trucks and vans), based on CY 2002-2008 crash and vehicle-registration data; this analysis was also detailed in the 2012 Kahane report. The principal findings and conclusions of the 2012 Kahane report were mass reduction in the lighter cars, even while holding footprint constant, would significantly increase fatality risk, whereas mass reduction in the heavier LTVs would reduce societal fatality risk by reducing the fatality risk of occupants of lighter vehicles colliding with those heavier LTVs. NHTSA concluded, as a result, any reasonable combination of mass reductions that held footprint constant in MY 2017-2021 vehicles – concentrated, at least to some extent, in the heavier LTVs and limited in the lighter cars – would likely be approximately safety-neutral; it would not significantly increase fatalities and might well decrease them.

NHTSA released a preliminary report (2016 Puckett and Kindelberger report) on the relationship between fatality risk, mass, and footprint in June 2016 in advance of the Draft TAR. The preliminary report covered the same scope as the 2012 Kahane report, offering a detailed description of the databases, modeling approach, and analytical results on relationships among vehicle size, mass, and fatalities that informed the Draft TAR. Results in the Draft TAR and the 2016 Puckett and Kindelberger report are consistent with results in the 2012 Kahane report with respect to mass disparity; chiefly, societal effects of mass reduction are small, and mass reduction concentrated in larger vehicles is likely to have a beneficial effect on fatalities, while mass reduction concentrated in smaller vehicles is likely to have a detrimental effect on fatalities. There are differences between the studies in how a proportional reduction of mass would be expected to affect societal fatalities directionally, but the estimated effects are functionally near zero in both cases.

For the 2016 Puckett and Kindelberger report and Draft TAR, NHTSA, working closely with EPA and the DOE, performed an updated statistical analysis of relationships between fatality rates, mass and footprint, updating the crash and exposure databases to the latest available model years. NHTSA analyzed updated databases that included MY 2003-2010 vehicles in CY 2005-2011 crashes. For this regulatory analysis, databases are the most up-to-date possible (MY 2004-2011 vehicles in CY 2006-2012), given the processing time for crash data and the need for enough crash cases to permit statistically meaningful analyses. As in previous analyses, NHTSA has made the new databases available to the public at http://www.nhtsa.gov/fuel-economy, enabling other researchers to analyze the same data and hopefully minimizing discrepancies in results that would have occurred because of inconsistencies across databases.

7.2.3 Analysis Supporting this Rulemaking

The basic analytical method used to analyze the impacts of weight reduction on safety for this final rule is the same as in the 2016 Puckett and Kindelberger report. NHTSA released the 2016 Puckett and Kindelberger report as a preliminary report on the relationship between fatality risk, mass, and footprint in June 2016 in advance of the Draft TAR. The 2016 Puckett and Kindelberger report covered the same scope as previous NHTSA reports, offering a detailed description of the crash and exposure databases, modeling approach, and analytical results on relationships among vehicle size, mass, and fatalities that informed the Draft TAR. The modeling approach described in the 2016 Puckett and Kindelberger report was developed with the collaborative input of NHTSA, EPA, and DOE, and subject to extensive public review, scrutiny in two NHTSA-sponsored workshops, and a thorough peer review that compared it with the methodologies used in other studies.

In computing the impact of changes in mass on safety, NHTSA is faced with competing challenges. Research has consistently shown that mass reduction affects “lighter” and “heavier” vehicles differently across crash types. The 2016 Puckett and Kindelberger report found mass reduction concentrated amongst the heaviest vehicles is likely to have a beneficial effect on overall societal fatalities, while mass reduction concentrated among the lightest vehicles is likely to have a detrimental effect on fatalities. To accurately capture the differing effect on lighter and heavier vehicles, NHTSA must split vehicles into lighter and heavier vehicle classifications in the analysis. However, this poses a challenge of creating statistically-meaningful results. There is limited relevant crash data to use for the analysis. Each partition of the data reduces the number of observations per vehicle classification and crash type, and thus reduces the statistical robustness of the results. The methodology employed by NHTSA was designed to balance these competing forces as an optimal trade-off to accurately capture the impact of mass-reduction across vehicle curb weights and crash types while preserving the potential to identify robust estimates.

For this final rule, as in the 2020 CAFE rule, NHTSA employed the modeling technique developed in the 2016 Puckett and Kindelberger report to analyze the updated crash and exposure data by examining the cross sections of the societal fatality rate per billion vehicle miles of travel (VMT) by mass and footprint, while controlling for driver age, gender, and other factors, in separate logistic regressions for five vehicle groups and nine crash types. NHTSA utilized the relationships between weight and safety from this analysis, expressed as percentage increases in fatalities per 100-pound weight reduction, to examine the weight impacts applied in this CAFE analysis. The effects of mass reduction on safety were estimated relative to (incremental to) the regulatory baseline in the CAFE analysis, across all vehicles for MY 2018 and beyond.

As in the 2012 Kahane report, 2016 Puckett and Kindelberger report, the Draft TAR, and the 2020 CAFE rule, the vehicles are grouped into three classes: passenger cars (including both two-door and four-door cars); CUVs and minivans; and truck-based LTVs. The curb weight of passenger cars is formulated, as in the 2012 Kahane report, 2016 Puckett and Kindelberger report, Draft TAR, and 2020 CAFE rule, as a two-piece linear variable to estimate one effect of mass reduction in the lighter cars and another effect in the heavier cars.

Comments on the NPRM for the 2020 CAFE rule included suggestions that the sample of LTVs in the analysis should not include the medium- or heavy-duty (i.e., truck-based vehicles with GVWR above 8,500 pounds) equivalents of light-duty vehicles in the sample (e.g., Ford F-250 versus F-150, RAM 2500 versus RAM 1500, Chevrolet Suburban 2500 versus Chevrolet Suburban 1500), or Class 2b and 3 vehicles. For the NPRM, NHTSA explored revising the analysis consistent with such comments. The process involved two key analytical steps: (1) removing all case vehicles from the analysis whose GVWR exceeded 8,500 pounds; and (2) re-classifying all crash partners with GVWR above 8,500 pounds as heavy vehicles. The direct effects of these changes are: (1) the range of curb weights in the LTV sample is reduced, lowering the median curb weight from 5,014 pounds to 4,808 pounds; (2) the sample size of LTVs is reduced (the number of case LTVs under this alternative specification is approximately 18 percent lower than in the central analysis); and (3) the relative impact of crashes with LTVs on overall impacts on societal fatality rates decreases, while the corresponding impact of crashes with heavy vehicles increases.

The results from the exploratory analysis of this alternative approach are provided in the Sensitivity Analysis section below. NHTSA sought comment on this alternative approach in the NPRM, but the review of public comments identified no comments on this topic. In turn, NHTSA will seek further input to inform the decision whether to incorporate the results into future versions of the CAFE Model. The primary functional change offered by the alternative approach is that the sample of vehicles classified as LTVs would be restricted to vehicles that would be subject to CAFE regulations; it is important to note that the LTVs in question are subject to other fuel economy regulations, hence their relevance within a study informing the CAFE Model is not immediately nullified by being outside the scope of CAFE regulations. At the statistical level, the concerns raised in NHTSA's response to comment on the 2018 CAFE NPRM remain. In particular, including Class 2b and 3 vehicles in the analysis to determine the relationship of vehicle mass on safety has the added benefit of improving correlation constraints. Notably, curb weight increases faster than footprint for large light trucks and Class 2b and 3 pickup trucks and SUVs, in part because the widths of vehicles are constrained more tightly (i.e., due to lane widths) than their curb weights. Including data from Class 2b and 3 pick-up truck and SUV fatal crashes provides data over a wider range of vehicle weights, which improves the ability to estimate the mass-crash fatality relationship. That is, by extending the footprint-curb weight-fatality data to include Class 2b and 3 trucks that are functionally and structurally similar to corresponding ½-ton models that are subject to CAFE regulation, the sample size and ranges of curb weights and footprint are improved. However, this result may arise due to the presence of non-linearities over the relatively large range of vehicle curb weights when Class 2b and 3 vehicles are included in the sample. Sample size is a challenge for estimating relationships between curb weight and fatality risk for individual crash types in the main analysis; dividing the sample further or removing observations makes it increasingly difficult to identify meaningful estimates and the relationships that are present in the data, as shown in the sensitivity analysis below. For the final rule, NHTSA has maintained its position that the benefit of the additional data points outweighs the concern that some of the vehicles used to determine the mass-safety coefficients are not regulated by CAFE vehicles.

NHTSA also explored three other alternative model specifications that are presented in the sensitivity analysis below. The first alternative centers on aligning CUVs and minivans with the rest of the sample, by splitting these vehicles into two weight classes. The key factor restricting this change historically has been a low sample size for these vehicles; the exploratory analysis examined whether the current database (which, due to the range of CYs covered, contains a smaller share of CUVs and minivans than the current fleet) contains a sufficient sample size to evaluate two weight classes for CUVs and minivans. A complicating factor in this analysis is that minivans tend to have higher curb weights than other CUVs, adding statistical burden in identifying meaningful effects of mass on societal fatality rates after accounting for body type in the weight class with the fewest minivans (i.e., lighter CUVs and minivans).

The second alternative centers on aligning passenger cars with the rest of the sample by including cars that are equipped with AWD. In previous analyses, passenger cars with AWD were excluded from the analysis because they represented a sufficiently low share of the vehicle fleet that statistical relationships between AWD status and societal fatality risk were highly prone to being conflated with other factors associated with AWD status (e.g., location, luxury vehicle status). However, the share of AWD passenger cars in the fleet has grown. Approximately one-quarter of the passenger cars in the database have AWD, compared to an approximately five-percent share in the MY 2000-2007 database. Furthermore, all other vehicle types in the analysis include AWD as an explanatory variable. Thus, NHTSA finds the inclusion of a considerable portion of the real-world fleet (i.e., passenger cars with AWD) to be a meaningful consideration.

The third alternative is a minor procedural question: whether to expand the calendar years and model years used to identify the distribution of fatalities across crash types. The timing of the safety databases places the years of the analysis used to establish the distribution of fatalities by crash type firmly within the central years of the economic downturn of the late 2000s and early 2010s. During these years, travel demand was below long-term trends, resulting in fewer crashes. In turn, applying the same window of calendar years and model years to the identification of the distribution of fatalities across crash types results in notably fewer crashes to incorporate into the analysis. NHTSA conducted exploratory analysis on the question of whether to add calendar years and model years to the range of crashes used to identify the distribution of fatalities across crash types; this analysis was conducted in concert with the two alternatives discussed directly above. Results incorporating these three alternatives are presented in the sensitivity analysis below.

