PROPERTY VALUE IMPACTS OF COMMERCIAL-SCALE SOLAR ENERGY IN MASSACHUSETTS AND RHODE ISLAND

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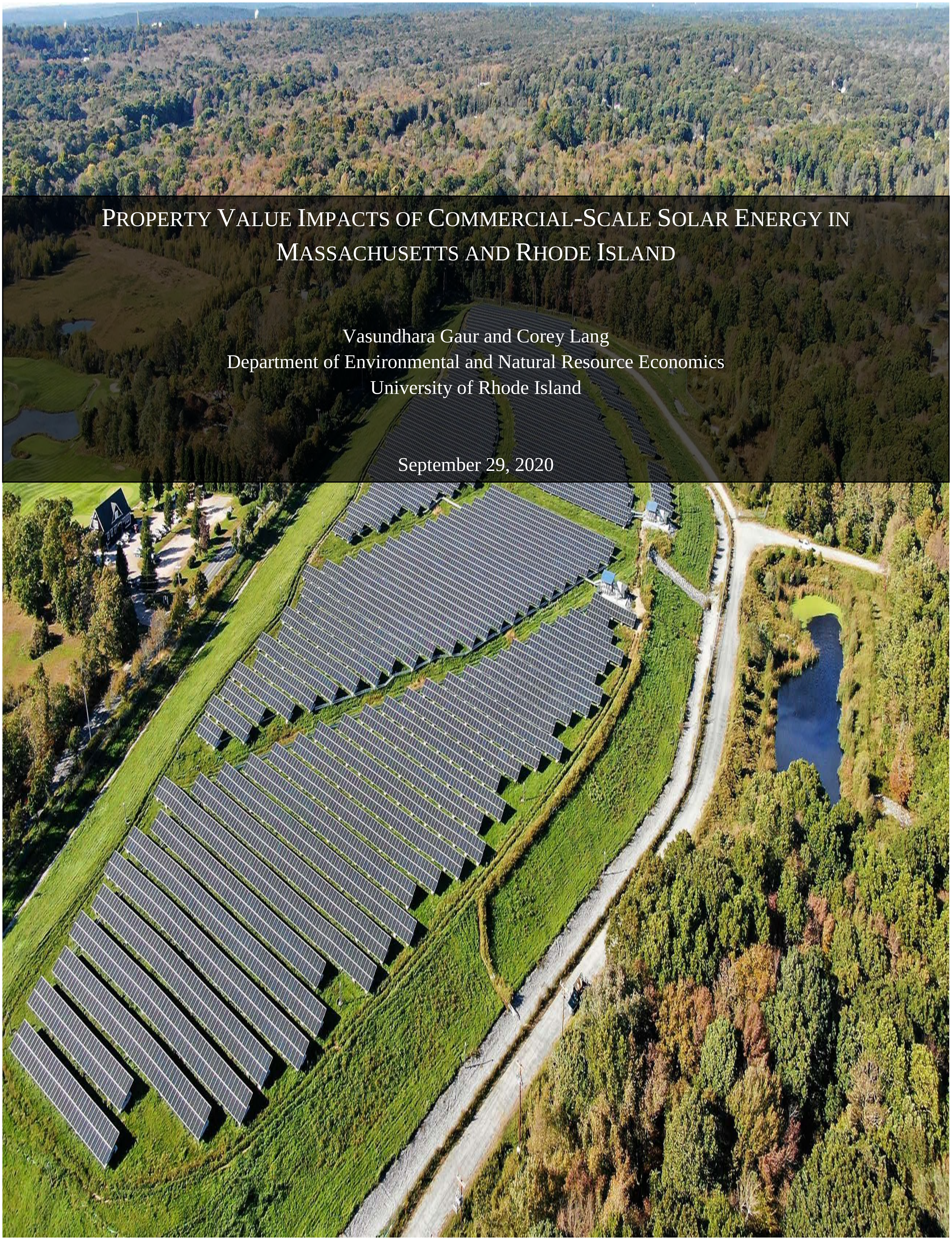

ABSTRACT

While utility-scale solar energy is important for reducing dependence on fossil fuels, solar arrays use significant amounts of land (about 5 acres per MW of capacity), and may create local land use disamenities. This paper seeks to quantify the externalities from nearby solar arrays using the hedonic method. We study the states of Massachusetts and Rhode Island, which have high population densities and ambitious renewable energy goals. We observe over 400,000 transactions within three miles of a solar site. Using a difference-in-differences, repeat sales identification strategy, results suggest that houses within one mile depreciate 1.7% following construction of a solar array, which translates into an annual willingness to pay of $279. Additional results indicate that the negative externalities are primarily driven by solar developments on farm and forest lands in non-rural areas. For these states, our findings indicate that the global benefits of solar energy in terms of abated carbon emissions are outweighed by the local disamenities.

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1 INTRODUCTION

Solar energy in the United States has grown at an average rate of 49% per year since 2009, making the US the second largest producer of solar energy in the world (EIA International Energy Outlook 2019). In 2019, solar energy accounted for 40% of all new capacity additions in the country, the largest ever in its history, and exceeding all other energy sources (Perea et al., 2020). By June 2020, the cumulative installed capacity of solar in the United States reached 81.4 gigawatts (GW), which is enough to power 15.7 million homes (Perea et al., 2020). Solar is predicted to overtake wind to become the largest source of renewable energy in the US by 2050, accounting for 46% of all energy produced from renewable sources (EIA Annual Energy Outlook 2018).

While there is a broad support for renewable energy in the United States (Bates & Firestone, 2015; Farhar, 1994; Firestone et al., 2018; Hoen et al., 2019; Krohn & Damborg, 1999), and for solar energy in particular (Carlisle et al., 2014, 2015; Farhar, 1994; Greenberg, 2009; Jacobe, 2013; Pew Research Center, 2019), the development of large-scale solar installations has not been obstacle free. One major hurdle to overcome before construction begins is the siting process. Solar installations require over ten times more land area than non-renewable sources to generate the same amount of energy, and the requirement of large tracts of land for their construction has become the largest cause of land use change in the United States (Trainor et al. 2016; Ong et al. 2013). Recently, the siting of large solar projects has become contentious in some parts of the country due to concerns about visual disamenities, impacts on ecosystems, siting of transmission lines, loss of a town's rural character, water pollution, fire risk, water use, and reduction in property values (Farhar et al., 2010; Gross, 2020; Lovich & Ennen, 2011). The debate is especially heated when solar development is proposed on existing farm and forest lands, which is common because these are the cheapest locations for development (Kuffner, 2018; Naylor, 2019).

The purpose of this paper is to quantify the externalities associated with proximity to utility-scale solar installations using hedonic valuation. Theory indicates that property values will reflect people's willingness to pay to avoid the cumulative disamenities of solar development (Bishop et al., 2019; Rosen, 1974). Our study focuses on the states of Massachusetts (MA) and Rhode Island (RI), which are ideal for two reasons. First, both states have recently experienced a sudden boom in the development of large-scale solar installations. This trend has been driven by the Renewable Portfolio Standards (RPS), regulations that require increased energy production from renewable energy sources, which have been adopted by both states. MA's RPS calls for 25% of electricity generated by renewable sources by 2030 and RI's RPS calls for 38.5% by 2035. Second, both states have high population density, ranked 2nd and 3rd among U.S. states. This level of development means that most solar sites are proximate to residential areas, which yields many observed transactions for precise estimates.

We analyze the impact of utility-scale solar installations sized 1 MW and above on nearby property prices in MA and RI.[1] We use a difference-in-differences (DID) identification strategy, which compares changes in housing prices after construction for nearby properties with those further away. We empirically estimate the spatial extent of treatment to be one mile from the solar installation and choose a cutoff for control properties of three miles. Our primary sample consists of 208 solar installations, 71,337 housing transactions occurring within one mile (treated group), and 347,921 transactions between one to three miles (control croup).

Across a variety of specifications, our results suggest that solar installations negatively affect nearby property values. Our preferred specification, which includes property fixed effects (i.e., repeat sales), month-year fixed effects, and county-year fixed effects, indicates that property values in the treatment group decline 1.7% (or $5,751) relative to the control group, and this estimate is statistically different from zero at the 1% level. These findings suggest that solar arrays create local, negative externalities, and the average household annual willingness to pay to avoid these externalities is $279. This helps explain local concerns and opposition and gives pause to current practices of not including proximate residents in siting decisions or compensating them after siting has occurred. While we cannot estimate producer and consumer surplus, we can compare external benefits and costs. Our estimates imply that the global positive external benefits of carbon mitigation are outweighed by local externalities costs at a ratio of 0.46. However, renewable energy in New England usually displaces natural gas use by power plants. Solar in more rural places (thus affecting fewer households) and solar that displaces coal would have a more favorable benefit-cost ratio.

We also examine heterogeneity in treatment effects in several ways. First, with respect to proximity, we find substantially larger negative impacts on homes located within 0.1 mile of

[1] Following the U.S. Energy Information Administration (EIA), we define large-scale solar installations as those with an installed capacity of 1 MW or larger.

solar installations (-7.0%). Second, we estimate a series of models exploring heterogeneity based on prior land use (farm or forest vs. landfills or industrial areas) and rural character of a municipality (defined based on population density). The results suggest that the overall negative effects of solar arrays on nearby property values are driven by farm and forest sites in non-rural areas (non-rural is most akin to suburban, as there are very few solar sites in urban areas). Solar developments on landfills and industrial areas or in rural areas have smaller and statistically insignificant effects on prices. We posit that solar arrays on farm and forest lands cause greater externalities, given the dual loss of open space amenities and gain of industrial disamenities, and that this effect hinges on the scarcity of open space typical in non-rural areas.

2 CONCEPTUAL FRAMEWORK

Environmental goods and services are often 'non-market goods', meaning they are not traded in any market. However, that does not mean that they have no value. Using economic theory, we can estimate environmental values by examining people's decisions and how they make choices and tradeoffs regarding such goods.

One way of valuing environmental goods and services is through the revealed preference method where the preferences of individuals are inferred through their actual buying and selling decisions in a related market. For example, air quality is not transacted in any market, but people 'reveal' their value for it when they buy homes away from urban and industrial areas with high traffic volumes and poor air quality. In this example, air quality is the non-market good, the 'actual buying and selling decision' is the choice of purchasing a house with specific characteristics, and the 'related market' is the housing market.

