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2022/04 February 2022
ISSN(ONLINE) 2284-0400

A regional Input-Output model of the Covid-19 crisis in Italy: decomposing demand and supply factors*

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Abstract

We extend the regional input-output model for the economic impact assessment of Covid-19 lockdowns in Italy proposed in Reissl et al. (2021) by incorporating the effects of changes in mobility on the level and composition of consumption demand. We estimate the model on sectoral data for 2020 and perform an out-of-sample validation exercise for the first half of 2021, finding that the model performs well. We then evaluate the relative importance of demand- and supply-side factors in determining our simulation results. During the national lockdown of spring 2020 the impacts of supply-side (labor) shocks can account for the vast majority of output losses. In the following stages of the epidemic income and mobility-related effects on final demand play pivotal roles at the aggregate and regional levels, as well as for most sectors. While policies supporting demand may hence be appropriate, their effectiveness may be hampered when demand is chiefly restrained by the mobility-related effect, and not by income.

Keywords: Input-output, Covid-19, Lockdown, Italy, Demand and Supply Shocks.

JEL Codes: C63, C67, D57, E17, I18, R15

*F. Lamperti acknowledges support from the H2020 project "Growth Welfare Innovation Productivity" (GROWINPRO), grant agreement No. 822781. The majority of the work on this paper was undertaken while S. Reissl was affiliated to IUSS Pavia.

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1 Introduction

In Italy, as in other European countries, the economic impact of the Covid-19 crisis and of the policies implemented to combat the virus was strongly heterogeneous both across regions and sectors. During spring 2020, Italy implemented a national lockdown, involving stay-at-home orders as well as wide-ranging closures in those manufacturing and service sectors which were deemed inessential. The national lockdown was then progressively lifted during summer and, during the second wave in fall, replaced by a system imposing different degrees of restrictions at the regional level, depending on local epidemiological dynamics. The need to respond promptly to the fast-evolving situation had to contend with the general unavailability of data and quantitative tools to inform such policies, mainly due to the unprecedented nature of the crisis and the usual delays in the publication of economic data.

In Reissl et al. (2021) we developed a computational regional input-output model using tables provided by the Istituto Regionale per la Programmazione Economica della Toscana (IRPET) to deliver a tentative quantitative assessment of the impact of lockdown measures implemented in Italy, at both the regional and sectoral level. Besides its regional dimension, which is a unique feature of our model, a key advantage of our approach lies in the simplicity of its assumptions and the small amount of data required for its estimation. Taking into account its simplicity, the model displayed a remarkable performance in reproducing both in-sample and out-of-sample dynamics at both sectoral and aggregate level, thereby representing a promising tool for a preliminary assessment of the effects of closures. The model thus aimed at serving as a laboratory to compare the direct and indirect economic costs associated with available policy options and to identify the most strongly impacted sectors and regions in advance. This in turn may help to improve the targeting of financial support policies.

Despite its advantages, the model also had some shortcomings. Above all, while it featured both demand and supply-side dynamics, the epidemic shock itself was modelled as a pure supply-side phenomenon, in the form of a constraint on sectoral labor availability as a consequence of mandated closures, limiting the productive capacity of sectors.

Other supply-side effects, in particular shortages of intermediate inputs could arise as an endogenous consequence of the labor shocks and in addition, final demand varied due to modelled effects of changes in aggregate output on consumption and investment demand. Although these factors are doubtlessly important in explaining the economic dynamics induced by the pandemic, they leave aside a potentially important demand-side effect: even independently of income effects, the implemented social distancing measures, as well as consumers' autonomous responses to the state of the epidemic, by impacting consumption habits, have likely affected *both the level and composition* of final consumption demand (Andersen et al., 2020; Baker et al., 2020; Coibion et al., 2020). For example, a shift in the spending of Italian families towards Food, Beverages and Tobacco is a likely explanation of the fact that, in terms of industrial production, this sector as a whole has been left almost unaffected by the Covid-19 crisis, despite the negative macroeconomic outlook and the lower demand coming from downstream sectors affected by closures. Conversely, accommodation services such as hotels were never mandated to close, but nonetheless experienced a dramatic decline in activity levels during the peaks of the epidemic when consumers' mobility plummeted, at first because of the national lockdown and subsequently as an autonomous precautionary response (Alexander and Karger, 2021).

Limitations in the design of the original model prevented the depiction of this type of demand-side shock. The present paper aims to fill this gap by proposing an extension of the original framework to capture the relationship between changes in mobility and households' consumption habits. This extension makes use of the 12 ISTAT expenditure functions, which have been integrated into the IRPET inter-regional IO tables. Similarly to Ferraresi et al. (2021), we group the 12 expenditure functions into 3 broad categories according to whether they refer to *essential*, *intermediate* or *inessential* needs. This grouping allows for consumption expenditures belonging to different classes to be influenced in different, possibly opposite ways by changes in mobility, and at the same time preserves the parsimony of the original framework, adding only 3 parameters to the model. These are estimated jointly with the 8 parameters already present in the original model following an estimation procedure already employed in Reissl et al. (2021). The estimated parameter values suggest that, when average personal mobility goes down, households' expenditure on essentials tends to rise slightly, whereas it slightly decreases for intermediates, and drops sharply for inessentials.

The dynamics of the model thus emerge from a complex interaction of exogenous and endogenous overlapping demand and supply-side effects, which at the sectoral and regional levels might offset or reinforce each other. For example, the closure of specific sectors may impact the supply of inputs to downstream sectors, affecting their productive capacity and possibly generating further bottlenecks in production networks. At the same time, closures also imply a reduction in the demand for intermediate inputs, thereby affecting the demand experienced by upstream sectors. A lower level of aggregate output also translates into a reduction of final demand which can cause a sharper decline in output and a slower recovery. The same happens when demand for certain categories of goods and services drops in response to the state of the pandemic but at the same time, the demand for other goods and services may rise due to the same effect. This may then give rise to shortages in supply even in sectors not directly affected by closures, thereby exacerbating the supply-side effects of the lockdown.

Quantifying the contribution of these demand and supply factors is key to identifying which types of policy responses are best-suited to stabilize the economy. We attempt to isolate the individual factors by running counter-factual scenarios in which different model blocks are switched off in order to identify their contribution to the overall dynamics emerging from the simulation of the complete model. We begin by examining the direct impacts on output of the labor shocks impacting sectors; then, we move to consider a basic version of the model where we account for the propagation of the shocks throughout the input-output network but we abstract from any possible feed-back on investment and household consumption. Third, we consider the model presented in Reissl et al. (2021) where reductions in output levels induced by the lockdown feed back on investment and, through an income effect, on households' final consumption demand. Finally, we inspect the dynamics under the new version of the model which also accounts for changes in households consumption patterns in response to (their perception of) the state of the epidemic, which is proxied by average personal mobility. In addition, we provide a thorough investigation of the augmented model to assess, in every period, a) whether the level of activity observed at sectoral level is determined by demand or by constraints on sectoral productive capacity and b) whether final demand, at different levels of aggregation, is driven by income or mobility effects.

Our results show that labor shocks and their propagation through input-output relationships are sufficient to explain most of the decline in aggregate output during the initial phase of national lockdown in early Spring 2020. At the apex of the lockdown, we also observe that demand exceeds output producible suggesting that output is ultimately supply-constrained. However, starting from May 2020 onwards, it is the decline in aggregate demand, partly caused by the reduction in income levels due to the closures themselves, that drives most of the loss experienced. Similarly, by looking at the regional and sectoral dimensions of the model, we observe that, over the same time span, productive capacity exceeds demand levels for all the Italian regions and for most of the productive sectors considered, suggesting that demand, and not supply, is constraining production. While this provides some support for fiscal policies designed to counteract negative demand effects by sustaining income levels, our analysis also highlights a possibly critical issue, in that demand levels appear to mainly be constrained by the presence of the mobility effect: as mobility drops in response to both mandatory restrictions imposed by the government and voluntary choices, possibly reflecting fear of contagion in a given region, consumers' habits change, shifting toward essential goods and services, and the overall level of consumption falls. During phases in which demand is chiefly driven by the mobility effect instead of income levels, the efficacy of fiscal policies to boost demand may be hampered. This highlights the urgency of studies aiming to understand the determinants and the complex reciprocal relationship between mobility and the dynamics of infections.

The article is organized as follows: section 2 briefly discuss the relevant literature for the purpose of our analysis and clarifies our contributions, section 3 provides an overview of the model, section 4 discusses the estimation and validation of the model, section 5 decompose the model dynamics so to identify the contributions of individual factors and discusses some policy implications, and, finally, section 6 concludes.

2 Input-Output models of the Covid-19 crisis and the role of demand *vs* supply factors

This paper contributes to a strand of literature aiming to analyze the economic effects of the pandemic by examining the propagation of epidemic-related shocks through production networks. The intuition underlying these contributions is that closures mandated by governments, by causing a temporary cessation of activities in entire branches of the economy, can cause a disruption of supply chains similar to those observed in the aftermath of natural disasters. Therefore, they can be analyzed using the input-output modelling techniques developed for disaster impact assessment (Galbusera and Giannopoulos, 2018). A first stream of works departs from the classical assumptions of fixed technical coefficients and zero demand price elasticities (i.e. fixed prices) at the core of the approach of Leontief (1986) and instead proceeds along lines similar to those pursued by Acemoglu et al. (2012) and Carvalho and Gabaix (2013), embedding input-output relationships into a general equilibrium framework allowing for factor substitution in response to changes in relative prices. Baqaee and Farhi (2020) and Baqaee and Farhi (2021a), for example, propose a neoclassical disaggregated general equilibrium model with input-output linkages to show how the effects of negative supply shocks associated with closures may be amplified due to complementarities in production and consumption. Baqaee and Farhi (2021b) find that, in a stylized quantitative model of the US, complementarities in production and the heterogeneous impacts on 'Keynesian' unemployment across markets strongly reduce the effectiveness of aggregate demand stimuli. Barrot et al. (2021) construct sectoral measures of the labor shocks associated with social distancing measures implemented in the US and analyze their sectoral effects through a general equilibrium production network model, finding that nonlinearities in production networks explain half of the observed decline in GDP.