The boundary between "lighter" and "heavier" cars is 3,201 pounds (which is the median mass of MY 2004-2011 cars in fatal crashes in CY 2006-2012, up from 3,106 pounds for MY 2000-2007 cars in CY 2002-2008 in the 2012 NHTSA safety database, and up from 3,197 pounds for MY 2003-2010 cars in CY 2005-2011 in the 2016 NHTSA safety database). Likewise, for truck-based LTVs, curb weight is a two-piece linear variable with the boundary at 5,014 pounds (again, the MY 2004-2011 median, higher than the median of 4,594 pounds for MY 2000-2007 LTVs in CY 2002-2008 and the median of 4,947 pounds for MY 2003-2010 LTVs in CY 2005-2011). CUVs and minivans are grouped together in a single group covering all curb weights of those vehicles; as a result, curb weight is formulated as a simple linear variable for CUVs and minivans. Historically, CUVs and minivans have accounted for a relatively small share of new-vehicle sales over the range of the data, resulting in less crash data available than for cars or truck-based LTVs. CUVs have increased their share of the fleet both across the years covered in the database and since, in turn increasing the importance of relationships between mass and societal fatality risk for CUVs. As the share of CUVs increases, any estimated beneficial mass reduction in CUVs will have a larger beneficial effect on overall societal fatality risk. As discussed in the sensitivity analysis below, NHTSA evaluated whether the current database contains sufficient observations of CUVs and minivans to separate these vehicles into two weight classes. The evidence does not support such a change under the current database; however, adding new calendar years and model years to the next database may yield sufficient observations to make this change. In sum, vehicles are distributed into five groups by class and curb weights: passenger cars < 3,201 pounds; passenger cars 3,201 pounds or greater; truck-based LTVs < 5,014 pounds; truck-based LTVs 5,014 pounds or greater; and all CUVs and minivans.

There are nine types of crashes specified in the analysis for each vehicle group: three types of single-vehicle crashes, five types of two-vehicle crashes; and one classification of all other crashes. Single-vehicle crashes include first-event rollovers, collisions with fixed objects, and collisions with pedestrians, bicycles, and motorcycles. Two-vehicle crashes include collisions with: heavy-duty vehicles; cars, CUVs, or minivans < 3,187 pounds (the median curb weight of other, non-case, cars, CUVs and minivans in fatal crashes in the database); cars, CUVs, or minivans ≥ 3,187 pounds; truck-based LTVs < 4,360 pounds (the median curb weight of other truck-based LTVs in fatal crashes in the database); and truck-based LTVs ≥ 4,360 pounds. Grouping partner-vehicle CUVs and minivans with cars rather than LTVs is more appropriate because their front-end profile and rigidity more closely resemble a car than a typical truck-based LTV. An additional crash type includes all other fatal crash types (e.g., collisions involving more than two vehicles, animals, or trains). Splitting the vehicles from this crash type involved in crashes involving two light-duty vehicles into a lighter and a heavier group permits more accurate analyses of the mass effect in collisions of two vehicles.

For a given vehicle class and weight range (if applicable), regression coefficients for mass (while holding footprint constant) in the nine types of crashes are averaged, weighted by the number of baseline fatalities that would have occurred for the subgroup MY 2008-2011 vehicles in CY 2008-2012 if these vehicles had all been equipped with electronic stability control (ESC). The adjustment for ESC, a feature of the analysis added in 2012, accounts for the fact that all mass reduction in future vehicles will apply to vehicles that are equipped with ESC, as required by NHTSA's regulations.

Table 7-1 presents the estimated percent increase in U.S. societal fatality risk per ten billion VMT for each 100-pound reduction in vehicle mass, while holding footprint constant, for each of the five vehicle classes.

Table 7-16 – Fatality Increase (%) per 100-Pound Mass Reduction While Holding Footprint Constant - MY 2004-2011, CY 2006-2012

Vehicle Class	Point Estimate	95% Confidence Bounds
Cars < 3,201 pounds	1.20	-.35 to +2.75
Cars > 3,201 pounds	0.42	-.67 to +1.50
CUVs and minivans	-0.25	-1.55 to +1.04
Truck-based LTVs < 5,014 pounds	0.31	- .51 to +1.13
Truck-based LTVs > 5,014 pounds	-0.61	-1.46 to +.25

Techniques developed in the 2011 (preliminary) and 2012 (final) Kahane reports have been retained to test statistical significance and to estimate 95 percent confidence bounds (sampling error) for mass effects and to estimate the combined annual effect of removing 100 pounds of mass from every vehicle (or of removing different amounts of mass from the various classes of vehicles), while holding footprint constant. Confidence bounds estimate only the sampling error internal to the data used in the specific analysis that generated the point estimate. Point estimates are also sensitive to the modification of components of the analysis, as discussed at the end of this section. However, this degree of uncertainty is methodological in nature rather than statistical.

None of the estimated effects has 95-percent confidence bounds that exclude zero, and thus are not statistically significant at the 95-percent confidence level. NHTSA has evaluated these results and provided them for the purposes of transparency. Sensitivity analyses have confirmed that the exclusion of these statistically-insignificant results would not affect our policy determination, because the net effects of mass reduction on safety costs are small relative to predominant estimated benefit and cost impacts. Among the estimated effects, the most important effects of mass reduction are, as expected, concentrated among the lightest and heaviest vehicles. Societal fatality risk is estimated to: (1) increase by 1.2 percent if mass is reduced by 100 pounds in the lighter cars; and (2) decrease by 0.61 percent if mass is reduced by 100 pounds in the heavier truck-based LTVs.

A key constraint limiting statistical significance is that the analysis focuses on societal fatality risk (i.e., all fatalities, including crash partners and people outside of vehicles, such as pedestrians, cyclists, and motorcyclists) rather than merely in-vehicle fatality risk, which yields estimates that are smaller in magnitude (and thus more difficult to identify meaningful differences from zero) than estimates representing changes in in-vehicle fatality risk. That is, compared to an analysis of in-vehicle fatality risk (which would tend to yield relatively large estimated effects of mass reduction – either relatively highly-beneficial to reduce mass in the heaviest vehicles, or relatively highly-detrimental to reduce mass in the lightest vehicles), the focus on societal fatalities tends to yield relatively small (net) effects of mass reduction on fatality risk. This arises because the effects of mass reduction inherently net out to some extent in two-vehicle crashes: Impacts of mass reduction that protect one set of occupants (i.e., occupants of the vehicle striking or being struck by the vehicle that has experienced mass reduction) are accompanied by impacts that make the other set of occupants more vulnerable (i.e., occupants of the vehicle that has experienced mass reduction).

NHTSA judges the central value estimates are the best estimates available; the estimates offer a stronger statistical representation of relationships among vehicle curb weight, footprint, and fatality risk than an assumption of no correlation whatsoever. NHTSA appropriately presents the statistical uncertainty. For example, the central values for the highest vehicle weight group (LTVs 5,014 pounds or heavier) and the lowest vehicle weight group (passenger cars lighter than 3,201 pounds) (which, based on fundamental physics, are expected to have the greatest impact of mass reduction on safety) are economically meaningful,[883] and are in line with the prior analyses used in past NHTSA CAFE rulemakings. As shown in Table 7-17, the estimated coefficients have trended to lower numerical values in successive studies, but remain positive for lighter cars and negative for heavier LTVs.

The regression results are constructed to project the effect of changes in mass, independent of all other factors, including footprint. With each additional change from the current environment (e.g., the scale of mass change, presence and prevalence of safety features, demographic characteristics), the results may become less representative. That is, although safety features and demographic factors are accounted for separately, the estimated effects of mass are identified under the specific mix of vehicles and drivers in the data. NHTSA notes that the analysis accounts for safety features that are optional but available across all model years in the sample (most notably electronic stability control, which was not yet mandatory for all model years in the sample), and calibrates historical safety data to account for future fleets with full ESC penetration to reflect the mandate.

NHTSA considered the near multicollinearity of mass and footprint to be a major issue in the 2010 Kahane report and voiced concern about inaccurately estimated regression coefficients. High correlations between mass and footprint and variance inflation factors have not changed from MY 1991-1999 to MY 2004-2011; large vehicles continued to be, on the average, heavier than small vehicles to the same extent as in the previous decade.

Nevertheless, multicollinearity appears to have become less of a problem in the 2012 Kahane, 2016 Puckett and Kindelberger/Draft TAR, and 2020 CAFE rulemaking analyses. Ultimately, only three of the 27 core models of fatality risk by vehicle type in the current analysis indicate the potential presence of effects of multicollinearity, with estimated effects of mass and footprint reduction greater than two percent per 100-pound mass reduction and one-square-foot footprint reduction, respectively; these three models include passenger cars and CUVs in first-event rollovers, and CUVs in collisions with LTVs greater than 4,360 pounds. This result is consistent

[883] NHTSA uses "economically meaningful results" to mean values that have an important, practical implication, but may be derived from estimates that do not meet traditional levels of statistical significance. For example, if the projected economic benefit of a project equaled $100 billion, the agency would consider the impact economically meaningful, even if the estimates used to derive the impact were not statistically significant at the 95-percent confidence level. Conversely, if the projected economic benefit of a project equaled $1, the agency would not consider the impact economically meaningful, even if the estimates used to derive the impact were statistically significant at the 99.99-percent confidence level. In the case above, the results associated with the lightest and heaviest vehicle types were considered to be economically meaningful because the associated safety costs were large, and the estimates had magnitudes meaningfully different from zero and were statistically significant at the 85-percent confidence level.

with the 2016 Puckett and Kindelberger report, which also found only three cases out of 27 models with estimated effects of mass and footprint reduction greater than two percent per 100-pound mass reduction and one-square-foot footprint reduction.

Multicollinearity is one of the important concerns regarding the robustness of the results, along with estimated statistical significance. An alternative gauge of the robustness of the results is stability in estimates over time. That is, concerns regarding limitations of the data and low levels of statistical significance may be dampened if related, but substantially different, analyses using the same methodology yield consistent results. Table 7-17 compares the fatality coefficients from the 2012 Kahane report (MY 2000-2007 vehicles in CY 2002-2008) and the 2016 Puckett and Kindelberger report and Draft TAR (MY 2003-2010 vehicles in CY 2005-2011).

Table 7-17 – Fatality Increase (%) per 100-Pound Mass Reduction While Holding Footprint Constant

Vehicle Class[884]	2012 Report Point Estimate	2016 Report/Draft TAR Point Estimate	2012 Report 95% Confidence Bounds	2016 Report 95% Confidence Bounds
Lighter Passenger Cars	1.56	1.49	+.39 to +2.73	-.30 to +3.27
Heavier Passenger Cars	.51	.50	-.59 to 1.60	-.59 to +1.60
CUVs and minivans	-.37	-.99	-1.55 to +.81	-2.17 to +.19
Lighter Truck-based LTVs	.52	-.10	-.45 to +1.48	-1.08 to +.88
Heavier Truck-based LTVs	-.34	-.72	-.97 to + .30	-1.45 to +.02

The most recent results are directionally the same as in 2012; in the 2016 analysis, the estimate for lighter LTVs was of opposite sign (but small magnitude). Consistent with the 2012 Kahane and 2016 Puckett and Kindelberger reports, mass reductions in lighter cars are estimated to lead to increases in fatalities, and mass reductions in heavier LTVs are estimated to lead to decreases in fatalities.