A common application of the revealed preference method is the hedonic housing price technique. First theorized by Rosen (1974), the hedonic price model (HPM) measures the implicit price of each attribute of a bundled good. Applied to the housing market, the idea is that the price of a property can be broken down into the price of its various attributes. These attributes can be structural (e.g. lot size, living area, number of bedrooms and bathrooms, presence of air conditioning or pool, etc.), neighborhood (e.g. school quality, proximity to shopping, etc.), and environmental (e.g. air and groundwater quality, tree cover, proximity to brownfield, etc.). More formally, let us consider a house i, and let P_i denote its price, S_i the set of structural characteristics, N_i the neighborhood characteristics, and E_i the environmental characteristics of that house. Then the hedonic price function of the house can be represented mathematically as a function of its characteristics:

$$P_i = f(S_i, N_i, E_i) \tag{1}$$

When purchasing a house, the consumers make tradeoffs between their desired quantities of each of these attributes and price. Further, in equilibrium, prices adjust to reflect willingness to pay for the bundled attributes. By examining transacted properties with sales price and attributes, the implicit value of each attribute can be estimated. In the context of solar development, the value that people place on solar arrays can be estimated by examining transactions in close proximity to solar arrays compared to those further away.

The HPM is a well-established and frequently used tool for measuring nonmarket values. It has been used extensively in the literature for estimating the willingness to pay for environmental amenities like air quality (Bajari et al., 2012; Bayer et al., 2009; Bento et al., 2014; Chay and Greenstone, 2005; Grainger, 2012; Lang, 2015; Ridker and Henning, 1967) and open space (Anderson and West, 2006; Black, 2018; Geoghegan et al., 1997; Irwin, 2002; Lang, 2018), and also environmental disamenities like brownfields (Haninger et al., 2017; Lang and Cavanagh, 2018; L. Ma, 2019) and electrical transmission lines (Hamilton and Schwann, 1995). Several hedonic studies also estimate the public's valuation of non-renewable energy sources and infrastructure, particularly coal plants (Davis, 2011), nuclear energy (Gawande and Jenkins-Smith, 2001; Tanaka and Zabel, 2018), petroleum storage (Zabel and Guignet, 2012), and hydraulic fracturing (Boslett et al., 2016, 2019; Gopalakrishnan and Klaiber, 2014; Muehlenbachs et al., 2015).

The HPM produces intuitive and policy relevant results. For example, Haninger et al. (2017) analyze federal brownfield remediation and find that properties in close proximity to EPA-funded remediated brownfields appreciate 5-11% following cleanup, and that in aggregate this valuation exceeds the costs of remediation and hence the federal program passes a benefit-cost test. Lang (2018) examines municipal land conservation spending in the United States, and estimates that properties on average appreciate 0.68–1.12% for every $1000 per household of open space spending authorized. The positive appreciation implies that the valuation of open space amenities exceeds the costs of additional taxes, and further that land conservation is underprovided. Muehlenbachs et al. 2015 analyze hydraulic fracturing ("fracking") in Pennsylvania and find that properties within 1km of a well pad decline in value 16.5%, but only when the properties use well water, public water supply houses are unaffected. These results suggest that perception of risk is focused on contaminated drinking water.

The HPM has become increasingly popular for the valuation of renewable energy in recent years, with the most frequent applications focusing on wind energy. Within the United States, studies that use data with large numbers of observations close to turbines find no significant impact on property prices. Hedonic studies that find no negative externalities from onshore wind energy development include Hoen et al. (2011) for 24 wind facilities across the United States; Lang et al. (2014) for 10 wind turbine sites in Rhode Island; Hoen et al. (2015) for 67 wind facilities (with over 45,000 turbines) installed all over the United States through 2011, and Hoen and Atkinson-Palombo (2016) for 41 turbines in densely populated areas of Massachusetts. In contrast, studies in European countries find that wind turbines have a significantly negative impact on nearby properties, though the magnitude of the effect differs by region (Dröes & Koster, 2016; Gibbons, 2015; Sunak & Madlener, 2016). Vyn (2018) finds the Canadian experience to be heterogeneous and dependent on community acceptance. More recently, hedonic methods have focused on estimating externalities from offshore wind turbines. While this literature is still in its infancy, early studies indicate no negative impacts to property values in the vicinity of offshore wind turbines (Jensen et al., 2018) and positive impacts to tourism (Carr-Harris & Lang, 2019).

Hedonic valuation has also been applied to residential rooftop solar. General consensus is that houses installed with rooftop photovoltaic (PV) panels sell for a premium, though there is regional variation in the size of the effect: 3.5% in California (Dastrup et al., 2012; Hoen et al., 2012), 5.4% in Hawaii (Wee, 2016), 17% in Arizona (Qiu et al. 2017), and 3.2% in Western Australia (Ma et al. 2016). However, this literature is only tangentially related as it is about quantifying internalities (valuation of personal financial benefits), not externalities, and has nothing to do with land use.

In sum, there exists little information on the externalities associated with large-scale solar installations within the United States. It is therefore necessary to understand the value people place on solar structures in order to help state and municipal policy makers implement policies and decisions that reflect public preferences.

3 DATA

To implement the hedonic analysis, we build a composite dataset that integrates: 1) the data on the location and attributes of all solar developments in MA and RI, and 2) the data on attributes and locations of residential properties in MA and RI.

3.1 Solar data

The dataset on solar installations is obtained from the Energy Information Administration's (EIA's) report EIA-860M, or the Monthly Update to the Annual Electric Generator Report. The EIA-860M contains data on the total capacity of electric generation facilities in the United States that have a capacity of 1 MW and above, their point location (latitude and longitude), and the month and year that generation begins. Figure 1 represents a map of 284 solar installations constructed prior to August 2019, which is when we set the cutoff for being in our sample. The installations are well dispersed across all regions in both states, which increases confidence that estimates will not be affected by unobserved regional differences. We exclude 76 solar installations (27% of all installations) that are built within 1 mile of each other, since property value impacts may be hard to measure for observations in the proximity of multiple installations.[2] This is similar to a sample cut made by Haninger et al. (2017).

Figure 2 graphs new and cumulative solar capacity by year. The first installation came online in December 2010. New capacity displays a continuous upward trend through 2014. There is a sharp fall in 2015, after which the trend rises again and peaks in 2017, before falling again in 2018. As of August 2019, the cumulative solar capacity in RI and MA is 817 MW. Capacity factors for this region are about 16.5% (EIA 2019), which means these solar installations are collectively producing 1180 GWh of electricity per year, which is enough to power 157,681 homes.

One limitation of our data is that we do not have shapefiles representing the exact footprint of the solar installations, thus we must approximate that using Geographic Information Systems (GIS) software. Solar installations require approximately 5 acres of land per MW of capacity (Denholm & Margolis, 2008; Ong et al., 2013). We assume that the point location is the

[2] Figure A1 in the online appendix represents a map of the resultant 208 solar installations.

centroid of the installation and then create a circle around it with an area equal to 5 times the capacity (in MW) of each array.[3]

We hypothesize that prior land use may affect property value impacts. Specifically, houses in proximity to farms and forests that are developed into solar may depreciate more than houses in proximity to a brownfield or capped landfill that is developed into solar.[4] Since farms, forests, and other open space are amenities and boost home values (Irwin, 2002; Lang, 2018), conversion of these types of lands may lead to larger price decreases because it is the combination of a loss of amenities and the gain of disamenities. To infer prior land use, we overlay the estimated circular footprints on 2005 land use data obtained from Massachusetts Bureau of Geographic Information and 2011 land use data obtained from Rhode Island Geographic Information System for the respective states. We then assign each installation a prior land use: 'greenfield' if it was formerly either a farm or forest land, and 'non-greenfield' if it was either a commercial site or a landfill.[5] 63% of installations and 70% of capacity is classified as greenfield (see Figure A2 in the online appendix).

3.2 Property data

We use ZTRAX housing transaction data from Zillow (http://www.zillow.com/data), which include information on property location (latitude and longitude), sales price, date of transaction, and many property characteristics (lot size, square feet of living area, number of bedrooms, number of bathrooms, year built, number of fireplaces, central air-conditioning, and

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[3] We manually crosscheck the EIA data with Google Maps, and correct the latitude and longitude when they do not correspond to the centroid of the array. We recognize that this approach could lead some properties to be misclassified as treatment or control, inducing a small amount of measurement error in treatment status. As a result, our DID estimates may be slightly attenuated.

[4] Solar developers prefer farm and forest lands because they have substantially lower construction costs compared to alternative sites like brownfields, landfills, superfunds and industrial lands.

[5] Several solar installations cover an area with multiple land uses. We obtain exactly one land use type per solar site in five additional steps. First, we classify the land use as 'landfill' if the installations have the term 'landfill' in their name, or if they are listed in the EPA's dataset of contaminated land. Second, we use a stratifying logic to group all land-use types under seven major categories: commercial, farm, forest, landfill, recreational, residential, and wetland. Third, we place *'transportation'*, *'urban public/institutional'*, *'industrial'*, *'powerline/utility'*, and *'junkyard'* under commercial; *'orchard'*, *'cropland'*, *'pasture'*, *'nursery'*, and *'cranberry bog'* under farm; *'spectator recreation'*, and *'participation recreation'* under recreation, *'multi-family residential'*, *'low density residential'*, *'medium density residential'*, *'very low density residential'*, and *'high density residential'* under residential; and *'forested wetland'*, *'water'*, and *'non-forested wetland'* under wetland. Fourth, we rank all land use categories under each installation by area, such that the land use with the greatest area gets the highest rank. We drop all land use categories but the ones with the highest rank to obtain exactly one land use per installation in the following four major categories: commercial, farm, forest, and landfill.

swimming pool). The data include 2,095,835 property transactions from January 2005 to June 2019 in the states of RI and MA. Houses with missing observations for sales price, bedrooms, full bathrooms, and half bathrooms are dropped. We also drop groups of single-family residential properties with the same latitudes and longitudes, but different addresses. Sales prices are adjusted to 2019 levels using the Northeast regional housing Consumer Price Index from Bureau of Labor Statistics. After dropping transactions with prices of $100 or less, since these are clearly not arms-length transactions, we drop transactions in the bottom and top 5% of the sales price distribution to get rid of outliers. Further, we drop observations that have more than four stories, six bedrooms, five full bathrooms, or three half bathrooms. Houses that underwent major reconstruction are dropped since they may have different attributes in previous transactions. We exclude homes that sell before they were built, as there is evidence these are lot sales without improved property. We also drop single-family residential properties with lot sizes larger than 10 acres, since large plots could be potential sites for solar development and price impacts of nearby solar could be completely different. Condominiums are assigned a lot size value of zero acres and are identified with an indicator variable. The subjective condition of properties is defined by a dummy variable equal to 1 indicating above average condition.