While the general equilibrium approach to input-output modelling is popular, it is also subject to some critiques and limitations. Koks et al. (2019) show that the strengths and weaknesses of this approach are almost specular to those of linear input-output modelling assuming fixed technical coefficients and zero demand price elasticities. In particular, as the former assumes higher elasticities of substitution in both production and consumption, it is often regarded as an under-estimator of disaster impacts, whereas the latter, characterized by zero-elasticity of substitution, as an over-estimator. In short and medium term analysis, fixed technical coefficients may represent an acceptable approximation and standard input-output models are often preferred to general equilibrium models (Oosterhaven and Bouwmeester, 2016) which may be more suitable for the estimation of long-term impacts (Rose and Liao, 2005; Okuyama, 2007). To account properly for short-term impacts, general equilibrium models often require elasticities of substitution close to zero, which brings them close to the classical Leontief case (Rose, 2004).[1]

As already explained in Reissl et al. (2021), the specific nature of the Covid-19 crisis provides further arguments in favor of assuming very low, or even zero, elasticities of substitution. Supply chains are typically characterized by strong and long-lasting business-to-business relationships across different tiers (Hallegatte, 2008). In the aftermath of a natural disaster these ties might be severed if upstream partners' productive capacity is affected by the destruction of their physical assets, which require time and effort to restore. However, this appears far more unlikely in the context of mandated closures which leave the productive facilities of affected units intact, thereby exerting only a temporary effect on their productive capacity. In addition, the pervasiveness of the closures across sectors and regions, in particular during the first wave of the epidemic in western countries, considerably reduces the possibility of quickly finding suitable and readily available replacements for current factors of production. On a methodological level, the substitution mechanism of general equilibrium models, typically relying on the standard assumption of rational and optimizing behavior, may be questioned in the context of the

[1] A relevant example, since it provides the calibration for Barrot et al. (2021), is Barrot and Sauvagnat (2016) where empirical estimates of downstream and horizontal pass-throughs are best matched when the elasticity of substitution between intermediate inputs is almost zero.

uncertainty implied by the Covid-19 crisis, as already pointed out by Okuyama (2007) in relation to natural disaster situations. Finally, since the estimation and calibration of general equilibrium models is very demanding (Okuyama, 2007; Albala-Bertrand, 2013; Oosterhaven and Bouwmeester, 2016), policy makers who are asked to act promptly during a pandemic may benefit more from the insights of a 'quick and dirty' input-output model (Mantell, 2005, p.635).

Classical input-output modelling techniques are however also subject to limitations. For instance, combining demand and supply shocks in the same framework is not trivial. Traditional Leontief (1986) models, in which output reacts to shocks to final demand, are unable to depict supply bottlenecks. Conversely, the supply-driven Ghosh (1958) model which assumes fixed output (i.e. allocation) coefficients instead of fixed input (i.e. technical) coefficients is unable to depict demand shocks. Most works in the tradition of Leontief (1986) have opted for a hybrid method to analyze the impact of Covid-19, amending the traditional input output approach to include supply-driven effects: the *hypothetical extraction* method aims to quantify the induced reduction in total output when a specific sector is removed from the input-output table and interprets the difference between the output of the complete system and the output of the restricted one as a measure of the loss induced by the sector's (temporary) unavailability. Several extensions and refinements of the method are now widely employed in the literature: for example, Dietzenbacher et al. (1993) focuses on the extraction of regions instead of sectors to quantify inter-regional linkages on the basis of a multiregional input-output table whereas Dietzenbacher et al. (2019) proposes an adaptation of the method to deal with the geographical specification of imports of inputs in the context of global multiregional input-output tables; finally, Dietzenbacher and Lahr (2013) proposes a refinement of the framework where a subset of sectors feature an exogenous output specification and an endogenous final demand.

The hypothetical extraction method has been applied by Bonet-Moròn et al. (2020), Sanguinet et al. (2021) and Pedauga et al. (2021) to assess the impact of Covid-19 in Colombia, Brazil, and Spain, respectively. A refinement of the methodology, which allows for a *partial* extraction of sectors, has been employed in Haddad et al. (2021) to assess the effects of Covid-19 policies implemented in the Brazilian State of São Paulo, and in Giammetti et al. (2021) to evaluate the role of the Italian domestic value chain in transmitting the economic impact of Covid-19 lockdown measures. While the hypothetical extraction method and its refinements are hence very useful to obtain an indication of the importance of different economic sectors (or regions) to the overall system, they are not meant to convey information about the possible emergence of supply bottlenecks or the potential inter-play between supply (i.e. availability/unavailability of primary and intermediate inputs) and demand factors in determining output levels.

In the multi-regional computational input-output model first presented in Reissl et al. (2021) and extended in the present work we try to provide such an assessment by proposing a framework in which supply shocks overlap with, and possibly generate, (intermediate and final) demand effects. Therefore, the dynamics of sectoral and aggregate output unfold as the result of the complex interplay between these factors, being either demand or supply-driven depending on the conditions prevailing during a certain stage of the simulation. Our framework is close in spirit to the extension of the *Sequential Inter-Industry model* (SIM) proposed in Romanoff and Levine (1986), which introduces time into IO modeling in order to enable a depiction of adjustment processes triggered by shocks to final demand and/or productive capacity. The extended SIM model is however considerably more complicated than our framework, incorporating e.g. different modes and durations of production as well as transportation delays. Given our goal of providing a parsimonious and "handy" approach, we hence only draw inspiration from its fundamental intuitions regarding time, as well as the twofold role of intermediate inputs which may both constrain production and, in the form of inventories, provide sectors with some absorptive capacity to face possible supply shocks.

In the context of the Covid-19 pandemic, our work is also closely related to that of Pichler et al. (2020, 2021), who also provide a computational input-output framework to analyze simultaneous demand and supply shocks and model the effects of the spring 2020 lockdown in the UK. Despite having been developed independently, the two approaches have many similarities, e.g. in the way labor shocks are constructed and treated in the model, but also notable differences, for example in the type of production function adopted (Pichler et al. (2020) employ a modified Leontief production function featuring a distinction between critical and non-critical inputs) and the fact that our work depicts input-output relationships at the regional, instead of national, level. In addition, while shocks and model parameters in Pichler et al. (2020) are mostly calibrated by transposing data elaborated in del Rio-Chanona et al. (2020) for the US to the UK, we instead calibrate the shocks directly on Italian data, estimate the model parameters using sectoral Italian time-series on industrial production and service-sector turnover and, finally, we provide a tentative output validation also at the regional level, besides the aggregate and sectoral ones. Finally, while both analyses aim at accounting for the heterogeneous impact of the epidemic on sectoral final demand patterns, these are introduced as exogenous shocks in Pichler et al. (2020) whereas we employ data to classify household consumption into three classes of expenditure which we estimate as functions of average mobility.

Regarding the role of demand effects, Guerrieri et al. (2020) argue that while COVID-19 epidemic-shutdowns are generally regarded as supply shocks, they may trigger a demand shortage that leads to a contraction in output larger than that implied by the supply shock itself. The relative dimension of these supply and demand effects is likely to significantly affect the efficacy of monetary and fiscal policies. For example, the traditional transmission mechanism of the Keynesian fiscal multiplier may be muted by the closure of productive sectors. At the same time, the provision of payments to workers affected by closures may offset negative income effects suffered by households, sustaining final demand and hence preventing output from sinking even below the level implied by the closure of productive sectors. However, such a policy may be less effective if households abstain from consuming or change their consumption habits in response to the dynamics of the epidemic. To date, however, only few works have attempted to decompose the economic effects of Covid-19 into demand and supply-side contributions.

Using a Bayesian structural vector autoregression estimated on monthly statistics of hours worked and real wages for the US to measure labor demand and supply shocks around the Covid-19 outbreak, Brinca et al. (2020) find that two thirds of the drop in aggregate growth rates of hours worked was attributable to labor supply. Bekaert et al. (2020) extract aggregate demand and supply shocks for the US economy from real-time survey data on inflation and real GDP growth and conclude that two thirds of the GDP loss in the first quarter of 2020 was attributable to a negative demand shock, whereas an aggregate supply shock explained two thirds of the decline in GDP observed in the second quarter. Using a simplified input-output framework, Pichler and Farmer (2021) attempt to shed light on the additional loss induced by the network structure of production and explore the role of alternative assumptions concerning sectoral output rationing choices. This paper aims to perform a similar exercise, but we use our more richly specified computational IO model to provide a more detailed decomposition of the dynamics of output at the aggregate, sectoral, and regional levels into the specific contributions to of a) the labor shocks induced by mandated closures; b) their upstream and downstream propagation through the IO network; c) the final demand effects endogenously induced by changes in output levels; and d) the changes in household consumption demand related to changes in mobility.

3 Model Description

The model builds on Reissl et al. (2021) and is based on the inter-regional IO tables provided by the Istituto di Programmazione Economica della Regiona Toscana (IRPET). It features $n = 32$ productive sectors and all $m = 20$ Italian regions. Each period of the simulation corresponds to a week. As in standard Input-Output modelling, constant prices and fixed technical coefficients with no factor substitutability (i.e. a Leontief technology) are assumed. Instead of purely focusing on final equilibrium positions following a shock, our model is simulated sequentially with each simulation period representing a week, the goal being to also depict the adjustment process following a shock. We assume that sectors in the model produce goods and services using labor and *previously accumulated stocks* of intermediate inputs, and that they order these intermediate inputs from other sectors based on their *expectations* about future demand for their output. This implies that the system will not adjust instantaneously to a new equilibrium position following a shock, but that it will instead go through a multi-period adjustment process. In addition to experiencing shocks to final demand as in the traditional Leontief (1986) framework, sectors may also (and possibly simultaneously) be subject to shocks to their productive capacity - determined by the availability of intermediate inputs and labor - i.e. supply-side shocks.