The estimated mass effect for heavier truck-based LTVs has higher statistical significance in this analysis and in the 2016 Puckett and Kindelberger report than in the 2012 Kahane report; both estimates are statistically significant at the 85-percent confidence level, unlike the corresponding estimate in the 2012 Kahane report. The estimated mass effect for lighter truck-based LTVs is insignificant and positive in this analysis and the 2012 Kahane report, while the corresponding estimate in the 2016 Puckett and Kindelberger report was insignificant and negative.

NHTSA believes the most recent analysis represents the best estimate of the impacts of mass reduction that results in changes in mass disparities on crash fatalities, although it is important to note that these best estimates are not significantly different from zero. We have conducted sensitivity analyses to illustrate the uncertainty of the estimates, and we have determined that

[884] Median curb weights in the 2012 Kahane report - 3,106 pounds for cars, 4,594 pounds for truck-based LTVs. Median curb weights in the 2016 Puckett and Kindelberger report - 3,197 pounds for cars, 4,947 pounds for truck-based LTVs.

inclusion of these estimates does not alter the agency's determination of what is maximum feasible because the effects are so small. We continue to believe that is reasonable for the analysis to continue to include the best available estimates despite their lack of statistical significance at the 0.05 level. Similar to past analyses, the most recent analysis uses the best available data and estimates. NHTSA feels it is inappropriate to ignore likely impacts of the standards simply because the best available estimates have confidence levels below 95 percent; uniform estimates of zero are statistically weaker than the estimates identified in the analysis, and thus are not the best available. Because the point estimates are derived from the best-fitting estimates for each crash type (all of which are non-zero), the confidence bounds around an overall estimate of zero would necessarily be larger than the corresponding confidence bounds around the point estimates presented here. Ultimately, the point estimates for the lightest and heaviest vehicles in the sample are the estimates that have shown consistent directionality (and, to a lesser extent, magnitude) across studies, and these estimates are the most important in representing the effects of changes in mass disparity. Thus, the point estimates for lighter passenger cars and heavier LTVs offer the highest informative value among the estimates in the analysis; the smaller estimates corresponding to vehicles near the median of the fleet curb weight distribution are likely to be less informative.

The sensitivity analysis in the accompanying FRIA Chapter 7 Expanded Sensitivity Analysis provides an evaluation of extreme cases in which all the estimated net fatality rate impacts of mass reduction are either at their fifth- or 95th-percentile values. The range of net impacts in the sensitivity analysis not only covers the relatively more likely case that uncertain, yet generally offsetting, effects are distinct from the central estimates considered here (e.g., in a plausible case where mass reduction in the heaviest LTVs is less beneficial than indicated by the central estimates, it would also be relatively likely that mass reduction in the lightest passenger cars would be less harmful, yielding a similar net impact), but also covers the relatively unlikely case that all of the estimates are uncertain in the same direction.

The 2012 Kahane report, the 2016 Puckett and Kindelberger, the Draft TAR, and the 2020 CAFE rule all have concluded that both mass disparity and vehicle size impact societal safety. Across recent rulemakings, the analyses have confirmed a protective effect of vehicle size (i.e., societal fatality risk decreases as footprint increases). As mentioned previously, NHTSA believes vehicle footprint-based standards help to discourage vehicle manufacturers from downsizing their vehicles, and therefore assume changes in CAFE standards will not impact vehicle size and size-related safety impacts. On the other hand, mass reduction is a cost-effective technology for increasing fuel economy. Therefore, NHTSA includes the assessment of safety impacts related to mass reduction and its potential impact on mass disparity. In this regard, the CAFE Model estimates of how mass reductions will be distributed across the new vehicle fleet and the effects of electrification which tends to increase vehicle mass, can strongly affect conclusions about the effects of standards on safety. As discussed throughout this mass-safety subsection, comprehensive consideration of the various studies and workshops on the impact of vehicle mass disparity on safety is presented and conclude there has been a relationship historically. The fleet simulation study, discussed in the next subsection, further supports the existence of this relationship and that this relationship will continue to exist in future vehicle designs. However, in the analysis presented here, the relationship between mass and safety was not estimated to be significantly different from zero at the 0.05 level.

Vehicle mass continued an historical upward trend across the model years in the newest databases. The average (VMT-weighted) masses of passenger cars and CUVs both increased by approximately 3 percent from MY 2004 to MY 2011 (3,184 pounds to 3,289 pounds for passenger cars, and 3,821 pounds to 3,924 pounds for CUVs). Over the same period, the average mass of minivans increased by 6 percent (from 4,204 pounds to 4,462 pounds), and the average mass of LTVs increased by 10 percent (from 4,819 pounds to 5,311 pounds). Historical reasons for mass increases within vehicle classes include - manufacturers discontinuing lighter models; manufacturers re-designing models to be heavier and larger; and shifting consumer preferences with respect to cabin size and overall vehicle size. Indeed, not only have vehicles increased in mass, but also footprint. Across vehicles involved in fatal accidents in the analysis, mean footprint increased by between approximately 3 percent (for CUVs) and 8 percent (for sedans).

The principal difference between heavier vehicles, especially truck-based LTVs, and lighter vehicles, especially passenger cars, is mass reduction has a different effect in collisions with another car or LTV. When two vehicles of unequal mass collide, the change in velocity (delta V) is greater in the lighter vehicle. Through conservation of momentum, the degree to which the delta V in the lighter vehicle is greater than in the heavier vehicle is proportional to the ratio of mass in the heavier vehicle to mass in the lighter vehicle.

The relationships among vehicle velocities and vehicle masses in inelastic collisions are given in Equation 7-1.

$$v_{1f} = \frac{C_R m_2(v_{2i} - v_{1i}) + m_1 v_{1i} + m_2 v_{2i}}{m_1 + m_2}$$

Equation 7-1 – Final Velocity for Focal Vehicle in an Inelastic Collision

Where:

v_1 is the velocity for a focal vehicle
v_2 is the velocity for a partner vehicle
i and f represent initial and final velocities respectively
m_1 and m_2 are the masses of the vehicles
C_R is the coefficient of restitution (which represents effects extending the time of deceleration and dissipating energy through deformation and heat transfer)

As the final velocity decreases, delta-v increases.[885] Thus, delta-v increases with the mass of the partner vehicle but is unchanged if both vehicles increase their mass proportionally.

Because fatality risk is a positive function of delta-v, the fatality risk in the lighter vehicle in two-vehicle collisions is also higher. Vehicle design can reduce the magnitude of delta-v to some degree (e.g., changing the stiffness of a vehicle's structure could dampen delta-v for both crash partners). These considerations drive the overall result: increased mass disparity is associated with an increase in fatality risk in lighter cars, a decrease in fatality risk in heavier LTVs, CUVs, and minivans, and has smaller effects in the intermediate groups. Mass reduction may also be harmful in a crash with a movable object such as a small tree, which may break if hit

[885] Delta-V refers to the change of in the velocity experienced during a crash.

by a high mass vehicle resulting in a lower delta-v than may occur if hit by a lower mass vehicle which does not break the tree and therefore has a higher delta-v. However, in some types of crashes not involving collisions between cars and LTVs, especially first-event rollovers and impacts with fixed objects or collisions with vulnerable road users (e.g., pedestrians and cyclists), mass reduction may not be harmful and may even be beneficial.

Ultimately, delta-v is a direct function of relative vehicle mass for given vehicle structures. Removing some mass from the heavier vehicle involved in an accident with a lighter vehicle reduces the delta-v in the lighter vehicle, where fatality risk is higher, resulting in a large benefit to the passengers of the lighter vehicle. This is partially offset by a small increase in the delta-v in the heavy vehicle; however, the fatality risk is lower in the heavier vehicle and remains relatively low despite the increase in delta-v. In sum, the change in mass and delta-v from mass reduction in heavier vehicles results in a net societal benefit.

These considerations drive the overall result that has been observed historically: Mass reduction in lighter cars is associated with an increase in societal fatality risk; mass reduction in heavier LTVs, CUVs, and minivans is associated with a decrease in societal fatality risk; and mass reduction in the intermediate groups has smaller effects. These results can be considered in concert to represent the potential effects of fleetwide mass reduction; in particular, certain ratios of mass reduction across the fleet may have little to no net effect on societal fatalities.

Mass reduction may also be harmful in a crash with a movable object such as a small tree, which may break if hit by a high mass vehicle resulting in a lower delta-v than may occur if hit by a lower mass vehicle which does not break the tree and therefore has a higher delta-v. However, in some types of crashes not involving collisions between cars and LTVs, especially first-event rollovers and impacts with fixed objects, mass reduction may not be harmful and may be beneficial. To the extent lighter vehicles may respond more quickly to braking and steering, or may be more stable because their center of gravity is lower, they may more successfully avoid crashes or reduce the severity of crashes.

Farmer, Green, and Lie, who reviewed the 2010 Kahane report, again peer-reviewed the 2011 Kahane report. In preparing his 2012 report (along with the 2016 Puckett and Kindelberger report and Draft TAR), Kahane also took into account Wenzel's assessment of the preliminary report and its peer reviews, DRI's analyses published early in 2012, and public comments such as the International Council on Clean Transportation's comments submitted on NHTSA and EPA's 2010 notice of joint rulemaking. These comments prompted supplementary analyses, especially sensitivity tests, discussed at the end of this section.

The regression results are best suited to predict the effect of a small change in mass, leaving all other factors, including footprint, the same. With each additional change from the current environment (e.g., the scale of mass change, presence and prevalence of safety features, demographic characteristics), uncertainty in the model results may increase. It is recognized that the light-duty vehicle fleet in the MY 2021-2026 timeframe will be different from the MY 2004-2011 fleet analyzed here.

Nevertheless, one consideration provides some basis for confidence in applying regression results to estimate effects of relatively large mass reductions or mass reductions over longer periods. The central results represent the findings from NHTSA's sixth evaluation of effects of mass reduction and/or downsizing, comprising databases ranging from MY 1985 to MY 2011.

Results of the six studies are not identical, but they have been consistent to a point. During this time period, many makes and models have increased substantially in mass, sometimes as much as 30-40 percent. If the statistical analysis has, over the past years, been able to accommodate mass increases of this magnitude, perhaps it will also succeed in modeling effects of mass reductions of approximately 10-20 percent, should they occur in the future.