Similar to prior land use, we hypothesize that existing development in areas surrounding solar arrays may impact property prices. Many rural areas pride themselves on their rural character and residents seek out that type of bucolic setting. Hence, construction of solar installations could be seen as an industrialization of the landscape and may cause larger negative impacts on property values. We proxy for rural character with municipality-level population density, which comes from the 2010 Census. We define an indicator variable $Rural$, which equals one if the town has a population density of 850 people per square mile or fewer. We chose this cutoff because 850 is the average population density of MA, which forms the bulk of the observations in our dataset, and, at this cutoff, almost a third of the properties and 60% of the solar installations are classified as rural, which we believe are reasonable proportions. However, we examine different cutoffs in the appendix. It is important to note non-rural properties should not be thought of as urban, but more suburban. Very few utility-scale solar developments are built in urban areas as there is just not space.

To build our main dataset, we spatially merge the solar data with the property dataset. We match every property to the nearest eventual site of solar development to infer proximity. We only include transactions occurring within three miles of any eventual solar installation to increase similarities in observable and unobservable characteristics for sample properties. For properties lying within three miles of two installations, we keep only those that transacted before both installations were built and those that transacted after both were constructed. This ensures cleaner identification of the pre-construction and post-construction periods in our model.

The final, composite dataset includes 419,258 property transactions representing 284,364 unique properties around 208 solar installations. Figure 3 shows the number of transactions by distance to nearest solar installation. We have roughly 18,000 transactions within half a mile, and 71,337 transactions within one mile of a solar installation. This is far more compared to many prior studies measuring externalities of wind energy, and it enables precise estimation of any effect that may be present. Further, 27.43% of transactions occur post-construction and 17.27% of the post-construction observations are within one mile.[6]

4 METHODS

We use the difference-in-differences (DID) method in the hedonic framework to analyze the causal impact of solar installations on housing prices. We compare treated properties located near large-scale solar installations to similar control properties that are further away from such installations. The treated properties are defined as those that lie within some distance *d* of a solar site, and control properties are greater than distance *d* (and less than three miles). Our basic empirical specification is:

$$P_{it} = \beta_1 Treated_i + \beta_2 Post_{it} + \beta_3 (Treated_i \times Post_{it}) + \gamma X_{it} + \epsilon_{it} \qquad (2)$$

Where P_{it} is the log sales price of house i at time t. $Treated_i$ is a dummy variable equal to 1 if a house is in the treatment group and 0 otherwise, $Post_{it}$ is an indicator for post-treatment, which equals 1 if a house sells after the construction of the nearest solar installation, X_{it} is a vector of housing variables (bedrooms, bathrooms, etc.), as well as census block fixed effects and month-year fixed effects. Month-year fixed effects capture macroeconomic trends that affect the entire region that could be correlated with solar development trends. Block fixed effects account for location-specific unobservable heterogeneity that could be correlated with solar development. Lastly, ϵ_{it} is the error term. β_1 is the pre-treatment price difference between treated and control

[6] Figure A3 in the online appendix presents the number of post-construction transactions by distance bin.

houses, and β_2 is the price difference between control properties, before and after treatment. The coefficient of interest is β_3, which is the differential price change from before to after solar development for treated properties relative to control properties.

In addition, we also estimate repeat sales models that include property fixed effects:

$$P_{it} = \beta_2 Post_{it} + \beta_3 (Treated_i \times Post_{it}) + \gamma X_{it} + \alpha_i + \epsilon_{it} \tag{3}$$

This model uses only within-property variation to identify β_3, and thus controls for time-invariant unobservables at the property level. In this specification, X_{it} only includes temporal fixed effects, as other housing variables are time-invariant. In addition to this specification, we also estimate a model that adds county-year fixed effects, which allows for different county-specific trends in the housing market. Across all specifications, our preferred model includes property, month-year, and county-year fixed effects, as it best controls for unobservable determinants of price and most flexibly controls for regional price trends, both of which could be correlated with solar development. In all models, we cluster standard errors at the census tract level to allow for correlated errors within a larger area.

Since the extent of treatment is unknown, we first seek to empirically identify *d*, the distance up to which the effects of constructing a solar installation persist, and this will define the boundary for our treatment group. Following similar strategies as Davis (2011), Muehlenbachs et al. (2015), and Boslett et al. (2019), we estimate a series of DID models similar to our preferred specification, except with treatment defined by successive tenth-mile increments and control always being 2-3 miles. Figure 4 plots the estimates for each tenth-mile increment ranging from zero to two miles; each point and confidence interval represents a separate regression. Results indicate large, negative impacts for houses within 0.1 mile, but with large standard errors. Point estimates bounce around some, but more or less show effects diminishing with distance as expected. Beyond one mile, all estimates are statistically insignificant. Given this evidence, in all future specifications, we define the treatment group to be within one mile and the control group to be 1-3 miles.

We extend the analysis to investigate heterogeneity in treatment effect in multiple ways. First, we estimate a model that allows for heterogeneity in the impact based on distance. We identified treatment extending to one mile with Figure 4, but Figure 4 also suggests that treatment effects could be substantially larger within 0.1 mile. To explore this possibility more formally, we develop a model that defines multiple distance bands. The first (outermost) band represents control properties located two to three miles away from the nearest solar installation (per usual). The second (outer-middle) band includes treated properties located 1 – 2 miles from the nearest solar installation. The third (middle) band includes treated properties located 0.5 – 1 mile from the nearest solar installation. The fourth (inner-middle) band includes treated properties located 0.1 – 0.5 miles from the nearest solar installation. Finally, the fifth (innermost) band consists of treated properties within a distance of 0.1 mile from the closest installation. Our specification is:

$$P_{it} = \beta_2 Post_{it} + \sum_{k=2}^{5} \beta_3^k \left(dist_i^k \times Post_{it}\right) + \gamma X_{it} + \alpha_i + \epsilon_{it} \tag{4}$$

where $dist_i^k$ is a dummy variable equal to 1 if a property i lies within the k^{th} distance band. P_{it}, $Post_{it}$, X_{it}, and α_i are as defined in Equation 3. Our coefficients of interest are β_3^k, which are the differential changes in property prices from before to after the construction of solar installations, for homes in distance band k, compared to changes in property values of control houses (lying in distance band 1).

Second, we investigate heterogeneity in treatment effect by two more characteristics: prior land use and rural character. This is done by a triple difference analysis in which we interact the treatment effect term in Equation 3 with a variable for our characteristic of interest. The specifications are as follow:

$$\begin{aligned} P_{it} = {} & \beta_2 Post_{it} + \beta_3 (Treated_i \times Post_{it}) + \beta_4 (Post_{it} \times Greenfield_i) \\ & + \beta_5 (Treated_i \times Post_{it} \times Greenfield_i) + \gamma X_{it} + \alpha_i + \epsilon_{it} \end{aligned} \tag{5}$$

$$\begin{aligned} P_{it} = {} & \beta_2 Post_{it} + \beta_3 (Treated_i \times Post_{it}) + \beta_4 (Post_{it} \times Rural_i) \\ & + \beta_5 (Treated_i \times Post_{it} \times Rural_i) + \gamma X_{it} + \alpha_i + \epsilon_{it} \end{aligned} \tag{6}$$

where $Greenfield_i$ is an indicator variable equal to 1 if a property is located within the vicinity of a solar installation that was built on land that was formerly a farm or forest, and $Rural_i$ is an indicator variable equal to 1 if property i lies in a town with a population density of 850 people per square mile or fewer.

Our coefficients of interest in Equations 5 and 6 are β_3 and β_5. β_5 is interpreted as the difference in price impacts for greenfields relative to non-greenfield sites (Eq. 5) and the difference in price impacts for homes in rural areas relative to non-rural ones (Eq. 6). In Equation 5, we expect β_5 to be negative. We hypothesize that developments on farm and forest lands will lead to larger negative impacts on housing prices due to the more dramatic change in landscape compared to a commercial site or landfill and the loss of open space amenities. We also expect a negative sign on β_5 in Equation 6, reflecting a loss in the rural character of a town due to the construction of solar installations.

Intuition would suggest a positive correlation between $Greenfield$ and $Rural$, which indeed plays out in the data. To try to separate the effects and test for multiplicative effects, we estimate a quadruple difference model that includes both $Greenfield$ and $Rural$ fully interacted with $Treated$ and $Post$.

4.1 Summary statistics and assumptions

Having defined treatment and control, we now evaluate the comparability of those groups. The summary statistics for key variables are given in Table 1. The first column represents the mean values of our full sample. The mean sales price is $338,320. The average property in our data has a lot size of half an acre, has living area of just under 3000 square feet, approximately 3 bedrooms, and is about 49 years old. About 21% of the properties are condominiums, 45% are located within 3 miles of a greenfield development, and 34% are rural.

The second and third columns in Table 1 compare pre-treatment housing attribute means between the 0 – 1 miles (treated) and 1 – 3 miles (control) observations to examine similarity between the treatment and control groups. In the last column, we report the normalized differences in means, which is the difference in means between the treatment and control groups divided by the square root of the sum of their variances. None of the covariates have a normalized difference exceeding 0.25, which is the limit beyond which the difference in means becomes substantial.

The critical assumption for the DID design to yield causal estimates is the parallel trends assumption, which requires that the treatment and control properties have the same trend in outcomes if treatment did not occur. A common way of assessing the plausibility of this assumption is to examine pre-treatment trends in sales prices for the treatment and control groups. In Figure 5 we plot pre-treatment average sales prices of treatment and control groups up to 2010, which is the year in which the first solar installations were constructed. The price trends are similar for both groups, thus boosting our confidence that the assumption holds, and the control group serves as a good counterfactual.

5 RESULTS

5.1 Main results

We present our main results in Table 2. Column 1 results are obtained from estimating Equation 2, which includes housing covariates (described in detail in the notes of the table), census block fixed effects, and month-year fixed effects. Columns 2 and 3 are results obtained from estimating repeat sales models described by Equation 3. Both columns include month-year fixed effects, and Column 3 additionally includes county-year fixed effects. The coefficient on *Treated* is insignificant in Column 1 suggesting that, controlling for housing characteristics and spatial and temporal fixed effects, treated properties are not statistically significantly different from control properties pre-construction. The DID coefficient of interest ranges between -0.016 to -0.026 and is statistically significantly different from zero across all models. Our preferred specification is Column 3 which includes property, month-year, and county-year fixed effects. This model indicates that on average, houses lying within one mile of solar installations sell for 1.7% less post construction relative to properties further away, all else equal. This finding confirms our hypothesis that nearby solar installations are a disamenity.