The ability to depict the reaction to heterogeneous and possibly overlapping shocks to both final demand and productive capacity makes the model very suitable for analyzing the economic effects of the epidemic and associated lockdown measures. In Italy, lockdown decrees contained heterogeneous restrictions across sectors (and, during the second wave, also across regions) which were imposed and subsequently lifted in multiple stages. At the same time, the epidemic also gave rise to changes in both the level and composition of final demand. Both types of shocks can be depicted in our model and, through the IO network, will give rise to feedback effects on sectors both up- and downstream of the directly affected ones. The presence of accumulated stocks of intermediate inputs, whereby every sector aims to hold inputs for production over some future horizon, provides sectors with what may be termed an 'absorptive capacity', possibly enabling them to avoid becoming constrained by the unavailability of an intermediate input arising from a supply shock. This may then in turn delay, dampen or prevent the further transmission of the supply shock across the IO network.

3.1 Notation & definitions

In the following description of the model, we use italic letters to denote scalars. Bold letters are used to refer to vectors, with bold capital letters denoting matrices. We use the subscripts $_t$ and $_j$ to denote simulation periods and sectors respectively, where $j \in \mathbb{N}^+ | 1 \leq j \leq n \times m$. A bar over a variable, such as $\overline{x}$, is used to denote the exogenous value of the variable as taken from our empirical IO table. The superscripts ^{e} and ^{d} are employed to indicate expected and demanded values respectively. Expectation superscripts are further differentiated into ^{short} and ^{long} to indicate short and long-term expectations. In addition, the ^{stock} superscript is employed to denote stock values (e.g. of inputs). Finally in discussions of final demand, the superscripts ^exo and ^end distinguish between exogenous and endogenous components.

3.2 Modelling the supply-side triggers of the crisis

In Reissl et al. (2021) the trigger of the model dynamics is represented by supply shocks generated by the closures of (parts of) certain sectors. These take the form of an empirically calibrated shock to the amount of labor available to a sector, expressed as a percentage drop compared to the business-as-usual situation.[2] A decline in available labor leads to several direct and indirect consequences: first, it translates directly into a proportional reduction of the affected sectors' productive capacity. Production being based on a Leontief technology employing labor along with stocks of intermediate inputs inherited from the past, the maximum output which each sector can produce is given by:

$$\mathbf{x_t^{max}} = min\left(\mathbf{l_t} \oslash \mathbf{a^l}, colmin\left(\mathbf{Z_{t-1}^{stock}} \oslash \mathbf{A}\right)\right) \tag{1}$$

where $\oslash$ indicates element-wise division, $\underbrace{\mathbf{l_t}}_{nm\times 1}$ and $\underbrace{\mathbf{Z_{t-1}^{stock}}}_{nm\times nm}$ indicate, respectively, sectors' stocks of labor and domestic inputs available for production at time t, and $\mathbf{a^l}$ and $\mathbf{A}$ are the corresponding technical coefficients. While sectors in the model may in principle hire workers if needed to undertake desired production, we assume that sectors subject to a lockdown are *not* able to do so, meaning that a negative labor shock puts an upper limit on the amount of labor input available to those sectors.[3]

[2] More precisely, we assume that whenever the facilities of firms operating in a particular sector in some region are mandated to close, only those workers employed in tasks that can be carried out through tele-working can continue to work. The calibration of these shocks for Italy is obtained by combining three components: a) a systematic tracking of the government decrees since the beginning of the pandemic, identifying at weekly frequency the sectors which were closed in every region, at the ATECO 5 digit level of disaggregation; b) data on employees at the regional and 5 digit ATECO sectoral level to map the sectors affected by the decrees into the 32 sectors of our model, in order to derive the share of the workforce potentially affected in each model sector; c) a sectoral index of tele-workability which, following Cetrulo et al. (2020), we derive from the data on tasks and activities performed in workplaces contained in the ICP-INAPP (Indagine Campionaria delle Professioni [Sample Survey of Professions]). The detailed procedure for the derivation of the labor shocks is provided in appendix B.

[3] In the equation shown in the text we purposely abstract from the presence of imported inputs (which do exist in the model) for simplicity, as they do not play any role in driving the dynamics of the model. The reason for this is that we assume, as is often done in the literature applying IO models to disaster

Second, since fewer workers and hence lower productive capacity imply that fewer intermediate inputs can be consumed in the production process, sectors' orders of intermediate inputs for short term production needs may be revised downward in order to account for the lower scale of feasible production imposed by the closures. Sector j computes its orders of domestic inputs for short term production purposes ($\mathbf{z_{j,t}^{d,short,C}}$) by pre-multiplying the minimum between short term expected demand, $x_{j,t}^{e,short}$, and the maximum amount the sector can produce given labor, $l_{j,t}/a_j^l$, by its technical coefficients:

$$\mathbf{z_{j,t}^{d,short,C}} = \mathbf{a_j^C} min\left(x_{j,t}^{e,short}, l_{j,t}/a_j^l\right) \tag{2}$$

where $\mathbf{a_j^C}$ is the $j-th$ column of the technical coefficient matrix $\mathbf{A}$. Unless demand expectations are already low, a negative shock to $l_{j,t}$ is hence likely to lead to a decline in j's orders for domestic inputs.

These two direct impacts, in turn, give rise to indirect consequences: first, if a sector's production is constrained by available labor, it is unable to completely fulfil orders from downstream sectors, thereby affecting their stocks of intermediate inputs and possibly generating further bottlenecks in the production process.[4]

Second, a decline in input orders coming from sectors directly affected by labor shocks translates into a lower demand for the output of upstream sectors. As their sales drop, their expectations for future sales also decline and induce them to cut production. But this, in turn, reduces their demand for intermediate inputs in the next periods, thereby possibly generating higher-order effects both upstream and downstream. This expectation channel operates both on short and long run expectations. Besides placing orders of inputs to meet short term production needs, according to equation 2, sectors also aim to maintain a stock of intermediate inputs to respond to the production needs expected over a longer, sector-specific, planning horizon. This target level of inventories serves as a buffer stock to weather delays or temporary breaks in the supply of inputs supplied by upstream sectors

analysis (see, for example, Hallegatte, 2008), that all imported inputs demanded are always delivered, such that no supply constraints can arise along this dimension.

[4]When demand for sector j's output $x_{j,t}^d$ exceeds the quantity produced, $x_{j,t}$, each downstream sector is delivered a fraction $\frac{x_{j,t}}{x_{j,t}^d}$ of its original orders, implying that the supply constraint is distributed homogeneously across downstream sectors.

and is defined as the amount of intermediate inputs required for production over the next γ_j periods, conditional on an average level of weekly sales expected in the long run $x_{j,t}^{e,long}$.[5] In order to keep the model simple and parsimonious, short-term expectations $x_{j,t}^{e,short}$ are assumed to be 'naive', i.e. equal to previous-period demand[6], whereas long-term expectations $x_{j,t}^{e,long}$ are modelled as a simple average of past demand over a total of β periods, where β is uniform across sectors. A detailed description of the expectations formation processes is given in appendix C.

Triggered by the negative and positive labor shocks associated with closures and subsequent re-openings, the simple behaviors described above are the major drivers for the propagation of the direct impacts of lockdowns throughout the production network of the economy in the original model. On the demand side, the only exogenous shock featured in the original model is related to the calibration of the export component of final demand on monthly sectoral export data, variations in which are formally treated as a shock to final demand. The procedure used to transform the raw export data into the format used in the model is outlined in Reissl et al. (2021).

The modelling of final demand in the original framework also encompasses endogenous reaction mechanisms for investment and consumption demand. Investment is assumed to react linearly to deviations of total gross output $\mathbf{x_{t-1}}$ from its business as usual level $\overline{\mathbf{x}}$ (i.e. the level displayed in the IO tables).[7] Consumption is partially endogenized using a 'bridge

[5]Sector j's demand for domestic inputs required for long-term production planning is given by:

$$\mathbf{z_{j,t}^{d,long,C}} = \frac{1}{\gamma_j}\left(\gamma_j \mathbf{a_j^C} x_{j,t}^{e,long} - \mathbf{z_{j,t}^{stock,C}}\right), \tag{3}$$

meaning that sectors are assumed to converge asymptotically to their target stock of inventories. Total orders of domestic inputs are then given by:

$$\mathbf{z_{j,t}^{d,C}} = max\left(\mathbf{0}, \mathbf{z_{j,t}^{d,short,C}} + \mathbf{z_{j,t}^{d,long,C}}\right) \tag{4}$$

[6]However, by assuming public knowledge about which sectors are targeted by closures, these naive expectations are augmented to account for the reduction of orders coming from downstream firms which are mandated to close. The assumption of public knowledge, in turn, appears to be a good approximation of reality both as a consequence of the public character and prominent media coverage of the measures implemented by the government, and in light of the persistent business relationships typically shared by firms operating along a same supply chain.