7.2.4 Sensitivity Analyses

Table 7-18 shows the principal findings and includes sampling-error confidence bounds for the five parameters used in the CAFE Model. The confidence bounds represent the statistical uncertainty that is a consequence of having less than a census of data. NHTSA's 2011, 2012, and 2016 reports acknowledged another source of uncertainty - The baseline statistical model can be varied by choosing different control variables or redefining the vehicle classes or crash types, which for example, could produce different point estimates.

Beginning with the 2012 Kahane report, NHTSA has provided results of 11 plausible alternative models that serve as sensitivity tests of the baseline model. Each alternative model was tested or proposed by: Farmer (IIHS) or Green (UMTRI) in their peer reviews; Van Auken (DRI) in his public comments; or Wenzel in his parallel research for DOE. The 2012 Kahane and 2016 Puckett and Kindelberger reports provide further discussion of the models and the rationales behind them.

Alternative models use NHTSA's databases and regression-analysis approach but differ from the baseline model in one or more explanatory variables, assumptions, or data restrictions. NHTSA applied the 11 techniques to the latest databases to generate alternative CAFE Model coefficients. The range of estimates produced by the sensitivity tests offers insight to the uncertainty inherent in the formulation of the models, subject to the caveat these 11 tests are, of course, not an exhaustive list of conceivable alternatives.

The central and alternative results follow, ordered from the lowest to the highest estimated increase in societal risk per 100-pound reduction for cars weighing less than 3,201 pounds.

Table 7-18 – Fatality Increase (%) Per 100-Pound Mass Reduction While Holding Footprint* Constant

		Cars	**Cars**	**CUVs &**	**LTVs†**	**LTVs†**
		< 3,201	≥ 3,201	Minivans	< 5,014	≥ 5,014
Baseline Estimate		1.20	0.42	-0.25	0.31	-0.61
95% Confidence Bounds (sampling error)	Lower:	-0.35	-0.67	-1.55	-0.51	-1.46
	Upper:	2.75	1.5	1.04	1.13	0.25
11 Alternative Models:						

1. Without CY control variables	0.26	-0.07	-0.58	0.35	-0.24
2. By track width & wheelbase	0.66	0.54	-0.48	-0.44	-0.90
3. Track width/wheelbase w. stopped veh data	0.73	-0.02	-0.18	-0.77	-1.91
4. Without non-significant control variables	0.98	0.26	0.14	0.36	-0.50
5. With stopped-vehicle State data	1.32	-0.17	-0.08	0.21	-1.55
6. CUVs/minivans weighted by 2010 sales	1.20	0.42	-0.06	0.31	-0.61
7. Including muscle/police/AWD cars/big vans	1.56	1.01	-0.25	0.87	0.43
8. Limited to drivers with BAC=0	1.72	1.33	0.01	0.35	-0.74
9. Control for vehicle manufacturer	2.09	1.51	-0.01	1.12	0.30
10. Limited to good drivers‡	2.15	1.80	-0.33	0.40	-0.45
11. Control for vehicle manufacturer/nameplate	2.26	2.70	-0.55	1.13	0.50

*While holding track width and wheelbase constant (rather than footprint) in alternative model nos. 2 and 3.
†Excluding CUVs and minivans.
‡BAC=0, no drugs, valid license, at most 1 crash and 1 violation during the past 3 years.

For example, in cars weighing less than 3,201 pounds, the baseline estimate associates 100-pound mass reduction, while holding footprint constant, with a 1.56 percent increase in societal fatality risk. The corresponding estimates for the 11 sensitivity tests range from a 0.26 to a 2.26 percent increase.

The sensitivity tests illustrate both the fragility and the robustness of baseline estimates. On the one hand, the variation among NHTSA's coefficients is quite large relative to the baseline estimate - In the preceding example of cars < 3,201 pounds, the estimated coefficients range from almost zero to almost double the baseline estimate. This result underscores the key relationship that the societal effect of mass reduction is small, a finding shared by Wenzel (2011, 2018). In other words, varying how to model some of these other vehicle, driver, and crash factors, which is exactly what sensitivity tests do, can appreciably change the estimate of the societal effect of mass reduction.

On the other hand, variations are not particularly large in absolute terms. The ranges of alternative estimates are generally in line with the sampling-error confidence bounds for the central estimates. Generally, in alternative models as in the central model, mass reduction tends to be relatively more harmful in the lighter vehicles and more beneficial in the heavier vehicles, just as they are in the central analysis. In all models, the point estimate of the coefficient is positive for the lightest vehicle class, cars < 3,201 pounds. In 10 out of 11 models, the point estimate is negative for CUVs and minivans, and in nine out of 11 models the point estimate is negative for LTVs ≥ 5,014 pounds. NHTSA believes the central case uses the most rigorous methodology, as discussed further above, and provides the best estimates of the impacts of differential mass reductions on safety.

In addition to the above sensitivity analyses, NHTSA conducted exploratory analyses on four candidate revisions to the model. The first candidate revision, per feedback on the 2018 CAFE NPRM, is the reclassification of Class 2b and Class 3 truck-based vehicles. In the exploratory analysis, NHTSA removed Class 2b and Class 3 truck-based vehicles as case vehicles, and re-assigned crash partner Class 2b and Class 3 vehicles from LTVs to heavy-duty vehicles. The second candidate revision is the inclusion of passenger cars equipped with AWD. The third candidate revision is splitting CUVs and minivans into two vehicle classes by curb weight, consistent with the treatment of passenger cars and truck-based LTVs. The fourth candidate revision is the expansion of the range of calendar years and model years used to establish the distribution of fatalities by crash type.

Results based on the candidate revisions are consolidated in Table 7-19.

Table 7-19 – Fatality Increase (%) per 100-Pound Mass Reduction While Holding Footprint Constant with Alternative Model Specifications - MY 2004-2011, CY 2006-2012

Vehicle Class	Point Estimates, Fatalities Weighted Across MY 2008-2011 in CY 2008-2012 (Original Weights)	Point Estimates, Fatalities Weighted Across MY 2007-2011 in CY 2007-2012	Point Estimates, Fatalities Weighted Across MY 2006-2011 in CY 2006-2012	Point Estimates, Fatalities Weighted Across MY 2004-2011 in CY 2006-2012 (Full Sample)
Cars < 3,201 Pounds (including AWD)	1.12%	1.12%	1.11%	1.12%
Cars 3,201+ Pounds (including AWD)	0.89%	0.87%	0.84%	0.86%
LTVs < 4,808 Pounds (No Class 2b/3)	0.26%	0.26%	0.26%	0.29%
LTVs 4,808+ Pounds (No Class 2b/3)	-0.16%	-0.17%	-0.16%	-0.17%
CUVs and Minivans < 3,955 Pounds	0.20%	0.19%	0.18%	0.18%
CUVs and Minivans 3,955+ Pounds	-0.52%	-0.52%	-0.53%	-0.51%

Under the alternative specification excluding Class 2b and Class 3 truck-based vehicles as case vehicles, the median curb weight for LTVs is 4,808 pounds, or 206 pounds lighter than in the central analysis. When splitting CUVs and minivans into two weight classes, the median curb weight for the vehicles is 3,955 pounds. Under this alternative specification, where Class 2b and

Class 3 truck-based crash partners are shifted from truck-based LTVs to heavy-duty vehicles, the median curb weight for LTV crash partners is 4,216 pounds, or 144 pounds lighter than in the central analysis.

Re-classifying Class 2b and Class 3 truck-based vehicles has a strong effect on the point estimate for heavier LTVs. Critically, removing the heaviest trucks as case vehicles yields a much smaller point estimate (reduction in societal fatality rates of between 0.16 and 0.17 percent per 100-pound mass reduction, versus 0.61 percent in the central analysis). This result is consistent with a relationship where a key share of the sensitivity of fatality risk is attributed to the mass of the heaviest vehicles in the fleet (i.e., supporting the role of mass dispersion in societal fatality rates). Importantly, the point estimate for lighter LTVs is not meaningfully different from the corresponding estimate in the central analysis (increase in societal fatality rates of between 0.26 and 0.29 percent per 100-pound mass reduction, versus 0.3 percent in the central analysis). Considered in concert, these results indicate that the most effective reductions in societal fatality rates via mass reduction in truck-based vehicles would arise not from light-weighting the heaviest vehicles subject to CAFE regulation, but rather from light-weighting similar, medium- and heavy-duty vehicles.

Including passenger cars with AWD in the analysis has little effect on the point estimate for lighter passenger cars (increase in societal fatality rates of approximately 1.1 percent per 100-pound mass reduction, versus 1.2 percent in the central analysis). However, this revision has a strong effect on the point estimate for heavier passenger cars (increase in societal fatality rates of between 0.84 and 0.89 percent per 100-pound mass reduction, versus 0.42 percent in the central analysis). This result supports a hypothesis that, after taking AWD status into account, mass reduction in heavier passenger cars is a more important driver of societal fatality rates than previously estimated. Although this result could be spurious, estimated confidence bounds (presented below) indicate that accounting for AWD status reduces uncertainty in the point estimate.

Splitting CUVs and minivans into two vehicle classes yields point estimates that are consistent with the point estimate for the consolidated CUV-minivan vehicle class (an average decrease in societal fatality rates of approximately 0.16 to 0.18 percent per 100-pound mass reduction across the two vehicle classes, versus a decrease of 0.25 percent in the central analysis). However, sample sizes half as large in the two vehicle classes relative to the consolidated vehicle class lead to very large estimated confidence bounds, as shown below. Due to this uncertainty, NHTSA does not feel that the current databases contain a large enough sample of CUVs and minivans to split these vehicles into two classes in the analysis; however, this issue will be re-examined when the next iteration of the databases is complete.

Extending the range of calendar years and model years used to establish the distribution of fatalities across crash types has a negligible effect on the point estimates. Based on the narrow ranges of results in Table 7-19, NHTSA finds evidence supporting a flexible approach in the choice of calendar years and model years used in this manner. All else being equal, extending the range helps to mitigate the potential for individual crash types with large estimated effects to drive spurious effects on overall estimates through unrepresentatively high estimated shares of overall fatalities. As a hedge in this direction, NHTSA applied the estimates from the alternative specification with two additional calendar years and model years (i.e., the second column from the right in Table 7-19) when evaluating 95-percent confidence bounds for the alternative models considered here.

The estimated confidence bounds are presented in Table 7-20.