We convert the percentage reduction to dollars by multiplying the coefficient and the average property price for treated properties prior to construction ($327,700), which equals $5,571. Assuming capitalization can be converted to a welfare measure in this context (see Kuminoff & Pope, 2014), we can then translate this price discount into an annual willingness to pay for avoiding proximity to solar. Assuming a 5% interest rate, average annual willingness to pay is $279 per household.

There are no other property value studies of solar arrays for us to compare our estimates to. To date, Botelho et al. (2017) is the only study to examine the negative externalities from large-scale solar facilities. Using a contingent valuation framework, they find that local residents in Portugal are willing to accept $12.93 – $56.64 per month on average as compensation for being in the vicinity of solar installations. While their methods are different and vicinity is defined differently, their results are consistent with ours ($25.17/month). In addition, Botelho et al. conduct a discrete choice experiment to delve into aspects of siting that drive the disamenity and estimate that respondents are willing to pay $8.65, $7.57, and $5.15 per month to avoid negative impacts on flora and fauna, landscape, and glare effects, respectively. Second, we extend the hedonic valuation literature on renewable energy to include large-scale solar.

First, we provide the first estimates of the non-market valuation of large-scale solar installation externalities in the United States.

5.2 Robustness checks

In Table 3 we present results from a series of robustness checks to ensure that the results from our preferred model are consistent to alternative data samples. In Column 1 we drop all observations with sales prices in the top and bottom 1% of the distribution (as opposed to 5% in the main sample) to assess whether the results are robust to including more high and low value properties. In Column 2 we restrict the sample to include only properties with a lot size of 5 acres or lesser, decreasing the maximum from 10 acres in our main sample. While it is unlikely that a solar array would be sited on a parcel of 5 – 10 acres, it is possible and so these properties may appreciate based on expectations of possible lease payments. Column 3 excludes all condominiums from the sample. Column 4 includes all 284 solar installations from our full sample, which means properties could be exposed to multiple treatments. Columns 5 and 6 explore different amounts of land required per MW of installed capacity, 4 acres in Column 5, and 6 acres in Column 6. By contracting and expanding the assumed size of installations, the set of properties that are designated as treatment control is altered. Across all columns, our coefficient of interest is statistically significant and the magnitude ranges between -0.014 to -0.017. In sum, we find that our results are robust across all specifications.

5.3 Heterogeneity in treatment effect

In Table 4, we examine the heterogeneity in treatment effect by three characteristics: proximity to solar installations, prior land use, and rural character of towns. Each panel represents a different regression and all panels include property fixed effects, month-year fixed effects, and county-year fixed effects.

In Panel A, we estimate the model described by Equation 4 that allows for heterogeneity in the impact on prices based on distance. The coefficient on the 1 – 2 miles band is statistically insignificant, which is congruent with our assumption that treatment effects do not persist beyond 1 mile. The coefficients on the 0.1 – 0.5 miles and 0.5 – 1 mile bands are significant and similar magnitude to the main results. The coefficient on the 0 – 0.1 mile band is -0.070, which is 4 times larger in magnitude than the 0.1 – 0.5 miles and 0.5 – 1 mile bands, though only significant at the 10% level. This suggests that property prices for homes lying within 0.1 mile from a solar installation fall by 7.0% ($23,682) post-construction, compared to houses further away. These results suggest extremely large disamenities for properties in very close proximity.

In Panel B, we provide estimates from the model described by Equation 5 where we explore heterogeneity by prior land use. The triple-interaction coefficient of interest is negative as expected, and implies that farm and forest lands that are developed into solar arrays decrease property values 0.8% more than brownfields and industrial areas. However, this coefficient is statistically insignificant, meaning the differential impact is imprecise and could even be zero.

In Panel C, we examine heterogeneity by rural character of towns and report the coefficients from the specification defined in Equation 6. The coefficient on $Treated \times Post$ is larger in magnitude (-0.024) than the main results. The coefficient on $Treated \times Post \times Rural$ is essentially the same magnitude as the coefficient on $Treated \times Post$, but the opposite sign. Taken together, these results suggest that the treatment effect in rural areas is effectively zero (a statistically insignificant 0.1%), and that the negative externalities of solar arrays are only occurring in non-rural areas. These findings go against our intuition. One possibility is that land is abundant in rural areas, so the development of some land into solar does little to impact scarcity, whereas in non-rural areas it makes a noticeable impact. A second possibility is that there are unobserved visibility differences across sites. If visibility is a key driver of negative impacts and installations in rural locations are less visible on average (due to land abundance for vegetative buffers), then this could produce the results observed.

In Panel D we further explore heterogeneity by land use and rural character. This is done by estimating a quadruple difference model that interacts the treatment effect term in Equation 2 with both the $Greenfield$ and $Rural$ indicator variables.[7] The coefficient on $Treated \times Post$, which represents the effect of non-greenfield solar arrays in non-rural areas is -0.014, which is slightly smaller than the overall average effect observed in Table 2, but is also imprecisely estimated. The coefficient on $Treated \times Post \times Greenfield$, which applies to greenfield sites in non-rural areas, is -0.036 and is statistically significant. This suggests a large additional effect of greenfield sites in non-rural areas relative to non-greenfield sites, and a total effect of -5.0%.

[7] Tables A2-A4 in the online appendix examine the robustness of the results presented in Table 4, including different regression specifications and different population density cutoff values that define $Rural$. The results are broadly consistent with the findings presented.

The coefficient on $Treated \times Post \times Rural$, which applies to non-greenfield sites in rural areas, is 0.002 and is statistically insignificant. This suggests no statistical difference between the property value effect of non-greenfield sites in rural versus non-rural areas. Lastly, the coefficient on $Treated \times Post \times Greenfield \times Rural$, which applies to greenfield sites in rural areas, is 0.056 and is statistically significant. This indicates a counter-effect to the negatives seen for $Treated \times Post$ and $Treated \times Post \times Greenfield$, and the total effect for greenfield sites in rural areas is a positive 0.008. The total effect is statistically indistinguishable from zero. Taken together, the results of Panel D suggest that the overall negative effects of solar arrays on nearby property values are driven by greenfield sites in non-rural areas. Similar developments on farm and forest lands in rural areas have no impact on nearby properties. These findings are consistent with the ideas that greenfield developments cause greater externalities, given the dual loss of open space amenities and gain of industrial disamenities, but that effect hinges on the scarcity of open space.

In the online appendix, we also present results that test for heterogeneity by size of installation and time since construction (see Tables A5 and A6). In both cases we find no evidence of differential property value impacts by size and by time.

6 Conclusion

This paper estimates the valuation of externalities associated with nearby utility-scale solar installations using revealed preferences from the property market. Using the DID empirical technique, we estimate regression models with treatment and control groups defined by distance to the nearest solar installation. We observe 71,337 housing transactions occurring within one mile (treated group), and 347,921 transactions between one to three miles (control croup) of 208 solar installations in MA and RI.

Our preferred model suggests that property values in the treatment group decline by 1.7% ($5,751) on average compared to those in the control group after the construction of a nearby solar installation, all else equal. This translates to an annual willingness to pay of $279 per household to avoid disamenities associated with proximity to the installations. However, this average effect obscures heterogeneity. We find substantially larger negative effects for properties within 0.1 miles and properties surrounding solar sites built on farm and forest lands in non-rural areas.

While a full cost-benefit analysis of solar arrays is beyond the scope of this paper, because we do not know anything about consumer and producer surplus, we can still compare the negative local externalities to the global benefits of carbon mitigation to gain a more holistic understanding of local opposition.[8] We therefore conduct the following back-of-the-envelope calculations. On the cost side, we first consider the point estimate from our preferred specification which translates to a loss of $5,751 per household for treated homes close to solar installations. Our complete sample (prior to any data cuts) consists of 289,254 unique properties located within 1 mile of all solar installations in the dataset. Put together, we estimate a net loss of $1.66 billion in aggregate housing value due to proximate solar installations in MA and RI.

To quantify the benefits from solar installations, we first calculate net generation from solar installations. Assuming a capacity factor of 16.5%, the 817 MW of installed solar capacity in MA and RI generates is 1,180,892 MWh (megawatt hours) of electricity per year.[9] Current non-renewable generation in MA and RI comes almost entirely from natural gas. According to the EIA, 0.42 mt (metric tons) of CO_2 are emitted from each MWh of electricity that is generated from natural gas, implying that a total of 495,975 mt of CO_2 are abated annually from solar energy generation. Assuming that an average solar installation lasts 30 years, we estimate 14.88 million mt of CO_2 are abated in their entire life-span. The EPA (Environmental Protection Agency) estimates a social cost of $51.80 per metric ton of CO_2, which translates to $771 million in lifetime benefits from the production of energy from solar installations (US EPA). We find that, considering only externalities, the benefit-cost ratio is 0.46, with a net loss of $893 million.

However, we caution against generalizing the benefit-cost findings to other regions in the United States for two main reasons. First, over 90% of the energy generated in MA and RI comes from natural gas, which emits only half as much CO_2 as coal. It is possible for benefits to outweigh the costs in states where coal dominates the fuel mix for electricity generation. Second, MA and RI are the 3rd and the 2nd most densely populates states in the country, respectively, which makes the siting of solar installations away from residential areas a herculean task. Careful siting of installations in states that have large tracts of open land available and around sparsely populated regions may allow for more favorable cost-benefit ratios.

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[8] To be sure, significant amounts of money are part of the market transactions. A developer quoted us that they offer landowners $15-20,000 per MW per year of installed capacity. It is unknown how much is profit and whether some portion of that could be used to compensate proximate households.

[9] $Net\ generation\ (MWh) = \%\ Capacity factor \times 365\ days \times 24\ hours \times Installed\ capacity\ (MW)$

The demographic and geographical differences across states have implications for their respective RPS goals. For densely populated New England states with ambitious RPS targets, wind energy may be the better choice. Onshore wind turbines require a fraction of the land area per MW of installed capacity compared to solar, while offshore turbines require none. Furthermore, unlike solar installations, wind turbines in the United States (both onshore and offshore), have been found to have no disamenities associated with their proximity (Carr-Harris & Lang, 2019; Hoen et al., 2011, 2015; Hoen & Atkinson-Palombo, 2016; Lang et al., 2014). Moving forward, states should customize plans to meet renewable energy targets that work best with their respective geographies.