[7]Formally, $\mathbf{i_t}$ being the vector of final demand for investment directed to each sector, we have:

$$\mathbf{i_t} = \bar{\mathbf{i}} + \alpha\,\frac{\bar{\mathbf{i}}}{\iota'\bar{\mathbf{i}}}\left(\iota'\mathbf{x_{t-1}} - \iota'\overline{\mathbf{x}}\right) \tag{5}$$

matrix' $\mathbf{H}$ which links the vector of gross output, $\mathbf{x}$, to the part of final consumption induced by the compensation of employees. As explained in Reissl et al. (2021), the $\mathbf{H}$ matrix is derived empirically following Miyazawa (1976) and can be multiplied by the vector $\mathbf{x}$ in order to obtain a vector representing the final demand for consumption induced by the compensation of employees which is consistent with that level of output.[8]

These two blocks, by impacting the level of final demand experienced by different sectors/regions, allows to enrich the analysis of the model by adding the typical propagation effects observed in standard IO applications examining the impacts of changes in final demand. However, they are still ultimately triggered by supply-side shocks as they are both driven by changes in the level of output which, abstracting from the exogenous shocks associated with the empirical calibration of exports, are entirely due to the labor shocks implied by lockdown measures. The present paper instead adds an important additional block to the analysis by modelling another exogenous source of variations in final demand for consumption.

3.3 Modelling the impact of Covid-19 on consumption habits

While induced effects, such as reactions of consumption to changes in output (and income) levels, are doubtlessly relevant, the epidemic also led to important *autonomous* changes in consumption expenditure, both in terms of levels and in terms of composition, i.e. distribution across sectors (Andersen et al., 2020; Baker et al., 2020; Coibion et al., 2020; Alexander and Karger, 2021). For instance, an individual may wish to make a particular consumption expenditure but be prevented from doing so by mandated restrictions to mobility. Conversely, consumers may decide to forego certain expenditures if they imply

where $\bar{\mathbf{i}}$ is the vector of investment demand taken from the IO table, α is a parameter determining the sensitivity of investment to changes in output and ι is a sum-vector with all elements equal to one. The term $\alpha\ \left(\iota'\mathbf{x_{t-1}} - \iota'\overline{\mathbf{x}}\right)$ gives the change in aggregate investment. This amount is pre-multiplied by $\frac{\bar{\mathbf{i}}}{\iota'\bar{\mathbf{i}}}$ such that sectoral shares of investment demand are kept equal to the values implied by the IO table.

[8] Formally, assuming that consumption demand induced by employee compensation depends on gross output *in the previous period*, we have an endogenous component of final consumption $\mathbf{c_t^{end}}$, which is given by:

$$\mathbf{c_t^{end}} = \mathbf{H}\ \mathbf{x_{t-1}} \tag{6}$$

having to visit a potentially crowded venue, even if the latter is open, due to fear of being infected. In both cases, consumers may redirect their consumption expenditure to alternative goods or services possibly also implying a change in the overall level of their expenditures independent of income effects. While mandated closures were likely the main driver of the economic losses experienced during the first nation-wide lock-down in Italy during spring 2020, changes in consumption patterns may have played an important role in explaining the dynamics observed during the second lockdown from fall 2020 onwards, in which outright closures of firms were much more limited, and resulting supply shocks much smaller.

In order to capture these effects we augment our model with a block in which household consumption expenditures on essential, intermediate and inessential goods and services are directly driven by changes in empirical mobility data. We obtain mobility data at the regional level for Italy from Facebook (`https://data.humdata.org/dataset/movement-range-maps`), which provides a daily composite index of mobility starting on March 1 2020, calculated relative to February 2020 as a baseline.[9] We convert the index to weekly values using simple averages. The resulting weekly indexes are plotted in appendix A.

Changes in mobility observed in these empirical data can be seen as the result of both compulsory measures, e.g. the enforcement of a stay-at-home policy, and autonomous decisions e.g. motivated by fear of contagion. Our approach thus relies on the idea that the impact of the epidemic on consumption habits will operate through or at least closely correlate with changes in average mobility, regardless of whether this is policy-induced or driven by households' perception of the severity of the epidemic.

Mobility indexes were chosen over other, epidemiological indicators such as new infections, new fatalities, and the Rt index - with all of which we also experimented - for several reasons. The Rt index is a leading indicator of the future evolution of contagion, rather than an indicator of the current (perceived) severity of the epidemic: during the late stages of the spring 2020 national lockdown in Italy, for example, a low Rt coexisted

[9]The index therefore takes a positive value if mobility on a given day exceeds the baseline and a negative value in the opposite case.

with dramatically high numbers of hospitalisations and deaths for an extended period. In addition, the Rt at times behaves somewhat erratically, particularly when infection numbers are low. The use of infection data, meanwhile, implies other problems, as records of new infections also depend on the amount of tests carried out and the efficacy of the tracing system. As such, the peak of new infections during the first wave of the epidemic in Italy was far lower than during the second wave, whereas the peaks of new fatalities instead suggest that the two waves were much more similar in terms of severity. New fatalities, finally, are limited in their ability to provide a picture of the current severity of the epidemic in that they substantially lag other indicators such as new infections or indeed the mobility index. These considerations motivate our choice of using average mobility data to model epidemic-induced changes in households' consumption patterns.

We begin from an extended IO table constructed by IRPET, which decomposes each of the 20 regional columns giving household consumption demand into 12 separate columns, corresponding to the 12 expenditure categories defined by ISTAT. These expenditure categories are then aggregated into three groups, designed to reflect different levels of 'necessity', by summing up the corresponding columns for each region, thereby obtaining three 'macro' expenditure categories:

- **Essential**: Food & Non-Alcoholic Beverages; Alcoholic Drinks & Tobacco; Accommodation, Water, Electricity, Gas & Other Combustibles; Health; Communication
- **Medium**: Clothing & Shoes; Furniture, Appliances & Maintenance; Education; Other Goods & Services
- **Inessential**: Transport; Recreation & Culture; Hotels & Restaurants

This categorization is quite similar to the one adopted in Ferraresi et al. (2021), but adopts a broader definition of essential goods & services by including housing and utilities, as well as communication services which, it may be argued, played an essential role during the pandemic.

Let $\mathbf{c^{mob}_{e,s,t}}$ denote the column vector of consumption demand from region s for essential goods & services in period t, where the superscript ^{mob} clarifies its dependence on mobility.

Using the usual notation, $\mathbf{\overline{c}_{e,s}}$ then contains the corresponding baseline values extracted from our extended IO table. $\mathbf{c^{mob}_{e,s,t}}$ hence contains the demand for consumption of essential goods & services originating in region s directed to every sector in *every region* of Italy. Equivalent vectors are defined for the intermediate (subscript m) and inessential (subscript i) consumption demands defined as above. Finally, let $\omega_{s,t}$ denote the value of the mobility index in region s in week t. The desired consumption expenditures on the three different categories of goods & services as a function of mobility are then calculated as:

$$
\begin{aligned}
\mathbf{c^{mob}_{e,s,t}} &= \mathbf{\overline{c}_{e,s}}(1 + tanh(\rho_e \omega_{s,t})) \\
\mathbf{c^{mob}_{m,s,t}} &= \mathbf{\overline{c}_{m,s}}(1 + tanh(\rho_m \omega_{s,t})) \\
\mathbf{c^{mob}_{i,s,t}} &= \mathbf{\overline{c}_{i,s}}(1 + tanh(\rho_i \omega_{s,t})),
\end{aligned}
\tag{7}
$$

where *tanh* indicates an hyperbolic tangent function, i.e. a non-linear S-shaped function bounded between -1 and $+1$, and ρ_e, ρ_m and ρ_i are parameters which determine the direction of the effect and the steepness of the function. For instance, if $\omega_{s,t} < 0$, meaning that mobility is lower than the baseline, and $\rho_i > 0$, mobility-induced consumption demand for inessential goods & services will decline relative to the baseline taken from the IO table, and vice-versa if $\rho_i < 0$. Furthermore, the greater the absolute value of ρ_i the greater the effect induced by a given change in mobility.

$\mathbf{c^{mob}_{s,t}} = \mathbf{c^{mob}_{e,s,t}} + \mathbf{c^{mob}_{m,s,t}} + \mathbf{c^{mob}_{i,s,t}}$ represents the total demand from region s taking into account only the mobility effect, i.e. leaving aside the income effect working through the matrix $\mathbf{H}$ outlined above. Note that, since the ρ parameters can take different values, the mobility effect can affect both the level and composition of consumption demand.

Besides this mobility effect, the model also features the income effect on consumption already present in Reissl et al. (2021) (see section 3.2), obtained as the product of the bridge matrix $\mathbf{H}$ and gross output in $t-1$, $\mathbf{x_{t-1}}$ (see equation (6)). This relationship can also be expressed at the regional level. For region s, we have:

$$\mathbf{c^{end}_{s,t}} = \mathbf{H_s}\ \mathbf{x_{s,t-1}} \tag{8}$$

Similarly, we can specify an exogenous and constant component of consumption for region s as the difference between total consumption from region s taken from the IO table, and the endogenous component calculated using the level of output taken from the IO table:

$$\mathbf{c^{exo}_{s}} = \mathbf{\overline{c}_s} - \mathbf{H_s}\ \mathbf{\overline{x}_s} \tag{9}$$

Total consumption demand of region s as a function of output $\mathbf{c^{out}_{s,t}}$, can then be expressed as the sum of these endogenous and exogenous components. Differently from the mobility effect, changes in output will only affect the level of consumption demand, leaving its sectoral composition unaltered.

$$\mathbf{c^{out}_{s,t}} = \mathbf{c^{exo}_{s}} + \mathbf{c^{end}_{s,t}} \tag{10}$$

$\mathbf{c^{out}_{s,t}}$ corresponds to the amount of goods and services that households from region s would consume given their income, *in the absence of the mobility effect.* Actual demand for consumption from region s is determined by a comparison between $\mathbf{c^{out}_{s,t}}$ and the amount of consumption suggested by the mobility effect, $\mathbf{c^{mob}_{s,t}}$.