Table 7-20 – Fatality Increase (%) per 100-Pound Mass Reduction While Holding Footprint Constant with Alternative Model Specifications - MY 2004-2011, CY 2006-2012; Fatalities Weighted Across MY 2006-2011 in CY 2006-2012

Vehicle Class	Point Estimates	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Cars < 3,201 Pounds (including AWD)	1.11%	-0.57%	2.80%
Cars 3,201+ Pounds (including AWD)	0.84%	-0.14%	1.82%
LTVs < 4,808 Pounds (No Class 2b/3)	0.26%	-0.83%	1.36%
LTVs 4,808+ Pounds (No Class 2b/3)	-0.16%	-1.47%	1.14%
CUVs and Minivans < 3,955 Pounds	0.18%	-2.94%	3.30%
CUVs and Minivans 3,955+ Pounds	-0.53%	-2.26%	1.21%
All CUVs and Minivans	-0.29%	-1.56%	0.99%

The estimated 95-percent confidence intervals are similar for lighter passenger cars with and without the inclusion of cars with AWD (-0.57 to 2.80 percent versus -0.35 to 2.75 percent) and CUVs and minivans as a combined class (-1.56 to 0.99 percent versus -1.55 to 1.04 percent). The latter result underscores the small impact that re-classifying Class 2b and Class 3 crash partners has on estimates in isolation.

The estimated confidence interval for heavier passenger cars is somewhat narrower when including vehicles with AWD (-0.14 to 1.82 percent versus -0.67 to 1.50 percent when excluding cars with AWD). Critically, combined with the increase in the magnitude of the point estimate, the alternative confidence interval indicates that the estimate is much closer to statistical significance at the 95-percent confidence level when including cars with AWD.

The confidence interval for lighter LTVs is somewhat larger when re-classifying Class 2b and Class 3 truck-based vehicles (-0.83 to 1.36 percent versus -0.51 to 1.13 percent), reflecting in part the effects of reducing the range of vehicles represented in the group. This effect is much stronger in the vehicle class affected most directly by this change, heavier LTVs. The upper bound of the 95-percent confidence interval is much larger when re-classifying Class 2b and Class 3 truck-based vehicles (-1.47 to 1.14 percent versus -1.46 to 0.25 percent). Thus, after removing the heaviest vehicles from the vehicle class, the point estimate changes from being at least economically meaningful to being simply statistically insignificant.

Lastly, the estimated confidence bounds for the separate CUV and minivan classes are much larger than the rest (-2.94 to 3.30 percent for lighter CUVs and minivans, and -2.26 to 1.21 percent for heavier CUVs and minivans). These results underscore the need for increased sample size before splitting CUVs and minivans into two vehicle classes.

7.2.5 Fleet Simulation Model

Commenters to recent CAFE rulemakings, including some vehicle manufacturers, have suggested that designs and materials of more recent model year vehicles may have weakened the historical statistical relationships between mass, size, and safety. NHTSA agreed that the statistical analysis would be improved by using an updated crash and exposure database reflecting more recent safety technologies, vehicle designs and materials, and reflecting changes in the vehicle fleet. As mentioned above, a new crash and exposure database was created with the intention of capturing modern vehicle engineering and has been employed for assessing safety effects for CAFE rules since 2012.

NHTSA has traditionally relied solely on real-world crash data as the basis for projecting the future safety implications for regulatory changes. NHTSA is required to consider relevant data in setting standards. Every fleet regulated by NHTSA's standards differs from the fleet used to establish said standard, and as such, the light-duty vehicle fleet in the MY 2024-2026 timeframe will be different from the MY 2004-2011 fleet analyzed in the 2012 study. This is not a new or unique phenomenon, but instead is an inherent challenge in regulating an industry reliant on continual innovation. The statistical analysis reviewed above is NHTSA's sixth evaluation of effects of mass reduction and/or downsizing, comprising databases ranging from MY 1985 to MY 2011. Despite continual claims that modern light-weight engineering will render current data obsolete, results of the six studies, while not identical, have been generally consistent in showing a small, negative impact related to increased mass disparity. NHTSA strongly believes that real-world crash data remain the best, most relevant data to measure the effect of mass reduction on safety.

However, because light-weight vehicle designs introduce fundamental changes to the structure of the vehicle, there remains a persistent question of whether historical safety trends will apply. To address this concern and to verify that real-world crash data remain an appropriate source of data for projecting mass-safety relationships in the future fleet, in 2014, NHTSA sponsored research to develop an approach to utilize experimental light-weight vehicle designs to evaluate safety in a broader range of real-world representative crashes. NHTSA contracted with George Washington University to develop a fleet simulation model to study the impact and relationship of light-weighted vehicle design with injuries and fatalities. The study involved simulating crashes on eight test vehicles, five of which were equipped with light-weight materials and advanced designs not yet incorporated into the U.S. fleet. The study assessed a range of frontal crashes, including crashes with fixed objects and other vehicles, across a wide range of vehicle speeds, and with mid-size male and mid-size female dummies. It is worth noting, given the questions raised about whether new materials and designs have weakened or eliminated the historical relationship between mass and safety, that the model year vehicles evaluated in this study are from ten to twenty years ago, and materials and designs have continued to evolve during that time.

The methodology focused on frontal crashes because of the availability of existing vehicle and occupant restraint models. Representative crashes were simulated between baseline and light-weight vehicles against a range of vehicles and roadside objects using two different size belted driver occupants (adult male and small female) only. No passenger(s) or unbelted driver occupants were considered in this fleet simulation. The occupant injury risk from each simulation was calculated and summed to obtain combined occupant injury risk. The combined occupant injury risk was weighted according to the frequency of real-world occurrences to develop overall societal risk for baseline and light-weighted vehicles. Note - The generic restraint system developed and used in the baseline occupant simulations was also used in the light-weighted vehicle occupant simulations as the purpose of this fleet simulation was to understand changes in societal injury risks (SIRs) because of mass reduction for different classes of vehicles in frontal crashes. No modifications to the restraint systems were made for light-weighted vehicle occupant simulations. Any modifications to restraint systems to improve occupant injury risks or SIRs in the light-weighted vehicle, would have conflated results without identifying effects of mass reduction only. The following sections provide an overview of the fleet simulation study:

In this study, there were eight vehicles as follows:

- 2001 model year Ford Taurus finite element model baseline and two simple design variants included a 25 percent lighter vehicle while maintaining the same vehicle front end stiffness and 25 percent overall stiffer vehicle while maintaining the same overall vehicle mass.

- 2011 model year Honda Accord finite element baseline vehicle and its 20 percent light-weight vehicle designed by Electricore. This mass reduction study was sponsored by NHTSA.

- 2009/2010 model year Toyota Venza finite element baseline vehicle and two design variants included a 20 percent light-weight vehicle model (2010 Venza) funded by EPA and International Council on Clean Transportation (ICCT) and a 35 percent light-weight vehicle (2009 Venza) funded by California Air Resources Board.

Light-weight vehicles were designed to have similar vehicle crash pulses as baseline vehicles. More than 440 vehicle crash simulations were conducted for the range of crash speeds and crash configurations to generate crash pulse and intrusion data points shown in Figure 7-5. The crash pulse data and intrusion data points will be used as inputs in the occupant simulation models.

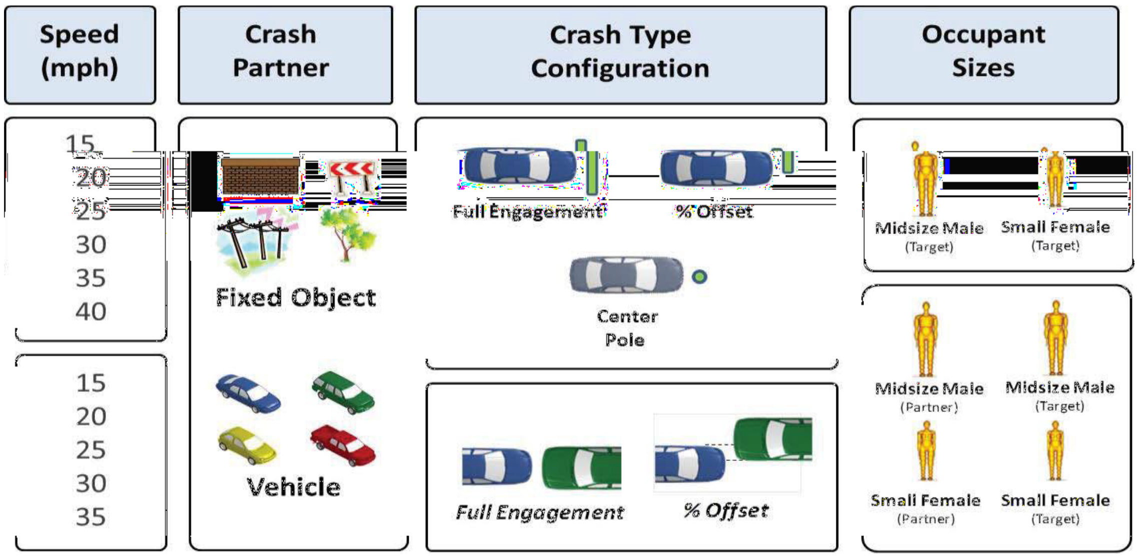
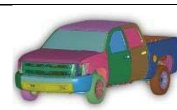


Figure 7-5 – Vehicle Crash Simulations

For vehicle-to-vehicle impact simulations, four finite element models were chosen to represent the fleet as shown in Table 7-21. The partner vehicle models were selected to represent a range of vehicle types and weights. It was assumed vehicle models would reflect the crash response for all vehicles of the same type, e.g. mid-size car. Only the safety or injury risk for the driver in the target vehicle and in the partner vehicle were evaluated in this study.

Table 7-21 – Base Vehicle Models Used in the Fleet Simulation Study

Vehicle Models		**FE Weight / No. Parts /Elements**	
Taurus (MY 2000 – 2007)			1505 kg / 802 / 973,351
Yaris (MY 2005 – 2013)			1100 kg / 917 / 1,514,068
Explorer (MY 2002 – 2005)			2025 kg / 923 / 714,205
Silverado (MY 2007 –2013)			2270 kg / 719 / 963,482

As noted, vehicle simulations generated vehicle deformations and acceleration responses utilized to drive occupant restraint simulations and predict the risk of injury to the head, neck, chest, and lower extremities. In all, more than 1,520 occupant restraint simulations were conducted to evaluate the risk of injury for mid-size male and small female drivers.

The SIR, as computed by Equation 7-2, for a target vehicle v in frontal crashes is an aggregate of individual serious crash injury risks weighted by real-world frequency of occurrence (v) of a frontal crash incident. A crash incident corresponds to a crash with different partners (Npartner) at a given impact speed (Pspeed), for a given driver occupant size (Loccsize), in the target or partner vehicle (T/P), in a given crash configuration (Mconfig), and in a single- or two-vehicle crash (Kevent). CIR (v) represents the combined injury risk (by body region) in a single crash incident. (v) designates the weighting factor, i.e., percent of occurrence, derived from National Automotive Sampling System Crashworthiness Data System (NASS CDS) for the crash incident. A driver age group of 16 to 50 years old was chosen to provide a population with a similar, i.e., more consistent, injury tolerance.

$$SIR_{frontal}(v) = \sum_{k=1}^{Kevent} \sum_{l=1}^{Loccsize} \sum_{m=1}^{Mconfig} \sum_{n=0}^{Npartner} \sum_{o=1}^{T/P} \sum_{p=1}^{Pspeed} w_{klmnop}(v) * CIR_{klmnop}(v)$$

Equation 7-2 – Societal Injury Risk

Figure 7-6 shows how change in societal risk is computed.