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Figures and Tables

Figure 1: Map of solar installations across Massachusetts and Rhode Island

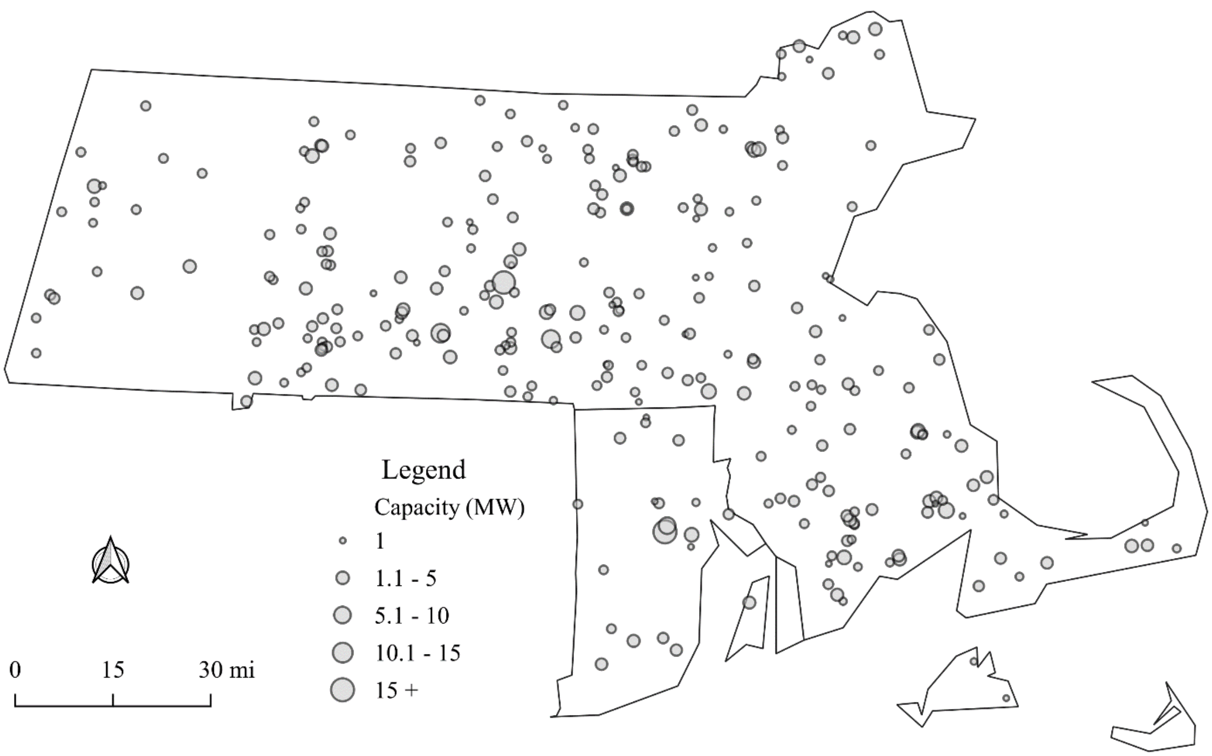


Figure 2: New and cumulative utility-scale solar capacity by year

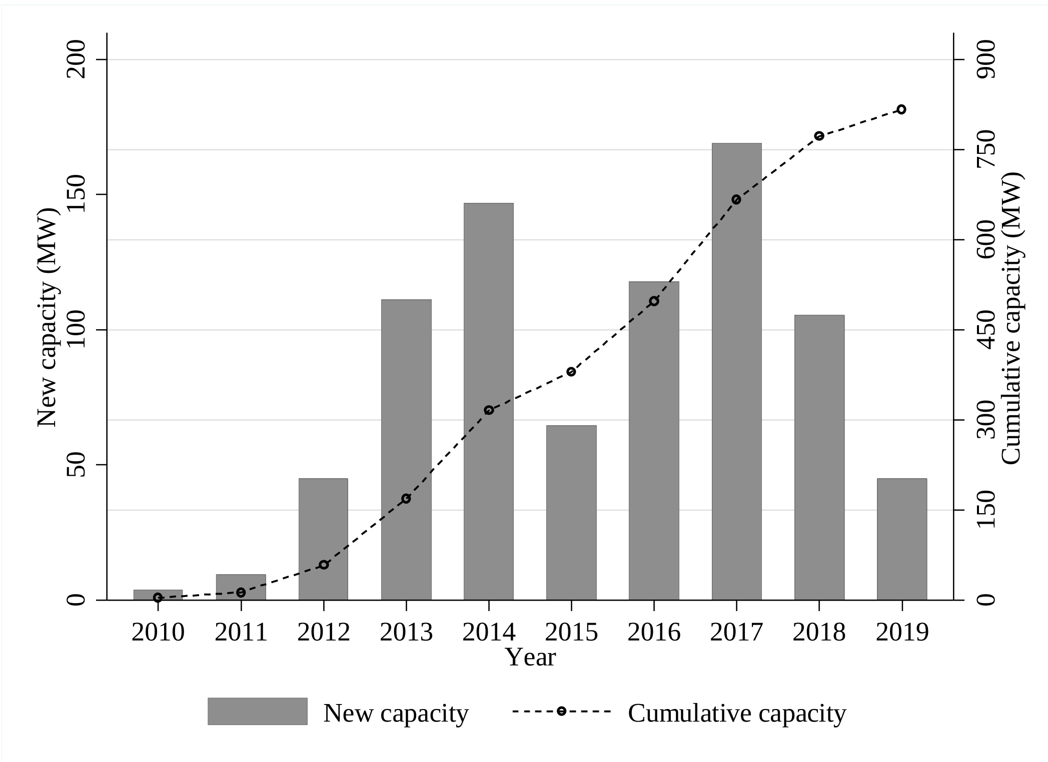
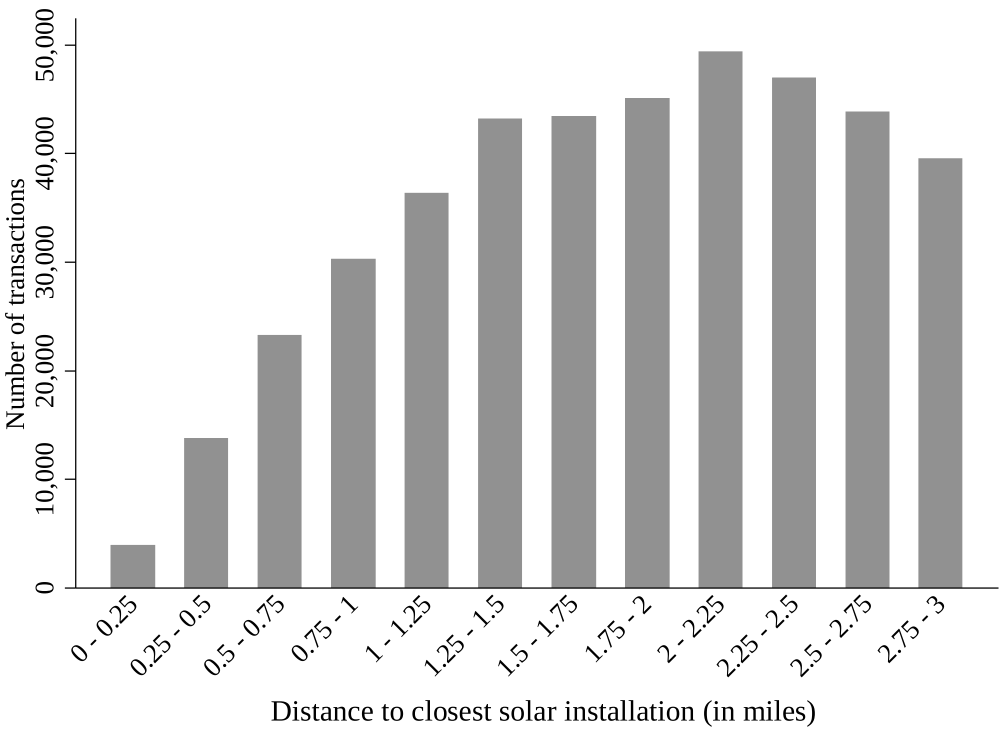
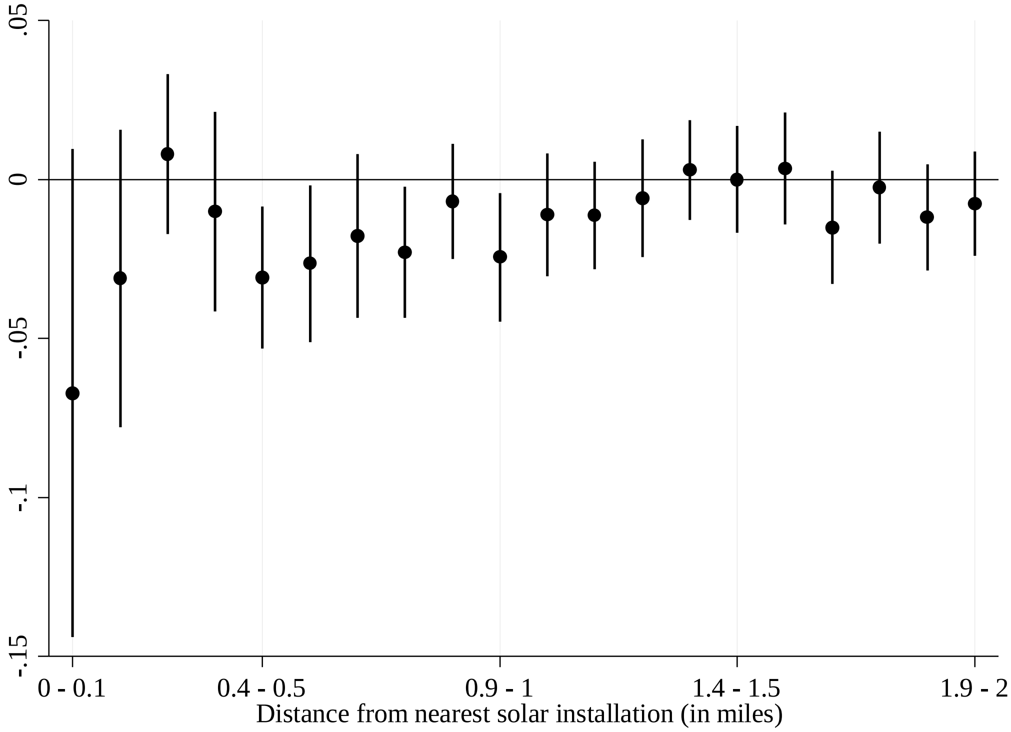