In particular, if $\iota'\mathbf{c^{mob}_{s,t}} \leq \iota'\mathbf{c^{out}_{s,t}}$ (where, as above, ι is a sum-vector with all elements equal to one), consumption is completely determined by the mobility effect: even though households would be willing to consume more given their income, the decline in mobility, reflecting their perception of the severity of the epidemic and/or containment policies implemented in the region, induce them to consume less overall. At the same time, the composition of consumption will also change, reflecting the demand allocated to each category of expenditure $\mathbf{c^{mob}_{e,s,t}}, \mathbf{c^{mob}_{m,s,t}}, \mathbf{c^{mob}_{i,s,t}}$.

If, instead, $\iota'\mathbf{c^{mob}_{s,t}} > \iota'\mathbf{c^{out}_{s,t}}$ aggregate consumption will be driven by the income effect, being equal to $\iota'\mathbf{c^{out}_{s,t}}$. Its sectoral composition, however, will still be dictated by the mobility effect to reflect changes in consumption habits induced by the epidemic, in that the share of consumption expenditure going to each sector in region s will be given by $\iota'\mathbf{c^{out}_{s,t}}\frac{\mathbf{c^{mob}_{s,t}}}{\iota'\mathbf{c^{mob}_{s,t}}}$.

3.4 Sequence of events

During each period (week) in the model, a particular set of events takes place in sequence:

1. Exogenous shocks to available labor are applied. Exogenous export demand is determined.

2. Endogenous elements of final demand are determined. Investment demand is calculated as a function of previous period output. Household consumption demand is calculated based on previous period output and the value of the regional mobility indexes.

3. Short and long-term demand expectations for each sector are calculated.

4. Maximum feasible production in each sector is determined based on stocks of intermediate inputs and available labor. Sectors may hire workers unless the availability of labor is constrained by a shock (lockdown).

5. Sectors make orders of domestically produced and imported intermediate inputs based on their demand expectations.

6. Based on intermediate orders and final demand, the total demand for the output of each sector is calculated. Production takes place.

7. Produced output is delivered. Stocks of inputs are adjusted based on amounts used in production and newly delivered, determining the stocks of inputs available for production in the next period.

4 Estimation & validation

To reduce the dimensionality of the parameter space for estimation we assume, as in Reissl et al. (2021), that there are 6 distinct γ_j parameters (which affect orders of intermediate inputs for long-term inventory formation through equation (3)), corresponding to six macro-sectors - agriculture (coinciding with sector 1), mining (sector 2), manufacture (composed of sectors 3 to 16), electricity generation (sector 17), construction (sector 18) and Services (sectors 19 to 32)-, such that sectors within each macro-sector j share the same parameter value γ_j. The model also contains parameter α which governs the sensitivity of investment to changes in output according to equation 5 and parameter β which gives the length of the past time span employed in computing long-term expectations (equation (14)). Finally, the present augmented version of the model adds the three parameters ρ_e, ρ_m and ρ_i which govern the reaction of consumption demand for essential, intermediate and inessential goods & services, respectively, to changes in mobility. This brings the total number of parameters to be estimated to 11.

In order to estimate these parameters we employ a similar procedure as in Reissl et al. (2021), based on the method of simulated moments (MSM). Our objective is to find a combination of parameter values which allows the model to reproduce, as closely as possible, a set of empirical time-series characterising the economic impact of the epidemic in Italy. The empirical time-series we use are:

- Monthly indexes of industrial production for 16 of our 32 sectors (namely sectors 3-16 and 18) from January to December 2020.
- Quarterly indexes of *revenue* for 4 of our 32 sectors (namely sectors 19-22) for all four quarters of 2020.
- Quarterly indexes of real household consumption expenditures, disaggregated into the three categories used in the model, for all four quarters of 2020.

All data are taken from the Italian national statistical agency ISTAT. No or only partial/sub-sectoral data are available for the other sectors contained in our model. As extensively discussed in Reissl et al. (2021),our objective is not to mimic some general, typically cyclical, characteristics (e.g. standard deviations or autocorrelation structures) of these relatively short time-series, but instead to capture the precise dynamics they exhibited over the course of the epidemic. We hence aim to reproduce the empirical time series themselves, observation for observation, as closely as possible with the model simulation output. As the available series since the beginning of the epidemic are now longer than was the case in Reissl et al. (2021), we could simplify our approach by choosing the sums of squared errors between simulated and empirical time-series as the target statistics to minimise. As explained by Franke (2009), the ability to explicitly declare which features of the empirical data one would like the model to reproduce is a key advantage of MSM-type approaches (see also Cochrane, 2005, p.278) which also imparts them with a high degree of transparency.

Formally, our estimation procedure aims to minimise the loss function:

$$\mathcal{L}(\Theta) = \ell(\Theta)'\mathbf{W}\ell(\Theta). \tag{11}$$

ℓ is an error vector of length 23, each element of which represents the sum of squared differences between one of the 23 empirical time-series listed above (in the order given above) and its simulated equivalent for a particular parameter vector Θ. $\mathbf{W}$ is a weighting matrix. As in Reissl et al. (2021) this is given by a diagonal matrix (23 by 23 here), each diagonal entry of which gives the weight of the corresponding sector/final demand component, as taken from our IO table, in total gross output as calculated from our IO table. Thus, for instance, the first diagonal element is given by the weight of sector 3 output at the national level in total gross output and the 21^{st} diagonal element is given by the weight of final consumption demand for essential goods and services at the national level in total gross output. In this way, our weighting matrix will assign a higher weight to the minimization of errors associated with time-series representing larger shares of Italian output. The use of a pre-specified weighting matrix is a common practice employed in both GMM and MSM. As argued by (Cochrane, 2005, p.199), the use of such a pre-defined matrix allows "to emphasize economically interesting results" and obtain estimates which "may give up something in asymptotic efficiency[10], but they are still consistent, and they can be more robust to statistical and economic problems".[11]

The estimation is carried out by finding the parameter combination which minimizes the loss function out of a set of 100000 different combinations obtained using Latin Hypercube sampling. Details on the procedure and a table showing the parameter space are provided in appendix D. The parameter combination at which the loss function takes its lowest value is reported in table 1. Most of the pre-existing parameters remain fairly close to the values estimated in Reissl et al. (2021). The estimated values of the expenditure function parameters indicate that the reaction of consumption expenditures to changes in mobility during the epidemic differs by category. While a given decline in mobility leads to a strong decrease in expenditure for inessential goods and services, this decline is more moderate in the case of our intermediate category. The parameter on essential expenditure instead takes a negative value, meaning that a reduction in mobility will induce an *increase* in consumption expenditure on such goods and services. These results are in line with the available empirical evidence highlighting that during the pandemic reductions in mobility, besides being associated with a general reduction in spending Baker et al. (2020), were also associated with a significant shift of consumer habits away from 'nonessential' to 'essential' goods and services (Baker et al., 2020; Alexander and Karger, 2021; Golsbee and Syverson, 2021).

Table 1: Estimated parameter values

Symbol	**Description**	**Value**
α	Investment adjustment parameter	0.044
β	Observations used for long-term expectation	58
γ_1	Desired inventories agriculture	17
γ_2	Desired inventories mining	20
γ_3	Desired inventories manufacturing	11
γ_4	Desired inventories electricity	30
γ_5	Desired inventories construction	23
γ_6	Desired inventories services	12
ρ_e	Consumption demand essential	-0.2
ρ_m	Consumption demand intermediate	0.4
ρ_i	Consumption demand inessential	2.4

[10]Indeed, given our choice of a pre-determined weighting matrix and the brevity of the post-Covid-19 time series, we refrain from making any claim about the (asymptotic) efficiency of the obtained parameter estimates.

[11]For a further discussion of our choice for the weighting matrix, see Reissl et al. (2021).