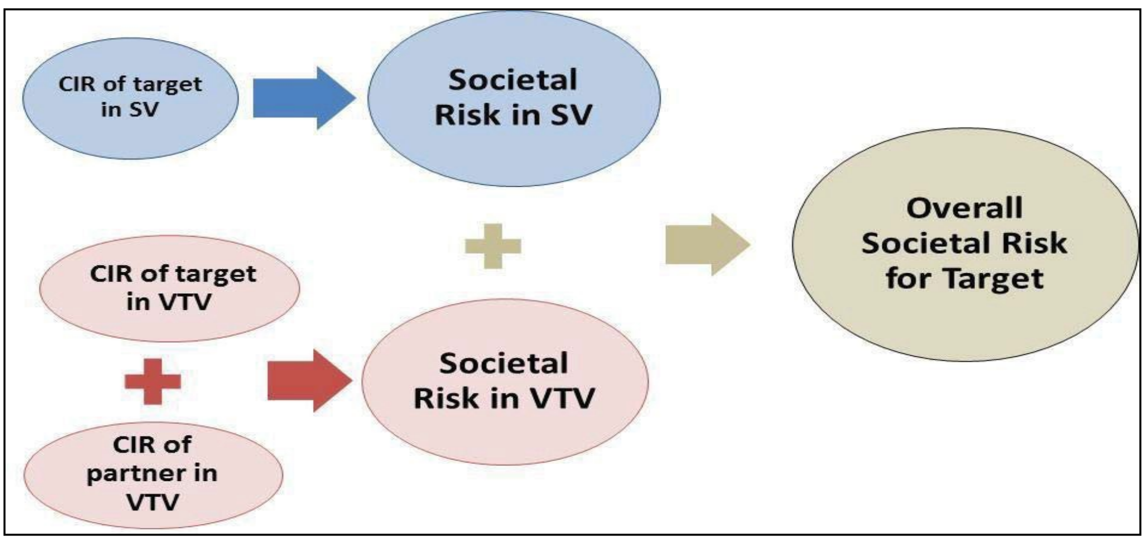


Figure 7-6 – Diagram of Computation for Overall Change in Societal Risk

The fleet simulation was performed using the best available engineering models, with base vehicle restraint and airbag settings, to estimate societal risks of future light-weight vehicles. The range of the predicted risks for the baseline vehicles is from 1.25 to 1.56 percent, with an average of 1.39 percent, for the NASS frontal crashes that were simulated. The change in driver injury risk between the baseline and light-weighted vehicles will provide insight into the estimate of modification needed in the restraint and airbag systems of light-weight vehicles. If the difference extends beyond the expected baseline vehicle restraint and airbag capability, then adjustments to the structural designs would be needed. Results from the fleet simulation study show that the trend of increased SIR for light-weighted vehicle designs, as compared to their baselines, occurs for both single vehicle and two-vehicle crashes. Results are listed in Table 7-22.

In general, the SIR in the frontal crash simulation associated with the small size driver is elevated when compared to that of the mid-size driver. However, both occupant sizes had levels of injury risk in the simulated impact configurations representative of the regulatory and consumer information testing. NHTSA examined three methods for combining injuries with different body regions. One observation was the baseline mid-size CUV model was more sensitive to leg injuries.

Table 7-22 – Overall Societal Risk Calculation Results for Model Runs, with Base Vehicle Restraint and Airbag Settings Being the same for All Vehicles, in Frontal Crash Only

Target Vehicle	Passenger Car Baseline	Passenger Car LW	CUV Baseline	CUV Low Option	CUV High Option
Weight (lbs)	3681	2964	3980	3313	2537
Reduction		716		668	1444
% mass reduction		19%		17%	36%
Societal Risk I	1.56%	1.73%	1.36%	1.46%	1.57%
Delta Increase		0.17%		0.10%	0.21%
Societal Risk II	1.43%	1.57%	1.14%	1.20%	1.30%
Delta Increase		0.14%		0.06%	0.16%
Societal Risk IIP	1.44%	1.59%			
Delta Increase		0.15%			
Societal Risk I - Target + Partner Combined AIS3+ risk of Head, Neck, Chest & Femur Societal Risk II - Target + Partner Combined AIS3+ risk of Head, Neck, and Chest Societal Risk IIP - Target + Partner Combined AIS3+ risk of Head, Neck, and Chest with A-Pillar Intrusion Penalty					

This study only looked at light-weight designs for a midsize sedan and a mid-size CUV and did not examine safety implications for heavier vehicles. The study was also limited to only frontal crash configurations and considered just mid-size CUVs whereas the statistical regression model considered all CUVs and all crash modes.

The change in the safety risk from the MY 2010 fleet simulation study was directionally consistent with results for passenger cars from the 2012 Kahane report, the 2016 Puckett and Kindelberger report, the 2020 final rule, and the analysis used for the NPRM and today's final rule. As noted, fleet simulations were performed only in frontal crash mode and did not consider other crash modes including rollover crashes.

This fleet simulation study does not provide information that can be used to modify coefficients derived for the final rule regression analysis because of the restricted types of crashes and vehicle designs. As explained earlier, the fleet simulation study assumed restraint equipment to be as in the baseline model, in which restraints/airbags are not redesigned to be optimal with light-weighting.

7.3 Impact of Vehicle Scrappage and Sales Response on Fatalities

The sales response discussed above in Chapter 4.1 impacts the number of vehicles produced in a given model year and, consequently, in service in subsequent years. Reduced new vehicle sales cause an increase in fatalities due primarily to slower adoption of safer vehicles while increased vehicle sales would have the opposite effect. The scrappage response described in Chapter 4.2 impacts safety because it changes the rate at which older, and less safe vehicles are retired from service. Collectively, sales and scrappage influence how quickly the fleet will "turn over" to newer vehicles, which tend to be safer than older vehicles. Any effects on fleet turnover caused by fuel economy standards increasing the price of new and used vehicles—either from changes in the pace of vehicle retirement or sales of new vehicles—will affect the distribution of both ages and model years present in the on-road fleet. Because each of these vintages carries with it inherent rates of fatal crashes, and newer vintages are generally safer than older ones, changing that distribution of ages within the fleet will change the total number of on-road fatalities under each regulatory alternative.

The agency uses the fatality risk of vehicles combined with the changes in VMT across alternatives to calculate the safety impact of fleet turnover. The fatality risk measures the likelihood that a vehicle will be involved in a fatal accident per mile driven. As described in Chapter 7.1, NHTSA calculates the fatality risk of a vehicle based on the vehicle's model year, age, and style, while controlling for factors that are independent of the intrinsic nature of the vehicle, such as behavioral characteristics. Newer vehicles will have a lower fatality risk than older vehicles, all else being equal. Fleetwide safety is also anticipated to benefit from both the improvement and increased prevalence of advance crash technologies as discussed in Chapter 7.1.12, hence more 'newer' vehicles on the road will have the ancillary effect of lowering the amount of fatalities in the existing fleet. As discussed in Chapter 4.3, we anticipate higher standards will slow fleet turnover which means miles that would have been driven in newer vehicles in our baseline will instead be driven in older vehicles in our alternatives. As a consequence, more miles will be driven in older vehicles with a higher fatality risk.

Relatedly, the dynamic fleet share model discussed above in Chapter 4.2.1.3 impacts the relative shares of passenger cars and light trucks produced in each model year (because as the fuel economy levels of both passenger cars and light trucks improve, the improvements add more value to the latter, the effect being amplified as fuel prices increase over time), and as cars and trucks have different fatality rates—in part due to their mass differences—variations in the market share of passenger cars and light-trucks across the alternatives will affect the estimated amount of fatalities. As light trucks, SUVs and passenger cars respond differently to technology applied to meet the standards—namely mass reduction—fleets with different compositions of body styles will have varying amounts of fatalities. Since mass-safety fatalities are calculated by multiplying mass point-estimates by VMT, which implicitly captures the impact of the dynamic fleet share model, the estimates of mass-safety fatalities in the previous section include the impact of vehicle prices and fuel savings on fleet composition.

7.4 Impact of Rebound Effect on Fatalities

The "rebound effect" is a measure of the additional driving that occurs when the cost of driving declines. More stringent standards reduce vehicle operating costs, and in response, some consumers may choose to drive more. Driving more increases exposure to risks associated with on-road transportation, and this added exposure translates into higher fatalities. NHTSA has calculated this impact by estimating the change in VMT that results from alternative standards. Estimates of the rebound effect in the literature differ significantly. For this analysis, we use a rebound effect of 10 percent. A full discussion of the basis for selecting this rate is provided in Chapter 4.3.3.

Rebound miles are not imposed on consumers by regulation. They are a freely chosen activity resulting from reduced vehicle operational costs. As such, NHTSA believes a large portion of the safety risks associated with additional driving are offset by the benefits drivers gain from added driving. The level of risk internalized by drivers is uncertain. This analysis assumes that consumers internalize 90 percent of this risk, which mostly offsets the societal impact of any added fatalities from this voluntary consumer choice.

The actual portion of risk from crashes that drivers internalize is unknown. We suspect that drivers are more likely to internalize serious crash consequences than minor ones, and some drivers may not perfectly internalize injury consequences to other individuals, especially occupants of other vehicles and pedestrians. However, legal consequences from crash liability, both criminal and civil, should also act as a caution for drivers considering added crash risk exposure. NHTSA considered several approaches to estimating internalized crash risk. The first assumes that drivers value harm to themselves as well as legal liability for causing harm to others. It considers that all fatalities in single vehicle crashes are fully valued, that there is roughly a 50 percent chance that each driver would be the one killed in multi-vehicle crashes, and that there is roughly a 50 percent chance that each driver would be at-fault in a multi-vehicle crash that they survived. This produces an estimate of roughly 88 percent.

Another approach assumes that drivers fully value all damage in single vehicle crashes, and only discount property damage incidents in multi-vehicle crashes. Based on data in Blincoe, *et al.* (2015),[886] multi-vehicle property-damage-only crashes account for about 7 percent of all societal crash costs, leaving 93 percent recognized under this approach. Yet another approach would assume drivers value injury crashes, but discount non-injury related costs such as property damage and traffic congestion. This approach results in roughly an 88 percent estimate of costs internalized. A fourth approach assumes that drivers fully value all quality-of-life losses associated with injury defined by the VSL, plus all personal expenses that result from external cost components not captured by the VSL. This approach results in an estimate that 86 percent of crash risk costs are internalized. Overall, while NHTSA recognizes this proportion is uncertain, we believe it is reasonable to assume that drivers internalize roughly 90 percent of the crash risk that results from added driving.