Figure 3: Number of transactions by distance to nearest solar installation



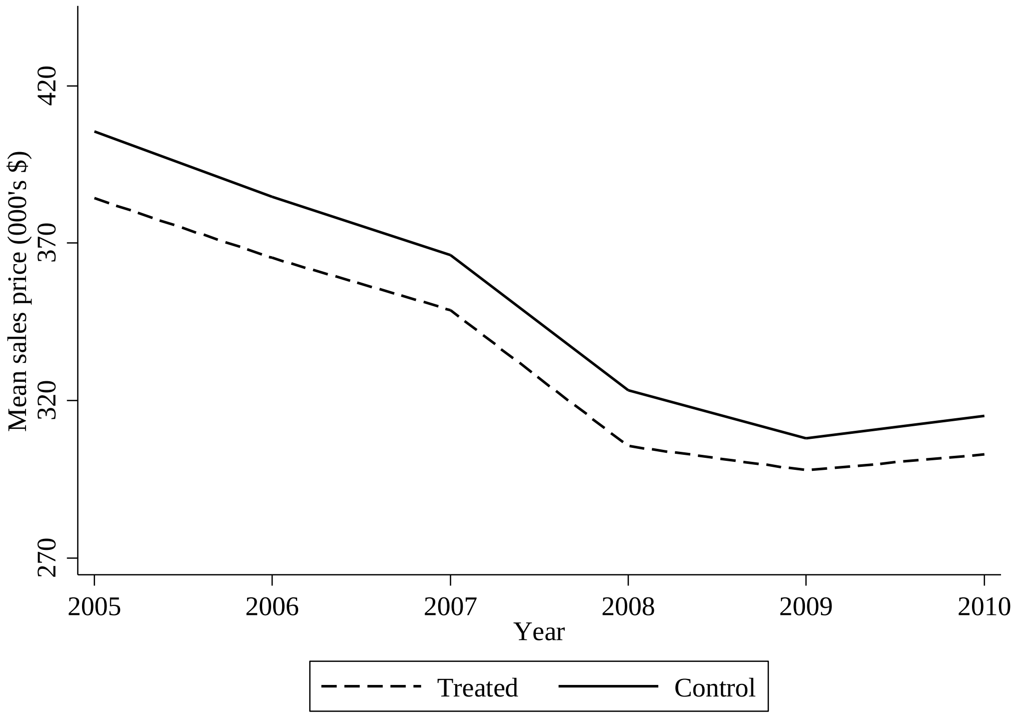
Notes: These transactions occur near eventual solar installations, since the data span across the years 2005 – 2019, and the construction of the installations is staggered throughout that time period.

Figure 4: Distance bin coefficient estimates



Notes: The treatment variable is defined as a bin variable, with treated properties lying within 1/10 mile distance bands up to 2 miles. Control properties are those lying 2 – 3 miles away from the nearest solar installation. The coefficients are obtained by estimating a series of DID models similar to Equation 2 that regresses log sales price on 1/10 mile distance bands up to 2 miles, along with month-year, county-year, and property fixed effects. Resulting coefficients and 95% confidence intervals are graphed.

Figure 5: Pre-treatment trends between treatment and control groups



Notes: The graph represents all transactions occurring pre-construction. Treated are properties within one mile of an eventual solar installation, and Control is between one and three miles. The sample size is 181,190.

Table 1: Housing attribute means by treatment status

Variables	Full sample	Pre-treatment means 0 - 1 mile	Pre-treatment means 1 - 3 miles	Normalized difference in means
Sales price (000's)	338.32	327.70	340.74	-3.11e-07
Lot size (acres)	0.49	0.50	0.48	0.017
House area (sq. feet)	2874.92	2849.70	2865.73	-5.83e-06
Bedrooms	2.91	2.88	2.91	-0.027
Full bathrooms	1.56	1.56	1.56	-0.012
Half bathrooms	0.52	0.52	0.52	-0.009
Age of home (years)	49.23	43.06	48.11	-0.003
Condo (1=yes)	0.21	0.22	0.21	0.058
Pool (1 = yes)	0.04	0.04	0.04	-0.027
Air conditioning (1 = yes)	0.43	0.47	0.43	0.121
Fireplace number	0.41	0.38	0.42	-0.076
Condition (1 = above average)	0.26	0.22	0.26	-0.150
Greenfield (1 = yes)	0.45	0.46	0.46	0.021
Rural (1 = yes)	0.34	0.40	0.34	0.199
Observations	419,258	51,471	252,773	

Notes: Sales prices are adjusted to 2019 levels using the CPI. Normalized difference in means calculated according to Imbens and Wooldridge (2009). Normalized differences exceeding 0.25 in absolute value are considered statistically different.

Table 2: Difference-in-differences estimates of the impact of solar installations on property prices

Independent variables	Dependent variable: Sale price (ln)		
	(1)	(2)	(3)
Treated	0.002		
	(0.005)		
Post	0.015***	0.011**	-0.006
	(0.004)	(0.005)	(0.004)
Treated × Post	-0.016***	-0.026***	-0.017***
	(0.005)	(0.007)	(0.006)
Fixed Effects			
Month-year	Y	Y	Y
Block	Y		
Property		Y	Y
County-year			Y
Observations	419,258	231,503	231,503
R^2	0.804	0.889	0.893

Notes: Treat = 1 if a house is within 1 mile of a solar construction and Post = 1 if a house sells post-construction. Column 1 includes the following control variables: lot size, house area, number of bedrooms, full bathrooms, half bathrooms, and fireplaces, indicator variables for condos, the condition of the house, and for the presence of a pool and air conditioning, capacity of installation (in MW) and greenfield. Standard errors are clustered at the tract level and shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table 3: Robustness checks

Independent variables	Dependent variable: Sale price (ln)					
	Price cuts at top and bottom 1%	Lot size no more than 5 acres	Drop Condos	Keep all installations	1 MW = 4 acres	1 MW = 6 acres
	(1)	(2)	(3)	(4)	(5)	(6)
Treated × Post	-0.015**	-0.016***	-0.014***	-0.017***	-0.016***	-0.017***
	(0.007)	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)
Observations	258,562	230,100	179,387	273,878	233,943	231,977
R^2	0.865	0.894	0.880	0.897	0.894	0.893

Notes: Treated = 1 if a house is within 1 mile of a solar construction, and Post = 1 if a house sells post-construction. All specifications include property, month-year, and county-year fixed effects. Standard errors are clustered at the tract level and shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table 4: Heterogeneity of treatment effects

Independent variables	Dependent variable: Sale price (ln)
Panel A: Heterogeneity by proximity	
(1 – 2 miles) × Post	-0.005
	(0.005)
(0.5 – 1 mile) × Post	-0.019***
	(0.007)
(0.1 – 0.5 miles) × Post	-0.017*
	(0.009)
(0 – 0.1 miles) × Post	-0.070*
	(0.038)
Panel B: Heterogeneity by prior land use	
Treated × Post	-0.013*
	(0.008)
Treated × Post × Greenfield	-0.008
	(0.011)
Panel C: Heterogeneity by population density	
Treated × Post	-0.024***
	(0.008)
Treated × Post × Rural	0.025**
	(0.011)
Panel D: Heterogeneity by population density and land use	
Treated × Post	-0.014
	(0.009)
Treated × Post × Greenfield	-0.036**
	(0.014)
Treated × Post × Rural	0.002
	(0.017)
Treated × Post × Greenfield × Rural	0.056**
	(0.022)
Observations	231,503

Notes: Treated = 1 if a house is within 1 mile of a solar construction and Post =1 if a house sells post-construction. In Panel A, (1 – 2 miles), (0.5 – 1 mile), (0.1 – 0.5 miles) and (0 – 0.1 mile) are dummy variables = 1 if properties lie within the respective distances from the nearest solar installation, and distance bin for 2 – 3 miles is omitted. Greenfield = 1 if the prior land use is farm or forest land, and Rural = 1 if the population density per square mile is ≤ 850. Panel B includes an interaction term Post*Greenfield and Panel C includes Post*Rural. Additional interactions included in Panel D are: Treated*Rural, Treated*Greenfield, Post*Rural, Post*Greenfield, Rural*Greenfield, Post*Greenfield*Rural, and Treated*Rural*Greenfield. All models include month-year, county-year, and property fixed effects. Standard errors are clustered at the tract level and shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

APPENDIX

This appendix provides supplemental figures and tables to our main results.

Figure A1 maps the location and capacities (in MW) of the 208 solar installations that are included in our main results.

Figure A2 depicts the increase in new and cumulative solar capacity over time by prior land use.

Figure A3 represents the number of sample post-treatment transactions by distance to nearest solar installation, in quarter mile intervals.

Figure A4 shows the distribution of solar installations by capacity.

Table A1 provides post-treatment means and the normalized differences in means between the treated and control groups for key property attributes.

Table A2 assesses robustness of results presented in Table 4 of the main text. We present two additional specifications: month-year fixed effects and block fixed effects in Column 1, and month-year and property fixed effects in Column 2. Column 3 is the same as the results presented in Table 4. In Panel A, we find that the large, negative coefficient found for $(0 - 0.1\ miles)\ x\ Post$ is only found when property fixed effects are included. In Panels B, C, and D, results are largely similar across columns.

Table A3 explores how different population density cutoff values that define the variable $Rural$ affect the results presented in Panel C of Table 4 in the main paper. 850 people/square mile is the cutoff used in the main text. The results in the first three columns (500 people/square mile, 850 people/square mile, and 1000 people/square mile) are quite consistent. The results in columns 4 and 5 (1200 people/square mile, 1500 people/square mile) are qualitatively similar to the previous results, but the coefficient on $Treated\ x\ Post\ x\ Rural$ is smaller in magnitude and not statistically significantly different from zero. In the final column (2000 people/square mile), the coefficient on $Treated\ x\ Post\ x\ Rural$ is negative and statistically insignificant, and the coefficient on $Treated\ x\ Post$ is statistically insignificant as well. The trend in results is expected as more areas are classified as rural. Given that we find that negative property value impacts of solar are strongest in non-rural (suburban) areas, as these places are increasingly classified as rural, the coefficient on $Treated\ x\ Post\ x\ Rural$ is a mixture of the zero impacts in rural areas and the negative impacts in non-rural areas.