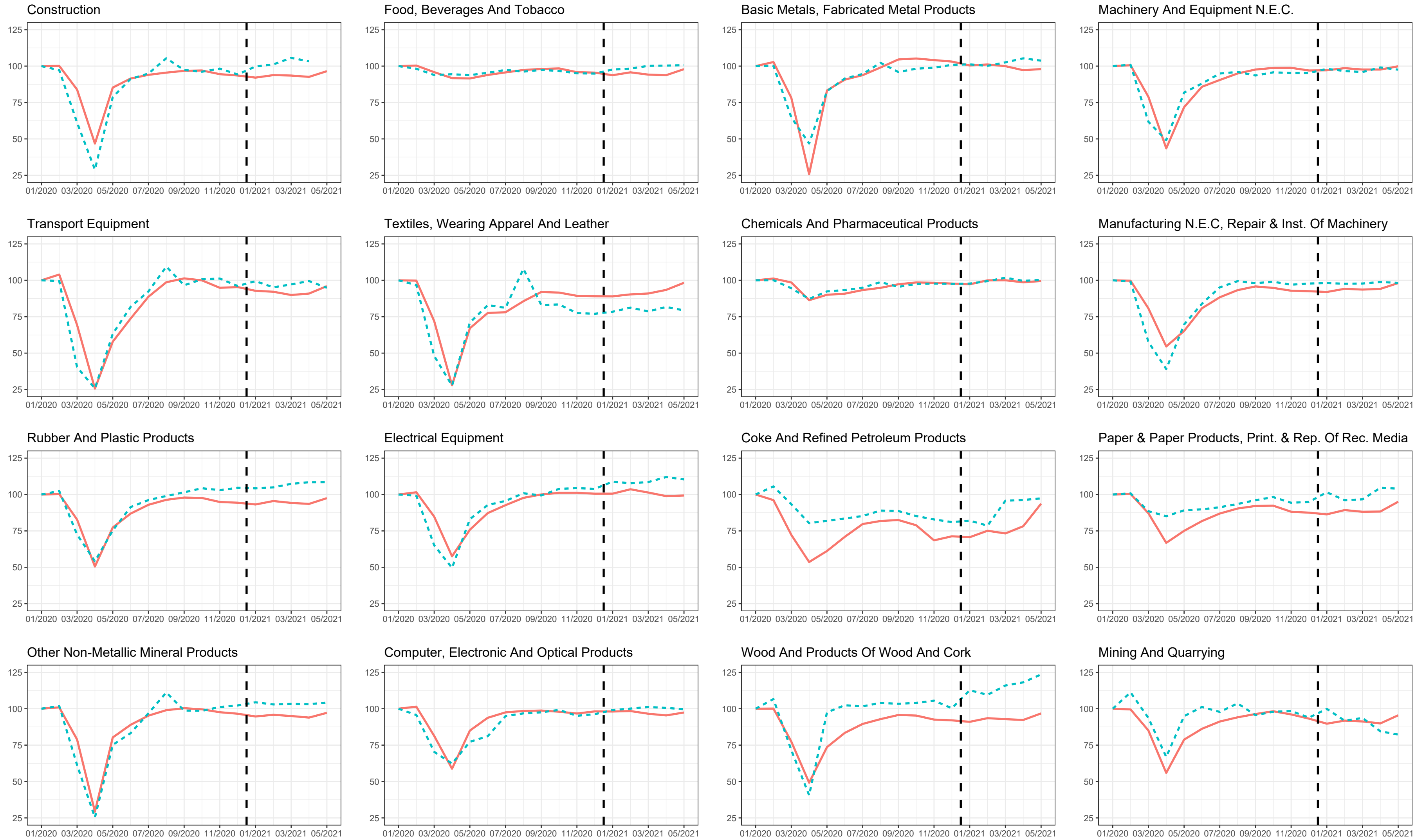

Figure 1: Empirical (dashed) and simulated (solid) monthly production

Table 2: Mean Absolute Prediction Errors (MAPE) for monthly industrial production indexes for in sample (2020) and out of sample (January-May 2021) periods

	In sample	**Out of sample**
Construction	5.58	7.56
Food, Beverages, And Tobacco	1.43	4.36
Basic Metals, Fabricated Metal Products	5.46	3.63
Machinery And Equipment N.E.C.	4.44	1.69
Transport Equipment	6.16	5.33
Textile, Wearing Apparel, And Leather	8.56	12.53
Chemicals And Pharmaceutical Products	1.66	0.91
Manufacturing N.E.C, Repair & Inst. Of Machinery	6.30	3.72
Rubber And Plastic Products	4.75	11.88
Electrical Equipment	4.91	8.73
Coke And Refined Petroleum Products	11.65	11.79
Paper & Paper Products, Print. & Rep. Of Rec. Media	6.10	11.15
Other Non-Metallic Mineral Products	4.91	8.28
Computer, Electronic And Optical Products	4.23	2.95
Wood And Products Of Wood, And Cork	10.40	22.69
Mining and Quarrying	6.89	6.24

In order to evaluate the performance of the estimated model, we graphically compare simulated and empirical time-series as is done in Reissl et al. (2021). Figure 1 plots the dynamics of the 16 industrial production indexes for which empirical monthly data are available for the period from January 2020 to May 2021, with all simulated observations beyond December 2020 representing out of sample forecasts. Plots are displayed in order of the size of the corresponding sectors, from largest to smallest. The figure shows that, despite its simplicity, the model is able to account for the significant heterogeneity in the observed sectoral dynamics, both in terms of the depth of the downturn and of the subsequent recovery profile, and, with a few exceptions (e.g. Coke and Refined Petroleum Products or Wood and Cork), it is capable of matching the dynamics of individual sectors quite closely, both in- and out-of-sample. Admittedly, sizeable errors may still arise for some sectors in absolute terms, but the explanatory power of the model should also be assessed in relation to the heterogeneity of the dynamics of the empirical series to be matched. In order to provide a more precise quantitative assessment of the fit between simulated and empirical time-series, table 2 shows the Mean Absolute Prediction Errors (MAPEs) for monthly industrial production indexes, explicitly separating in-sample (i.e. the whole of 2020) and an out-of-sample (i.e. January to May 2021) predictions.

Figure 2 plots the quarterly empirical time-series of service sector revenues for those sectors for which data are available, together with the quarterly simulated series of production for those same sectors. The plots show all quarters of 2020, as well as the first quarter of 2021 (out-of-sample). With the exception of sector 22 (Publishing, Motion Picture, Video, Sound And Broadcasting Activities), the model does a good job at reproducing the qualitative dynamics of the empirical series, though with the same caveats on sectoral absolute forecast errors already discussed for the industrial production series. For a quantitative assessment, table 3 displays Mean Absolute Errors of the predictions for services.

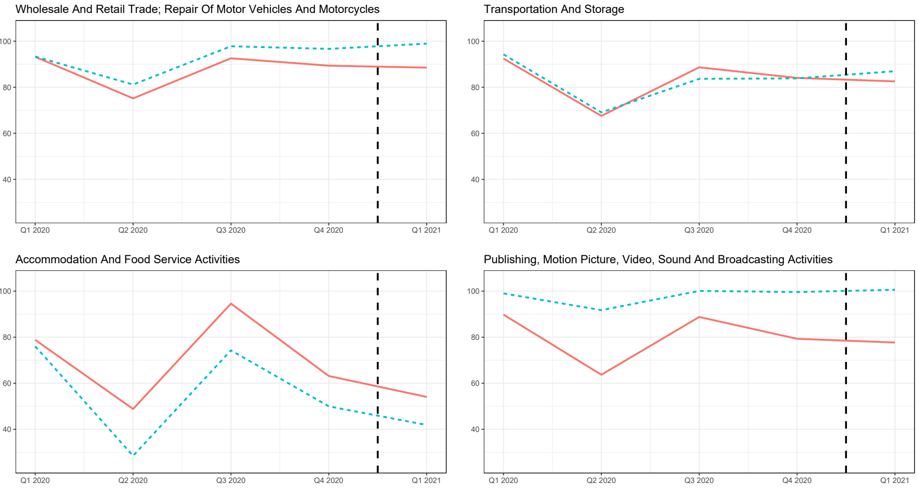

Figure 2: Empirical (dashed) and simulated (solid) quarterly service sector revenue

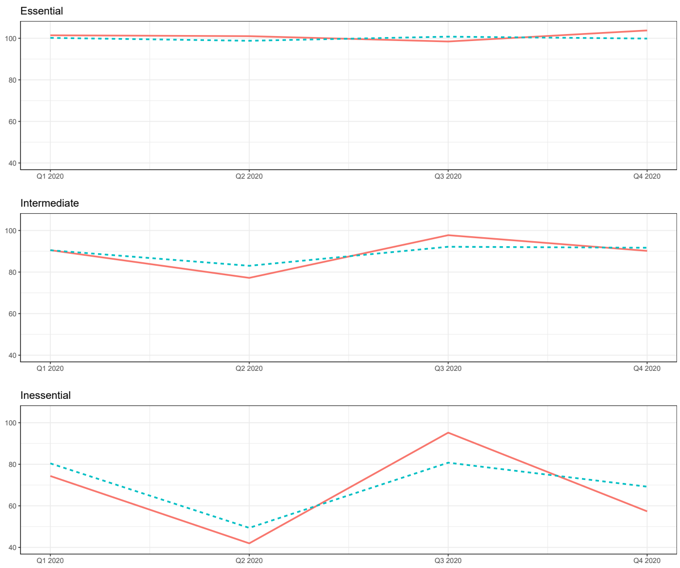

Figure 3: Empirical (dashed) and simulated (solid) quarterly consumption expenditure

Figure 3 shows that the model is also able to fairly closely reproduce the dynamics of the different categories of household consumption expenditure, though in the case of both intermediate and inessential goods & services it somewhat over-estimates both the decline during the first wave of the epidemic (Q2 2020) and the subsequent recovery during (Q3 2020). MAPEs for the expenditure time-series are also displayed in table 3.

Table 3: Mean Absolute Prediction errors for quarterly service sector revenue and consumption expenditure indices for in sample (2020) and out of sample (Q1 2021) periods

	In sample	Out of sample
Wholesale & Retail Trade; Repair of Mot. Veh. & Motorcyc.	4.66	10.42
Transportation & Storage	2.13	4.43
Accommodation And Food Service Activities	14.15	12.19
Publishing, Motion Picture, Video, Sound & Broadcast. Act.	17.22	22.92
Essential consumption	2.43	-
Intermediate consumption	3.23	-
Inessential consumption	9.96	-

The simulation output of the model can also be used to calculate a quarterly time-series of Italian GDP, which we compare to the empirical one in figure 4. Even though GDP data is not directly employed in our estimation procedure, the model is able to reproduce it relatively closely. It does tend however to slightly under-estimate GDP, in particular in Q2 2020 and from Q4 2020 to Q1 2021. The first line of table 4 compares simulated and empirical annualized declines in Italian GDP for 2020 and presents the in- and out-of-sample MAPEs calculated on the quarterly predictions displayed in figure 4.