Note that none of these estimates account for net consumer surplus, implying that the full value of added driving gained or lost through the rebound effect is somewhat higher than these estimates. Based on this, we assume that 90 percent of the societal cost of additional motor vehicle crashes occurring due to rebound mileage is offset by the internalized acceptance of

[886] Blincoe, L., Miller, T.R., Zaloshnja, E., Lawrence, B. A., (May 2015, Revised) The Economic and Societal Impact of Motor Vehicle Crashes, 2010, (DOT HS 812 012), National Highway Traffic Safety Administration, Washington, D.C.

safety risk, and an additional portion is offset by added consumer surplus drivers obtain while assuming this risk. An estimate of this consumer surplus is provided in Chapter 6.1.5 of this document.

7.5 Fatalities by Source

To calculate safety impacts, the model produces a dynamic total fleetwide safety impact that reflects the interaction of added rebound VMT, mass/safety impacts, and shifts in VMT among vehicles of different ages due to sales/scrappage impacts. Because these factors are interactive, the model does not predict which fatalities are "only" attributable to the sales/scrappage response; it calculates a fleet response, and that fleet is the result of all those integrated modules. For this reason, we treat the sales/scrappage fatalities to be the residual from the total after accounting for rebound and mass/safety impacts, which can be more directly measured.

Rebound fatalities are computed by taking the difference in per vehicle rebound miles in the regulatory alternative and the baseline case multiplied by the baseline fatality rate per mile and baseline vehicle count. Fatalities due to rebound are computed as shown in Equation 7-3.

$$Rebound\ Fatalities_{Alt} = \left[\frac{R\ VMT_{Alt} - NR\ VMT_{Alt}}{Veh_{Alt}} - \frac{R\ VMT_{Base} - NR\ VMT_{Base}}{Veh_{Base}}\right] * \ Fatality\ Rate_{Base} * Veh_{Base}$$

Equation 7-3 – Fatalities Due to Rebound

Where "RVMT" is VMT including rebound miles, "NRVMT" is VMT excluding rebound miles, "Veh" is the quantity of vehicles, and "Alt" represents the alternative being examined and "Base" is the baseline value. The rebound fatalities will show as zero for the baseline scenario, and all alternatives will show fatalities due to rebound miles using the baseline vehicle counts. The formula specifies vehicle counts to clarify that vehicle counts will change over time among alternatives.

The fatalities due to mass reduction use the baseline vehicle counts and baseline per vehicle VMT including rebound. As with the fatalities attributable to rebound, the fatalities attributable to changes in mass reduction are calculated inherently as incremental values, relative to the baseline standards (the values will appear as zero for baseline standards in the outputs). The equation used to calculate the fatalities due to curb weight (mass)changes is as shown in Equation 7-4.

$$\Delta CW\ Fatalities_{Alt} = (Fatality\ Rate_{Alt} - Fatality\ Rate_{Base}) * R\ VMT\ _{Base}$$

Equation 7-4 – Fatalities Due to Curb Weight Change

NHTSA then computed the sales/scrappage fatalities as the remainder, as was done in the NPRM.

$$Sales/Scrap\ Fatalities = \left(Fatalities_{Alt} - Fatalities_{Aug}\right) - Rebound\ Fatalities - \ \Delta CW\ Fatalities$$

Equation 7-5 – Fatalities Due to Sales/Scrappage

7.6 Non-fatal Crash Impacts

Fatalities are valued as a societal cost within the CAFE Model's cost and benefit accounting. Their value is based on the comprehensive value of a fatality, which includes lost quality of life and is quantified in the VSL as well as economic consequences such as medical and emergency care, insurance administrative costs, legal costs, and other economic impacts not captured in the VSL alone. These values were derived from data in Blincoe et al. (2015), adjusted to 2018 economics, and updated to reflect the official DOT guidance on the VSL. This gives a societal value of $10.8 million for each fatality.[887] To estimate the impact of CAFE standards on non-fatal crash impacts, different methods were used for each of the three safety categories. These methods replace the previous method of scaling up the costs of non-fatal injuries and vehicle damage as a constant multiplier applied to increased fatality costs as was used in the 2020 CAFE final rule.

7.6.1 Non-fatal Sales Scrappage Impacts

To estimate the impacts on nonfatal injuries and property-damaged vehicles due to VMT shifts caused by changes in fleet turnover, we replicated the process used for fatalities, using effectiveness rates and target population proportions that are specific to these two nonfatal groupings. The same data and methods described previously in this section to compute the impact of advanced crash avoidance technologies on fatalities can also be used to examine the effectiveness of these technologies against non-fatal and PDO crashes. Effectiveness rates against nonfatal injuries and PDOs are identical for the two lane-change and blind spot technologies shown in Table 7-22. For the two frontal impact technologies, the central effectiveness rate noted in Table 7-22 was used rather than the reduced rates that were applied against fatalities. That is, we assume that effectiveness against crashes is a reasonable proxy for effectiveness against nonfatal injuries and PDOs. The percentages of target population applicable to these crashes was taken from Wang (2019) using results specific to these types of crashes. The inputs and results are summarized for nonfatal injuries in Table 7-23 through Table 7-25, and for PDOs in Table 7-26 through Table 7-28.[888]

[887] *See* TSD 7.7 Valuation of Safety Impacts for further discussion of comprehensive value of a fatality.
[888] *See* previous discussion in this section for the studies and methodology used to create these estimates.

Table 7-23 – Phased Impact of Crashworthiness Technologies on Non-Fatal Injury Rates, Forward Collision Crashes

MY	Forward Collision Warning		Automatic Emergency Braking			Weighted Effectiveness
	Eff.	% Inst.	Eff.	% Inst.	% T.P.	
2015	21.0%	0.047	46.0%	0.011	32.4%	0.004757
2016	21.0%	0.176	46.0%	0.120	32.4%	0.029822
2017	21.0%	0.305	46.0%	0.270	32.4%	0.060915
2018	21.0%	0.466	46.0%	0.445	32.4%	0.097904
2019	21.0%	0.417	46.0%	0.583	32.4%	0.115115
2020	21.0%	0.313	46.0%	0.687	32.4%	0.123549
2021	21.0%	0.209	46.0%	0.792	32.4%	0.131982
2022	21.0%	0.104	46.0%	0.896	32.4%	0.140415
2023	21.0%	0	46.0%	1	32.4%	0.148849
2024	21.0%	0	46.0%	1	32.4%	0.148849
2025	21.0%	0	46.0%	1	32.4%	0.148849
2026	21.0%	0	46.0%	1	32.4%	0.148849
2027	21.0%	0	46.0%	1	32.4%	0.148849
2028	21.0%	0	46.0%	1	32.4%	0.148849
2029	21.0%	0	46.0%	1	32.4%	0.148849
2030	21.0%	0	46.0%	1	32.4%	0.148849
2031	21.0%	0	46.0%	1	32.4%	0.148849
2032	21.0%	0	46.0%	1	32.4%	0.148849
2033	21.0%	0	46.0%	1	32.4%	0.148849
2034	21.0%	0	46.0%	1	32.4%	0.148849
2035	21.0%	0	46.0%	1	32.4%	0.148849

Table 7-24 – Phased Impact of Crashworthiness Technologies on Non-Fatal Injury Rates, Lane Departure Crashes

MY	Lane Departure Warning		Lane Keep Assist		% T.P.	Weighted Effectiveness
	Eff.	% Inst.	Eff.	% Inst.		
2015	10.0%	0.177	20.0%	0.000	17.6%	0.003112
2016	10.0%	0.198	20.0%	0.088	17.6%	0.006575
2017	10.0%	0.280	20.0%	0.205	17.6%	0.01213
2018	10.0%	0.382	20.0%	0.320	17.6%	0.017967
2019	10.0%	0.479	20.0%	0.442	17.6%	0.023962
2020	10.0%	0.442	20.0%	0.558	17.6%	0.027392
2021	10.0%	0.324	20.0%	0.676	17.6%	0.029461
2022	10.0%	0.207	20.0%	0.794	17.6%	0.03153
2023	10.0%	0.089	20.0%	0.911	17.6%	0.033599
2024	10.0%	0	20.0%	1	17.6%	0.03516
2025	10.0%	0	20.0%	1	17.6%	0.03516
2026	10.0%	0	20.0%	1	17.6%	0.03516
2027	10.0%	0	20.0%	1	17.6%	0.03516
2028	10.0%	0	20.0%	1	17.6%	0.03516
2029	10.0%	0	20.0%	1	17.6%	0.03516
2030	10.0%	0	20.0%	1	17.6%	0.03516
2031	10.0%	0	20.0%	1	17.6%	0.03516
2032	10.0%	0	20.0%	1	17.6%	0.03516
2033	10.0%	0	20.0%	1	17.6%	0.03516
2034	10.0%	0	20.0%	1	17.6%	0.03516
2035	10.0%	0	20.0%	1	17.6%	0.03516

Table 7-25 – Phased Impact of Crashworthiness Technologies on Non-Fatal Injury Rates, Blind Spot Crashes and Combined Total – All Three Crash Types, and Final Multiplier

MY	Blind Spot Detection		Lane Change Assist		% T.P.	Weighted Effectiveness	Three Techs Average Eff. Impact	Multiplier/ Fatalities
	Eff.	% Inst.	Eff.	% Inst.				
2015	3.0%	0.082	26.0%	0.123	6.9%	0.002385	0.010253	1.398385
2016	3.0%	0.124	26.0%	0.186	6.9%	0.003601	0.039998	2.45713
2017	3.0%	0.155	26.0%	0.233	6.9%	0.004503	0.077548	2.606141
2018	3.0%	0.191	26.0%	0.287	6.9%	0.00555	0.121421	2.746386
2019	3.0%	0.222	26.0%	0.333	6.9%	0.006425	0.145502	2.520716
2020	3.0%	0.252	26.0%	0.376	6.9%	0.007265	0.158205	2.416556
2021	3.0%	0.283	26.0%	0.424	6.9%	0.008192	0.169635	2.407186
2022	3.0%	0.314	26.0%	0.472	6.9%	0.009119	0.181064	2.399058
2023	3.0%	0.345	26.0%	0.520	6.9%	0.010045	0.192494	2.39194
2024	3.0%	0.376	26.0%	0.568	6.9%	0.010972	0.194981	2.323211
2025	3.0%	0.384	26.0%	0.617	6.9%	0.01185	0.195859	2.326417
2026	3.0%	0.335	26.0%	0.665	6.9%	0.012613	0.196622	2.329189
2027	3.0%	0.287	26.0%	0.713	6.9%	0.013376	0.197385	2.331945