Table A4 explores how different population density cutoff values that define the variable $Rural$ affect the results presented in Panel D of Table 4 in the main paper, similar to Table A3. We specify different cutoff values of population density per square mile and report results using our main specification. The coefficients are consistent with the results of Panel D in Table 4, for all cutoff values except the highest one (2000 people/square mile).

Table A5 explores heterogeneity in treatment effect by the size of the solar installations. We define $LargeCapacity$ as an indicator variable = 1 if the size of the installation (in MW) is greater than the median value in our sample (2 MW). We find no evidence of heterogeneity by installation size, the coefficient is small and statistically insignificant, implying no additional disamenities from solar developments larger than 2 MW. We additionally explore an alternative specification (results not provided) where capacity is treated as a linear variable and is interacted with $Treated \times Post$. These estimates yield the same conclusion to those in Table A3. This result indicates that the presence of utility-scale solar is a disamenity regardless of size. Given that the smallest installations in our analysis are still quite large at five acres in size (about 3.8 football fields), it could be that there is no additional impact of size because it is difficult or even impossible to see beyond five acres from ground level. However, one limitation of this analysis is that the range of observed sizes is narrow. Of the 208 installations in our dataset, almost 50% have a capacity of 2 MW or lesser, and only 13 (6%) are 5 MW or larger.

Table A6 examines heterogeneity in treatment effect by time elapsed. We split our $Post$ variable into two sub-categories: $Post\ (Less\ than\ 3\ years)$ and $Post\ (3\ or\ more\ years)$, where $Post\ (Less\ than\ 3\ years)$ is a dummy variable = 1 if a property transacts less than three years post-construction, and $Post\ (3\ or\ more\ years)$ is a dummy variable = 1 if a property transacts 3 or more years post-construction. We interact both variables with $Treated$, and find that both coefficients are significant and almost equal across the board, implying no change in the effect over time.

Figure A1: Map of solar installations at least 1 mile apart across Massachusetts and Rhode Island

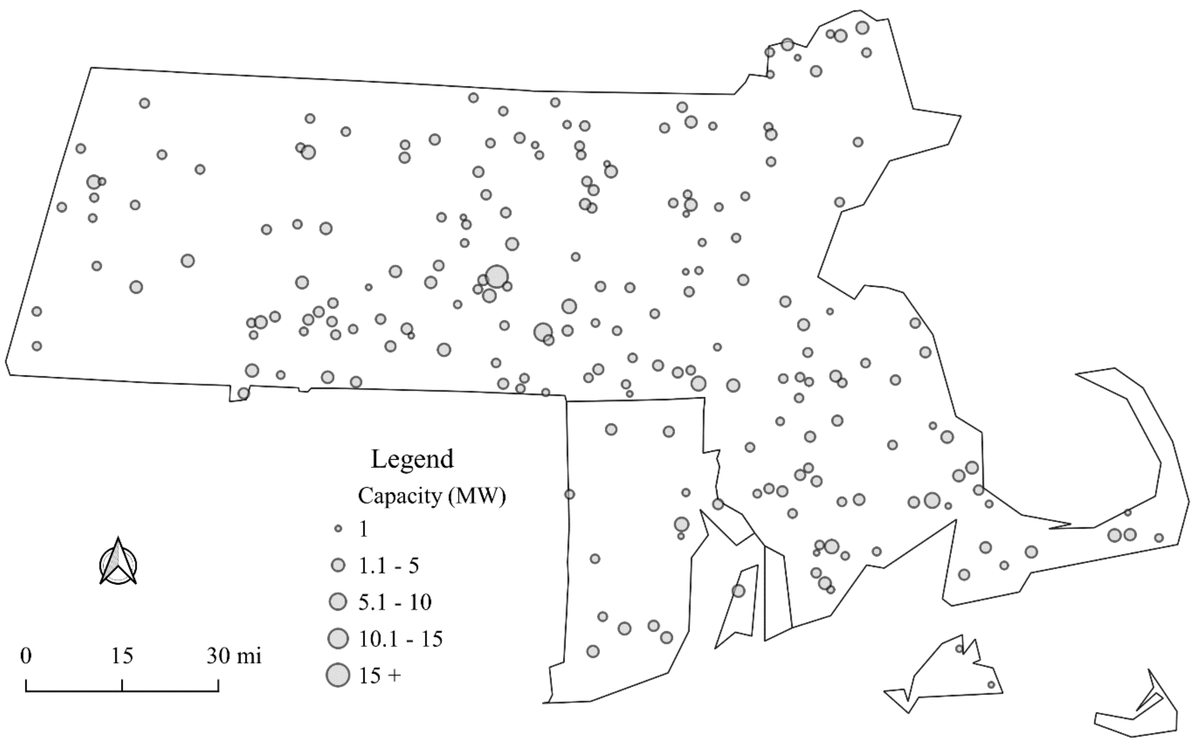


Figure A2: New and cumulative capacity by year and land use

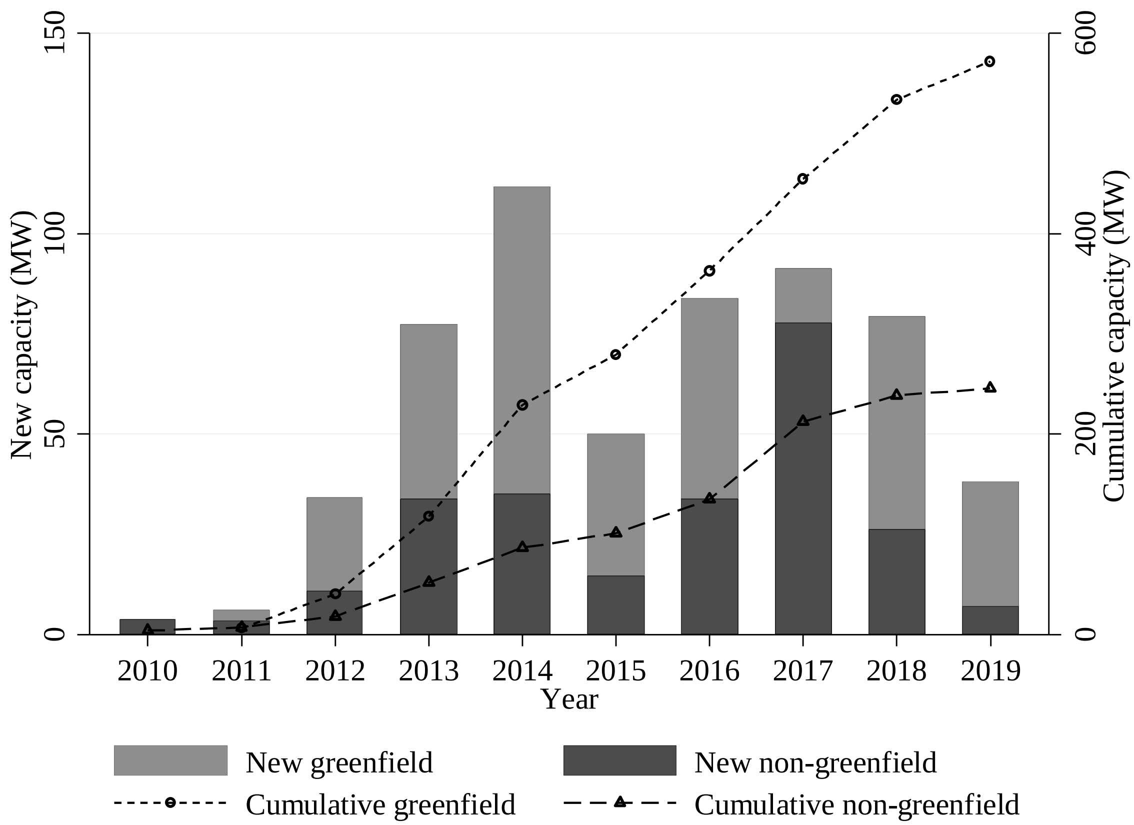
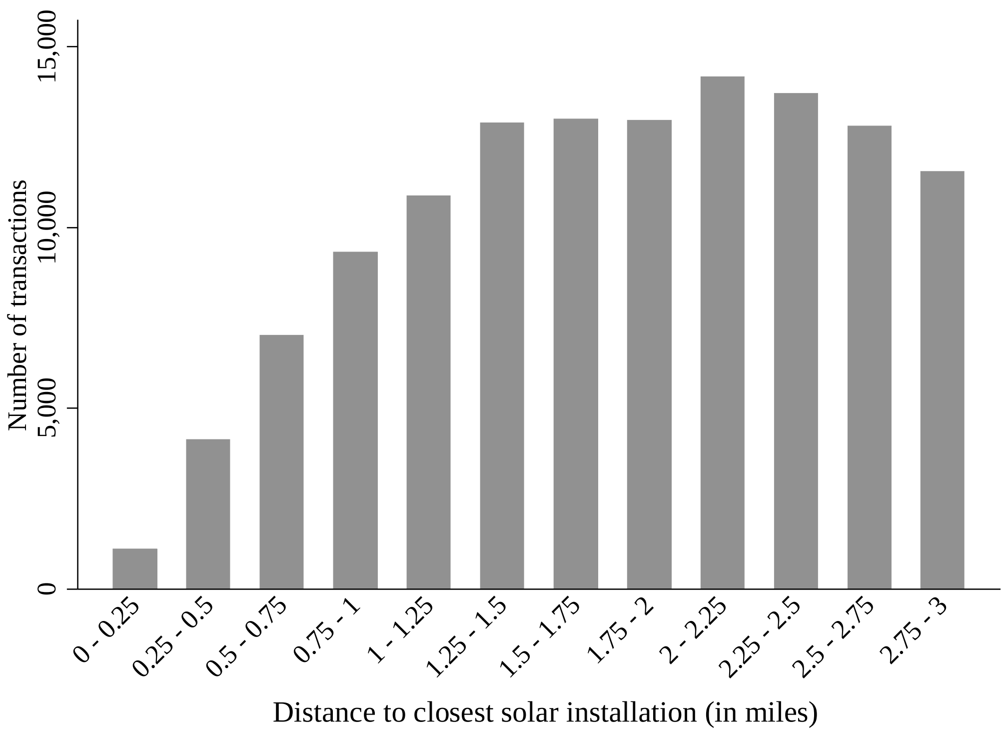


Figure A3: Number of post-construction transactions by distance to nearest solar installation



Notes: These transactions occur near eventual solar installations, since the data span across the years 2005 – 2019, and the construction of the installations is staggered throughout that time period.