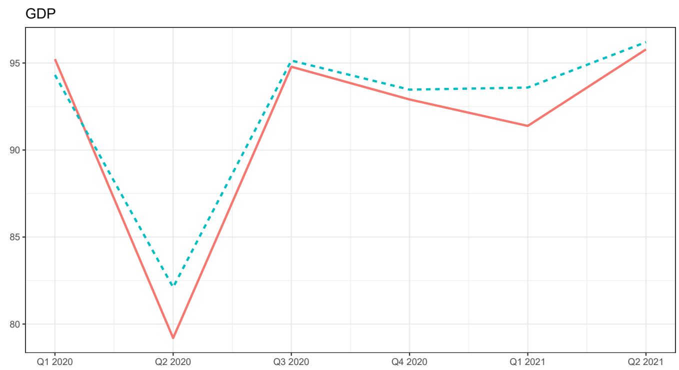

Figure 4: Empirical (dashed) and simulated (solid) quarterly GDP

One of the major advantages of the use of inter-regional input-output tables is the ability to also simulate regional GDP. Empirical GDP data for the Italian regions are available only at annual frequency, and are published with a very long delay: at the time of writing, there are no estimates yet for 2020. While in Reissl et al. (2021) we were consequently unable to provide a validation of the simulated regional time-series against empirical data, in the present paper we carry out a tentative regional validation by comparing our simulated regional GDP series to the Bank of Italy quarterly indicator of economic activity in the Italian regions (ITER) presented in Di Giacinto et al. (2019). The indicator is constructed using a series of regional data available with considerably smaller delays, such as employment, exports and bank loans. The authors demonstrate that ITER does a very good job in predicting the actual ex-post estimates of regional GDP. We make use of observations of this quarterly indicator for 2020, which have been made available to us by the Bank of Italy for five large regions (Piedmont, Lombardy, Veneto, Lazio and Campania) as well as four macro-regions (North-West, North-East, Central and Mezzogiorno, i.e. the South and the Islands).[12]

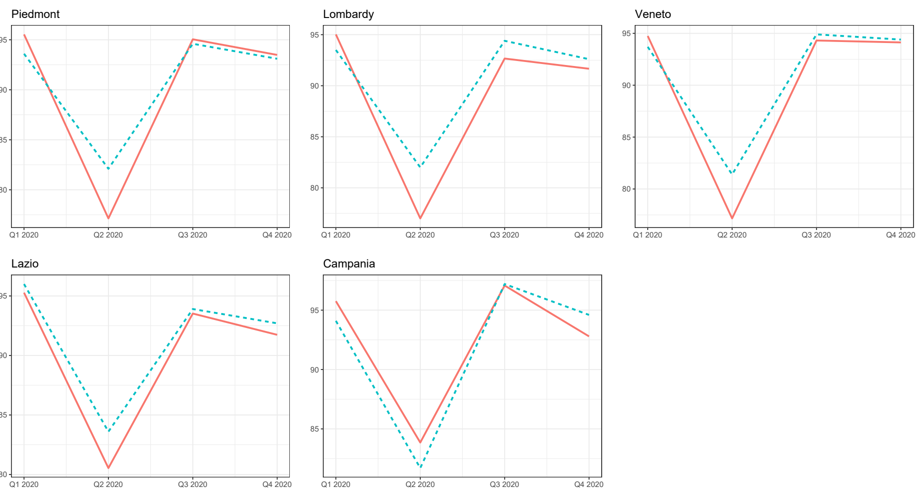

Figure 5: ITER (dashed) and model simulated (solid) quarterly prediction for five large Italian regions

In figures 5 and 6 we compare the ITER estimates provided by the Bank of Italy to simulated indexes of GDP for the regions/macro-regions from our model. The model provides estimates that are quite consistent with the ITER indicators. Table 4 gives a

[12]The composition of the macro-regions is as follows:

- North-West: Aosta Valley, Liguria, Lombardy, Piedmont
- North-East: Trentino-South Tyrol, Veneto, Friuli-Venezia Giulia, Emilia-Romagna
- Central: Tuscany, Umbria, Marche, Lazio
- Mezzogiorno: Abruzzo, Molise, Campania, Apulia, Basilicata, Calabria, Sicily, Sardinia

quantitative assessment by comparing the simulated annual losses in simulated regional GDP for 2020 to the annualized declines in the ITER indicators. In-sample MAPEs[13] calculated by comparing quarterly ITER predictions and quarterly simulated values from the model are also displayed.

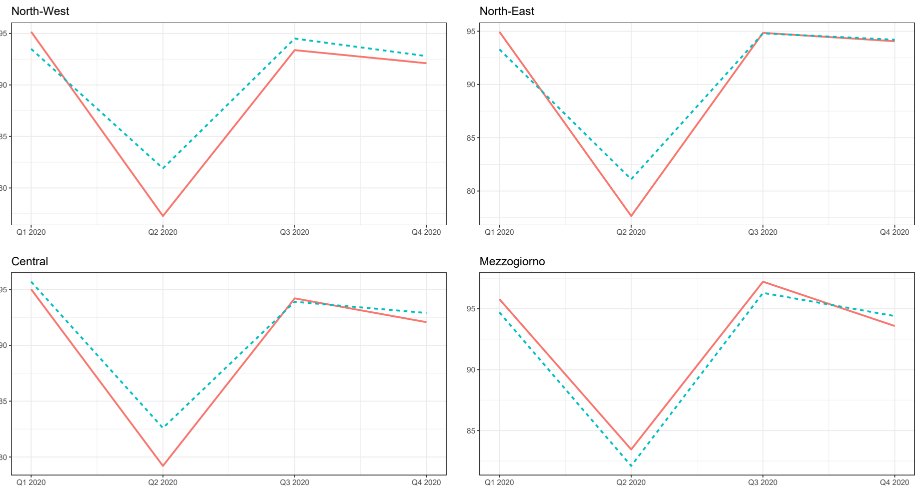

Figure 6: ITER (dashed) and model simulated (solid) quarterly predictions for the four Italian macro-regions

Table 4: Comparing empirical GDP and ITER estimates to simulated GDP (annual loss and quarterly mean absolute error for 2020)

	Annualized decline		Quarterly MAPE	
	GDP	Simulated GDP	In Sample	Out of sample
Italy	-8.74	-9.47	1.19	1.31
	ITER	Simulated GDP	In Sample	Out of sample
Piedmont	-9.20	-9.70	1.93	-
Lombardy	-9.40	-10.91	2.30	-
Veneto	-8.90	-9.91	1.54	-
Lazio	-8.40	-9.73	1.28	-
Campania	-8.10	-7.63	1.44	-
North-West	-9.10	-10.52	2.03	-
North-East	-9.10	-9.62	1.32	-
Central	-8.70	-9.87	1.30	-
Mezzogiorno	-8.20	-7.49	1.04	-

The analysis performed in this section demonstrates the model's ability to provide broadly accurate evaluations of the effects of the epidemic and the associated lockdown measures in Italy at the aggregate, *regional, and sectoral* levels. The possibility to jointly explore

[13]For the sake of precision, let us point out that while the formula remains the same, the label Mean Absolute Prediction Error is somewhat misleading in this case since, ITER itself being a prediction of regional output, differences between ITER and simulated data cannot be regarded as forecast errors. Therefore, in this case the MAPE should be interpreted as a measure of the consistency between our predictions and those implied by a well-established and reliable indicator provided by the Bank of Italy.

these two latter dimensions represents a key advantage of our approach.

5 Decomposing supply- and demand-side effects

Having performed a validation exercise on the extended model, we move on to a more detailed analysis of the simulation results. In particular, the current section aims to explore the relative importance of supply- and demand-side drivers of the simulated dynamics, as well as the relative strength of the mobility and output effects influencing final demand during different phases of the epidemic.

We begin by examining the dynamics of aggregate gross output at weekly frequency produced by four versions of the model.

- *Only labor shocks* - The first and most basic version aims to isolate the direct impacts of the labor shocks associated with lockdown measures on sectors' production. All other things being equal, a reduction in labor available to sectors translates into a proportional drop of their output level. For example, a 20% decrease in the workforce within a given sector translates, given the fixed labor coefficients, into a reduction of 20% of the output delivered. Beyond this, no other effects of the labor shocks (i.e. possible feedback effects on the production of other sectors) are activated in this model version, and final demand is kept constant.

- *Labor shocks + IO propagation* - The second scenario considers, besides the direct effects associated with the labor shocks, also the induced effects due to the propagation of the original shocks through the input-output network, for example through their impact on sectors' (short and long term) sales expectations, sectors' intermediate inputs orders, and the possible emergence of supply bottlenecks. All changes in final demand remain switched off also under this scenario, meaning that the matrix $\mathbf{H}$ is deactivated, that α is set to zero and therefore investment does not react to changes in output levels, that no mobility effect is considered (i.e. ρ_e, ρ_m, ρ_i are also set to zero), and that exports demand is kept constant rather than varying exogenously, being calibrated on actual data.[14]

- *No mobility effect* - The third scenario adds some final demand effects to the previous one, allowing final demand to change endogenously due to the effects of changes in gross output on investment (using the estimated value of α) and consumption demand (reactivating the bridge matrix $\mathbf{H}$). Exports, which were kept constant in previous scenarios, are now empirically calibrated and hence vary over time. This version is equivalent to the model presented in Reissl et al. (2021), though simulated using the parameters estimated in the present paper.

- *Full model* - The fourth and last scenario instead features the full specification of the model, including the novel mobility effect on consumption demand, activated by setting ρ_e, ρ_m, ρ_i to their estimated values.