MY	Blind Spot Detection		Lane Change Assist		% T.P.	Weighted Effectiveness	Three Techs Average Eff. Impact	Multiplier/ Fatalities
	Eff.	% Inst.	Eff.	% Inst.				
2028	3.0%	0.239	26.0%	0.761	6.9%	0.014139	0.198148	2.334687
2029	3.0%	0.191	26.0%	0.809	6.9%	0.014902	0.198911	2.337415
2030	3.0%	0.143	26.0%	0.857	6.9%	0.015665	0.199674	2.340127
2031	3.0%	0.095	26.0%	0.905	6.9%	0.016428	0.200437	2.342826
2032	3.0%	0.047	26.0%	0.953	6.9%	0.017191	0.201201	2.34551
2033	3.0%	0	26.0%	1	6.9%	0.017934	0.201943	2.348108
2034	3.0%	0	26.0%	1	6.9%	0.017934	0.201943	2.348108
2035	3.0%	0	26.0%	1	6.9%	0.017934	0.201943	2.348108

Table 7-26 – Phased Impact of Crashworthiness Technologies on PDO Crash Rates, Forward Collision Crashes

MY	Forward Collision Warning		Automatic Emergency Braking			Weighted Effectiveness
	FCW Eff.	% Inst.	AEB Eff.	% Inst.	% T.P.	
2015	21.0%	0.047	46.0%	0.011	36.8%	0.005416
2016	21.0%	0.176	46.0%	0.120	36.8%	0.033958
2017	21.0%	0.305	46.0%	0.270	36.8%	0.069363
2018	21.0%	0.421	46.0%	0.445	36.8%	0.107987
2019	21.0%	0.417	46.0%	0.583	36.8%	0.131081
2020	21.0%	0.313	46.0%	0.687	36.8%	0.140684
2021	21.0%	0.209	46.0%	0.792	36.8%	0.150287
2022	21.0%	0.104	46.0%	0.896	36.8%	0.15989
2023	21.0%	0	46.0%	1	36.8%	0.169493
2024	21.0%	0	46.0%	1	36.8%	0.169493
2025	21.0%	0	46.0%	1	36.8%	0.169493
2026	21.0%	0	46.0%	1	36.8%	0.169493
2027	21.0%	0	46.0%	1	36.8%	0.169493
2028	21.0%	0	46.0%	1	36.8%	0.169493
2029	21.0%	0	46.0%	1	36.8%	0.169493
2030	21.0%	0	46.0%	1	36.8%	0.169493
2031	21.0%	0	46.0%	1	36.8%	0.169493
2032	21.0%	0	46.0%	1	36.8%	0.169493
2033	21.0%	0	46.0%	1	36.8%	0.169493
2034	21.0%	0	46.0%	1	36.8%	0.169493
2035	21.0%	0	46.0%	1	36.8%	0.169493

Table 7-27 – Phased Impact of Crashworthiness Technologies on PDO Crash Rates, Lane Departure Crashes

MY	Lane Departure Warning		Lane Keep Assist		% T.P.	Weighted Effectiveness
	LDW Eff.	% Inst.	LKA Eff.	% Inst.		
2015	10.0%	0.177	20.0%	0.000	12.0%	0.002131
2016	10.0%	0.198	20.0%	0.088	12.0%	0.004503
2017	10.0%	0.280	20.0%	0.205	12.0%	0.008307
2018	10.0%	0.382	20.0%	0.320	12.0%	0.012304
2019	10.0%	0.479	20.0%	0.442	12.0%	0.016409
2020	10.0%	0.442	20.0%	0.558	12.0%	0.018758
2021	10.0%	0.324	20.0%	0.676	12.0%	0.020175
2022	10.0%	0.207	20.0%	0.794	12.0%	0.021592
2023	10.0%	0.089	20.0%	0.911	12.0%	0.023009
2024	10.0%	0	20.0%	1	12.0%	0.024078
2025	10.0%	0	20.0%	1	12.0%	0.024078
2026	10.0%	0	20.0%	1	12.0%	0.024078
2027	10.0%	0	20.0%	1	12.0%	0.024078
2028	10.0%	0	20.0%	1	12.0%	0.024078
2029	10.0%	0	20.0%	1	12.0%	0.024078
2030	10.0%	0	20.0%	1	12.0%	0.024078
2031	10.0%	0	20.0%	1	12.0%	0.024078
2032	10.0%	0	20.0%	1	12.0%	0.024078
2033	10.0%	0	20.0%	1	12.0%	0.024078
2034	10.0%	0	20.0%	1	12.0%	0.024078
2035	10.0%	0	20.0%	1	12.0%	0.024078

Table 7-28 – Phased Impact of Crashworthiness Technologies on PDO Crash Rates, Blind Spot Crashes and Combined Total – All Three Crash Types, and Final Multiplier

MY	Blind Spot Detection		Lane Change Assist		% T.P.	Weighted Effectiveness	Three Techs Average Eff. Impact	Multiplier/ Fatalities
	Eff.	% Inst.	Eff.	% Inst.				
2015	3.0%	0.082	26.0%	0.123	12.0%	0.004151	0.011698	1.59543
2016	3.0%	0.124	26.0%	0.186	12.0%	0.006268	0.044728	2.747706
2017	3.0%	0.155	26.0%	0.233	12.0%	0.007838	0.085508	2.873632
2018	3.0%	0.191	26.0%	0.287	12.0%	0.009659	0.129951	2.939325
2019	3.0%	0.222	26.0%	0.333	12.0%	0.011182	0.158673	2.748887
2020	3.0%	0.252	26.0%	0.376	12.0%	0.012644	0.172087	2.628588
2021	3.0%	0.283	26.0%	0.424	12.0%	0.014257	0.18472	2.621245
2022	3.0%	0.314	26.0%	0.472	12.0%	0.01587	0.197353	2.614876
2023	3.0%	0.345	26.0%	0.520	12.0%	0.017483	0.209986	2.609298
2024	3.0%	0.376	26.0%	0.568	12.0%	0.019096	0.212668	2.533943
2025	3.0%	0.384	26.0%	0.617	12.0%	0.020623	0.214195	2.544212
2026	3.0%	0.335	26.0%	0.665	12.0%	0.021951	0.215523	2.553089
2027	3.0%	0.287	26.0%	0.713	12.0%	0.023279	0.216851	2.561919
2028	3.0%	0.239	26.0%	0.761	12.0%	0.024607	0.218179	2.570702
2029	3.0%	0.191	26.0%	0.809	12.0%	0.025935	0.219507	2.579438
2030	3.0%	0.143	26.0%	0.857	12.0%	0.027264	0.220835	2.588127
2031	3.0%	0.095	26.0%	0.905	12.0%	0.028592	0.222163	2.59677
2032	3.0%	0.047	26.0%	0.953	12.0%	0.02992	0.223491	2.605367
2033	3.0%	0	26.0%	1	12.0%	0.031212	0.224784	2.613688
2034	3.0%	0	26.0%	1	12.0%	0.031212	0.224784	2.613688
2035	3.0%	0	26.0%	1	12.0%	0.031212	0.224784	2.613688

Based on a comparison of the combined average effectiveness impacts for the three crash severity groups (fatalities, non-fatal injuries, and property damage), it is apparent that these advanced crash avoidance technologies will reduce non-fatal injuries and property damage crashes by more than they would fatalities.[889]

7.6.2 Non-fatal Rebound VMT Crash Impacts

Additional mileage driven due to the rebound effect increases exposure to risk and thus increases the probability of additional fatalities, non-fatal injuries, and property damage. As was done for fatalities, we estimate the resulting additional numbers of non-fatal injuries and vehicles involved in PDO crashes explicitly (as the product of the change in miles driven and non-fatal injuries per mile, and similarly for PDO crashes) using the per-mile rates projected by our CAFE Model. This produces estimates of increased incidence of nonfatal injuries and PDO vehicles. We apply our average monetary values (noted in Chapter 7.7) to the estimated numbers of additional non-fatal injuries and property damage to vehicles.

[889] For example, for MY 2035, the combined effectiveness for PDO crashes is .224784, as shown in the second to last column of Table 7-28, which is 2.613 times the .0860 combined effectiveness for fatalities, as seen in Table 7-13, which shows the disproportionality impact of crash avoidance technologies on non-fatal accidents.

7.6.3 Non-fatal Mass/Size Safety impacts

For mass/safety, extensive research documented elsewhere in this TSD establish relationships between changes in vehicle mass that increase mass disparity and safety. These relationships are used as inputs in the CAFE Model to determine how predicted changes in vehicle mass initiated to improve CAFE will impact motor vehicle fatalities. Research into the effect of changes in mass on safety has typically been confined to fatality impacts, but logically, the same physics that increase or decrease fatality risk should impact injury and property damage risk in a directionally consistent manner. For non-fatal crash impacts, we assume that the rates of non-fatal injuries and property damage to vehicles projected by our models will change in the same proportion to changes in vehicles' mass disparities as do those vehicles' fatality rates. This produces estimates of changes in incidence for nonfatal injuries and PDO vehicles due to mass changes in the new vehicle fleet for each model year. We apply our average monetary values (see Chapter 7.7) to the estimated numbers of additional non-fatal injuries and property damage to vehicles.

7.7 Valuation of Safety Impacts

Fatalities, nonfatal injuries, and property damage crashes are valued as a societal cost within the CAFE Model's cost and benefit accounting. Their value is based on the comprehensive value of a fatality, which includes lost quality of life and is quantified in the (VSL as well as economic consequences such as medical and emergency care, insurance administrative costs, legal costs, and other economic impacts not captured in the VSL alone. These values were derived from data in Blincoe et al. (2015), adjusted to 2018 economics, and updated to reflect the official DOT guidance on the VSL.[890] Nonfatal injury costs, which differ according to severity, were weighted according to the relative incidence of injuries across the Abbreviated Injury Scale (AIS). To determine this incidence, the agency applied a KABCO/MAIS translator to GES KABCO based injury counts from 2010 through 2015. This produced the MAIS based injury profile. This profile was used to weight nonfatal injury unit costs derived from Blincoe et al, adjusted to 2018 economics and updated to reflect the official DOT guidance on the VSL. Property-damaged vehicle costs were also taken from Blincoe et al and adjusted to 2018 economics. VSL does not impact property damage. This gives societal values of $10.8 million for each fatality, $132,000 for each nonfatal injury, and $7100 for each property damaged vehicle.

7.8 Summary of Safety Impacts

The previous discussion documents the methods used to determine the safety impacts of higher CAFE standards on vehicle occupants and their value to society. The resulting estimates are generated inside the CAFE Model and are detailed in Chapter 5 of the Final Regulatory Impact Analysis (FRIA) accompanying this final rule.

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[890] https://www.transportation.gov/office-policy/transportation-policy/revised-departmental-guidance-on-valuation-of-a-statistical-life-in-economic-analysis. (Accessed: February 14, 2022).