Figure A4: Frequency of solar installations by capacity

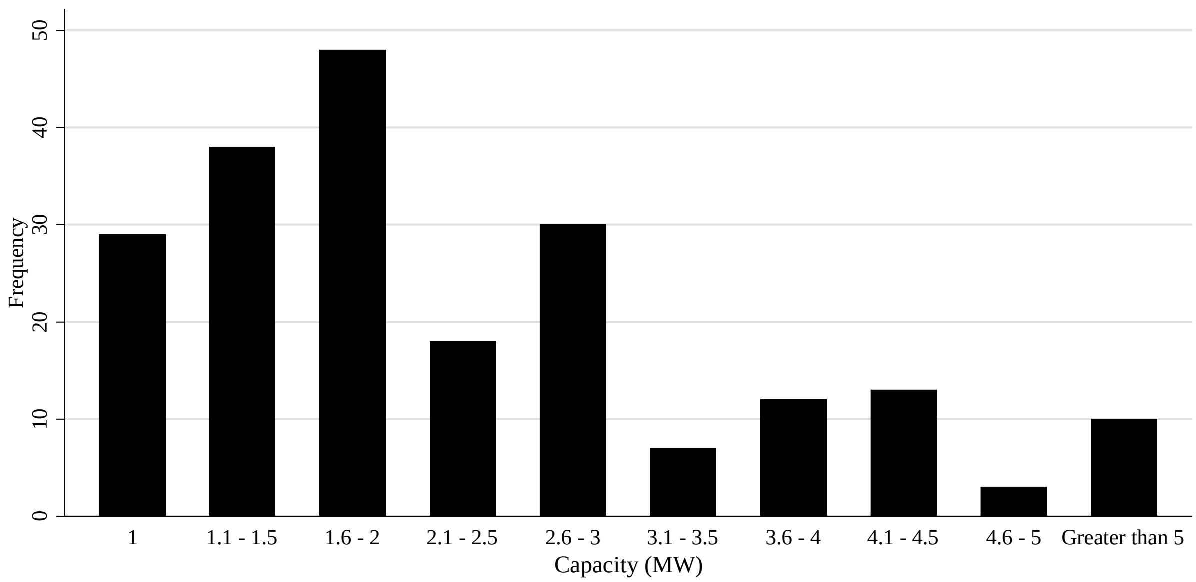


Table A1: Housing attribute means by treatment status, post construction

Variable	Post-treatment means		Normalized difference in means
	0 - 1 mile	1 - 3 miles	
Price (000's)	321.02	341.25	-4.64e-07
Lot size (acres)	0.48	0.50	-0.013
House area (sq. feet)	2872.97	2913.40	-1.47e-05
Bedrooms	2.90	2.93	-0.024
Full bathrooms	1.56	1.57	-0.020
Half bathrooms	0.53	0.53	0.001
Age of home (years)	52.17	54.95	-0.001
Condo (1=yes)	0.21	0.20	0.041
Pool (1 = yes)	0.04	0.04	-0.033
Air conditioning (1 = yes)	0.45	0.43	0.078
Fireplace number	0.35	0.40	-0.117
Condition (1 = above average)	0.25	0.28	-0.013
Greenfield (1 = yes)	0.39	0.42	-0.095
Rural (1 = yes)	0.40	0.32	0.239
Observations	19,866	95,148	

Table A2: Heterogeneity of treatment effects

Independent variables	Dependent variable: Sale price (ln)		
	(1)	(2)	(3)
Panel A: Heterogeneity by proximity			
(1 – 2 miles) × Post	-0.009*	-0.006	-0.005
	(0.005)	(0.006)	(0.005)
(0.5 – 1 mile) × Post	-0.019***	-0.027***	-0.019***
	(0.007)	(0.009)	(0.007)
(0.1 – 0.5 miles) × Post	-0.025***	-0.030***	-0.017*
	(0.008)	(0.011)	(0.009)
(0 – 0.1 miles) × Post	-0.037	-0.092**	-0.070*
	(0.028)	(0.036)	(0.038)
Panel B: Heterogeneity by prior land use			
Treated × Post	-0.013	-0.024**	-0.013*
	(0.008)	(0.010)	(0.008)
Treated × Post × Greenfield	-0.009	-0.005	-0.008
	(0.010)	(0.014)	(0.011)
Panel C: Heterogeneity by population density			
Treated × Post	-0.022***	-0.034***	-0.024***
	(0.008)	(0.010)	(0.008)
Treated × Post × Rural	0.024**	0.034**	0.025**
	(0.010)	(0.014)	(0.011)
Panel D: Heterogeneity by population density and land use			
Treated × Post	-0.013	-0.024*	-0.014
	(0.010)	(0.013)	(0.009)
Treated × Post × Greenfield	-0.029**	-0.030	-0.036**
	(0.014)	(0.019)	(0.014)
Treated × Post × Rural	0.008	0.011	0.002
	(0.014)	(0.019)	(0.017)
Treated × Post × Greenfield × Rural	0.041**	0.051**	0.056**
	(0.019)	(0.026)	(0.022)
Fixed Effects			
Month-year	Y	Y	Y
Block	Y		
Property		Y	Y
County-year			Y
Observations	419,258	231,503	231,503

Notes: Treated = 1 if a house is within 1 mile of a solar construction and Post =1 if a house sells post-construction. In Panel A, (1 – 2 miles), (0.5 – 1 mile), (0.1 – 0.5 miles) and (0 – 0.1 mile) are dummy variables = 1 if properties lie within the respective distances from the nearest solar installation, and distance bin for 2 – 3 miles is omitted. Greenfield = 1 if the prior land use is farm or forest land, and Rural = 1 if the population density per square mile is ≤ 850. Panel B includes an interaction term Post*Greenfield and Panel C includes Post*Rural. Additional interactions included in Panel D are: Treated*Rural, Treated*Greenfield, Post*Rural, Post*Greenfield, Rural*Greenfield, Post*Greenfield*Rural, and Treated*Rural*Greenfield. All models include month-year, county-year, and property fixed effects. Standard errors are clustered at the tract level and shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table A3: Heterogeneity of treatment effects by population density

Independent variables	Population density per square mile cutoff					
	500	850	1000	1200	1500	2000
Treated × Post	-0.020***	-0.024***	-0.024***	-0.023***	-0.018**	-0.006
	(0.006)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
Treated × Post × Rural	0.022*	0.025**	0.023**	0.016	0.008	-0.013
	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Observations classified as rural						
Solar installations	40%	61%	69%	76%	82%	87%
Properties	16%	32%	39%	46%	53%	62%
Observations	231,503	231,503	231,503	231,503	231,503	231,503
R^2	0.894	0.894	0.894	0.894	0.894	0.894

Notes: Dependent variable is Sale price (ln) in all specifications. Treated = 1 if a house is within 1 mile of a solar construction, Post =1 if a house sells post-construction, and Rural = 1 if the population density per square mile is ≤ column heading value. All models include month-year, county-year, and property fixed effects. Standard errors are clustered at the tract level and shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table A4: Heterogeneity of treatment effects by population density and land use

Independent variables	Population density per square mile cutoff					
	500	850	1000	1200	1500	2000
Treated × Post	-0.014*	-0.014	-0.016	-0.014	-0.006	0.005
	(0.008)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)
Treated × Post × Greenfield	-0.018	-0.036**	-0.028*	-0.031**	-0.041***	0.005
	(0.012)	(0.014)	(0.015)	(0.015)	(0.016)	(0.010)
Treated × Post × Rural	0.000	0.002	0.008	0.002	-0.013	-0.055***
	(0.018)	(0.017)	(0.016)	(0.016)	(0.015)	(0.018)
Treated × Post × Greenfield × Rural	0.038*	0.056**	0.039*	0.040*	0.057***	-0.029**
	(0.023)	(0.022)	(0.021)	(0.021)	(0.021)	(0.014)
Observations classified as rural						
Solar installations	40%	61%	69%	76%	82%	87%
Properties	16%	32%	39%	46%	53%	62%
Observations	231,503	231,503	231,503	231,503	231,503	231,503
R^2	0.894	0.894	0.894	0.894	0.894	0.894

Notes: Dependent variable is Sale price (ln) in all specifications. Treated = 1 if a house is within 1 mile of a solar construction, Post =1 if a house sells post-construction, and Rural = 1 if the population density per square mile is ≤ column heading value. All models include month-year, county-year, and property fixed effects. Standard errors are clustered at the tract level and shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table A5: Heterogeneity of treatment effects by solar installation size

Independent variables	Dependent variable: Sale price (ln)		
	(1)	(2)	(3)
Treated × Post	-0.012*	-0.024***	-0.019***
	(0.007)	(0.009)	(0.007)
Treated × Post × LargeCapacity	-0.011	-0.005	0.004
	(0.011)	(0.015)	(0.012)
Fixed Effects			
Month-year	Y	Y	Y
Block	Y		
Property		Y	Y
County-year			Y
Observations	419,258	231,503	231,503
R^2	0.801	0.889	0.893

Notes: Treated = 1 if a house is within 1 mile of a solar construction and Post =1 if a house sells post-construction and LargeCapacity = 1 if the capacity of the installation is greater than 2 MW. Column 1 includes the following housing controls: lot size, house area, number of bedrooms, full bathrooms, half bathrooms, and fireplaces, a set of dummy variables for the age of the house at purchase, indicator variables for condos, the condition of the house, and for the presence of a pool and air conditioning. Standard errors are clustered at the tract level and shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table A6: Heterogeneity of treatment effects by years since construction of installation

Independent variables	Dependent variable: Sale price (ln)		
	(1)	(2)	(3)
Treated × Post (Less than 3 years)	-0.016**	-0.026***	-0.016**
	(0.006)	(0.009)	(0.007)
Treated × Post (3 or more years)	-0.016**	-0.024***	-0.016**
	(0.006)	(0.008)	(0.007)
Fixed Effects			
Month-year	Y	Y	Y
Block	Y		
Property		Y	Y
County-year			Y
Observations	419,258	419,258	231,503
R^2	0.491	0.801	0.889

Notes: Post (Less than 3 years) = 1 if a house sells within 3 years post-construction, and Post (3 or more years) = 1 if a house sells 3 or more years post-construction. Columns 1 includes the following controls: lot size, house area, number of bedrooms, full bathrooms, half bathrooms, and fireplaces, a set of dummy variables for the age of the house at purchase, indicator variables for condos, the condition of the house, and for the presence of a pool and air conditioning, capacity of installation (in MW) and greenfield. Standard errors, clustered at the tract level, are in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.