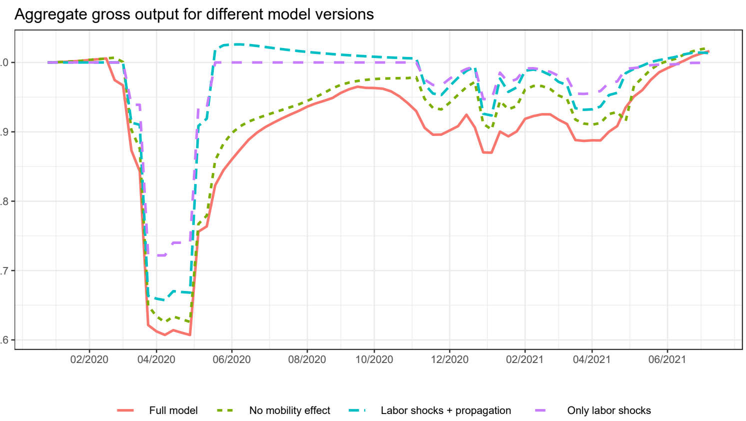

Figure 7: Simulated aggregate gross output from full model, model without mobility effects, model without final demand variations, and model with only direct effects of labor shocks

Figure 7 shows the simulated time-series for aggregate gross output from January 2020 to July 2021 for all four specifications of the model, relative to the baseline taken from the IO table. During the first lockdown (spring 2020), all model versions produce sizeable declines in output which do however differ substantially in their magnitude. In particular, the figure shows that the addition of propagation effects through the IO network strongly increases the decline in output compared to scenario where only the direct impacts of

[14] All remaining parameters are set to their estimated values provided in table 1.

the labor shocks are considered. In particular, the series showing the model featuring only labor shocks reaches a minimum of around 0.72 in April 2020, with the addition of propagation effects bringing this number to around 0.65. A further but somewhat smaller decline is induced by each of the two scenarios where final demand is allowed to vary; the version excluding the mobility effect brings the minimum to around 0.625 with the series showing the full model having a minimum value of around 0.6. A very interesting insight is highlighted by the path of the recovery following the re-openings after the first lockdown. This recovery is very prompt in the scenarios which only consider supply factors. By mid May, 2020, weekly gross output has recovered to its baseline level in the *Labor Shocks* scenario. Under the *Labor Shocks + Propagation* scenarios, in which the indirect effects of labor shocks are also considered, output even overshoots its pre-crisis level. This overreaction is a consequence of the increased orders of intermediate inputs coming from sectors attempting to restore their desired stock of input inventories which are eroded during the lockdown, when factors consumed in production could not be replenished due to the presence of bottlenecks in their supply. This indicates that while supply factors, such as sectoral supply shortages, played a major role during the first stages of the crisis, demand factors - partly induced by the very supply shocks themselves - are instead important to understand the slower and only partial recovery observed after the lockdown was lifted in late spring 2020. Indeed, in the two model specifications in which final demand is allowed to vary, the recovery is much slower and aggregate output remains considerably below its pre-crisis level, as observed in reality: including the effects of the variation of exports and of the output effect on investment and consumption already considerably weakens the recovery following the end of the national lockdown. The addition of the mobility effect adds a further slight slowdown to the shape of this recovery.

However, one should not be tempted to use this observation to draw conclusions on the relative size of the output and mobility effects since in the full model specification the two effects are not additive: as outlined previously, the value taken by aggregate final consumption at regional level is determined, in each period, by the minimum level of consumption at regional level induced by the mobility and output effect. To assess the relative importance of these two effects, figure 8 shows the ratio between total consumption demand given by the mobility effect and total consumption demand given by the output effect for the full model. Though the dynamics observed represent a nationwide aggregation of possibly highly heterogeneous regional situations, the plot suggests that the mobility effect was prevailing during the national lockdown, when infection numbers in Italy were high and mobility restrictions were very tight, but was then outweighed by the output effect during and after the re-opening, when infection numbers became low and mobility approached its pre-pandemic values.

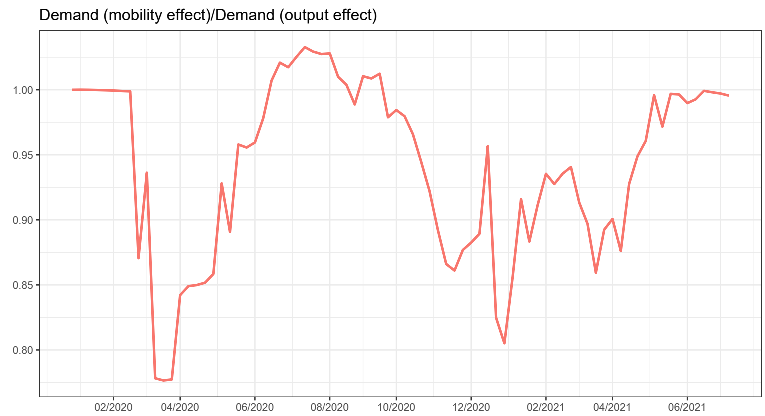

Figure 8: Ratio between total consumption demand given by the mobility effect and total consumption demand given by the output effect for the full model

The second lockdown regime in Italy was implemented at the beginning of November 2020. Under this regime, regions moved between different 'zones' (red, orange and yellow, with the much later addition of white), implying different levels of restrictions and extents of business closures depending on regional dynamics of epidemiological variables (for details see appendix B). Figure 8 shows that the mobility effect plays a very prominent role in driving consumption demand from fall 2020 until late May, 2021, when the output and mobility effects appear to roughly balance. As a consequence, between fall 2020 and late spring 2021, the mobility effect embedded in the full model specification significantly worsens the output dynamics compared to the *No Mobility effect*, *Labor Shocks + Propagation*, and *Only Labor Shocks* scenarios (see figure 7). In particular, the latter two scenarios produce effects that are fairly slight in the aggregate and mostly driven by the direct effect of the labor shocks, whereas their propagation through the IO network only adds a small additional drop to the total loss. This result can be explained as a consequence of the much more limited scope of the closures implemented under the system of regionally-specified lockdowns. While the smaller scope of closures reduced the importance of supply factors compared to the first lockdown, the decline in mobility emerging as a consequence of the second wave of contagion induced significant demand effects.

Having observed the dynamics of aggregate output in the four scenarios to assess the contribution of the different blocks of the model to the total loss experienced, we move on to investigate the related question of whether the output observed in a given simulation period is demand or supply-determined.

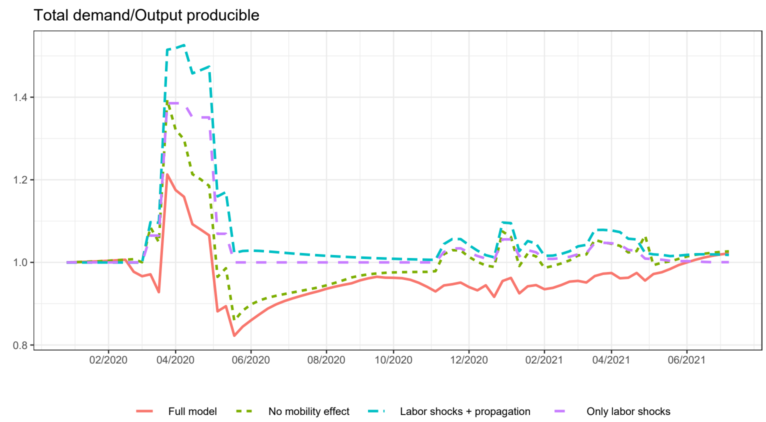

Figure 9: Ratio between total demand (final & intermediate) and total output producible for the four model versions

For this purpose, figure 9 plots the ratio between total demand (i.e. the sum of final and intermediate demand across all regions and sectors), and total output producible (i.e. the sum of all output which can be produced given available labor and intermediate inputs across all sectors and regions), at weekly frequency. A value greater than 1 hence indicates that total demand exceeds total output producible during the week in question. The figure shows that during the first lockdown, aggregate output is chiefly driven by supply-side constraints in all the four versions of the model, though in the full model specification total demand dropped below productive capacity for a brief period just after the Covid-19 outbreak, when the mobility effect began to arise.

Following the lifting of the national lockdown in late spring 2020 productive capacity bounces back quickly, driving the ratio toward one, or even below in the two specifications featuring demand effects. In these two latter scenarios aggregate output hence appears to not be constrained by supply bottlenecks following the first lockdown.[15] The second wave and the implementation of the zone system of regionally-specified lockdowns, however, leads to a marked difference between the full model and the other versions. In the first three partial specifications of the model, aggregate output is once more constrained by supply during the second lockdown despite the much more limited scope of business closures as demand reacts only slightly (in the *No Mobility effect* version) or, by assumption, not at all (under *Labor Shocks + Propagation*, and *Only Labor Shocks*). In the full model specification, demand reacts comparatively strongly due to the inclusion of the mobility effect, and the ratio between demand and output producible remains steadily below one until June, 2021.

Figure 10 plots the simulated regional percentage losses in gross output, relative to the baseline taken from the IO table, for two phases of the simulation; one from January to October 2020, comprising the first national lockdown and the subsequent partial recovery, and one from November 2020 until the end of the simulation in early July 2021, comprising the second set of lockdown measures. The figure confirms the results already discussed in Reissl et al. (2021) revealing the presence of a highly diversified regional impact across both simulation phases. During the first simulation phase, northern and central regions such as Lombardy, Veneto, Lazio and Tuscany are hit particularly hard, while during the second phase, losses are even more geographically variegated as they also depend on how much time each region spent in the different zone regimes. Regarding the decomposition of the contributions of the four model specifications, figure 10 shows that at the regional level, results are fairly uniform in that, while output losses differ across regions, the distances between the losses predicted by the four model versions are quite similar for

[15]For the sake of clarity, we again point out that that the plots shown thus far provide an aggregate picture and that the situation may differ substantially at sectoral and/or regional level. The later part of this section hence attempts to provide a more disaggregated view of the model dynamics.

each region within each simulation phase. The full model always predicts the highest loss while the model featuring only the direct effects of labor shocks always exhibits the smallest. In some cases (such as Veneto in phase one), the losses predicted by the model featuring only direct effects of labor shocks and the one incorporating IO propagation effects are equal or very similar; this is due to the overshooting effect exhibited by the model with propagation effects (which was shown in the aggregate in figure 7) balancing out most or all of the additional loss which the latter model version generates during the first lockdown.

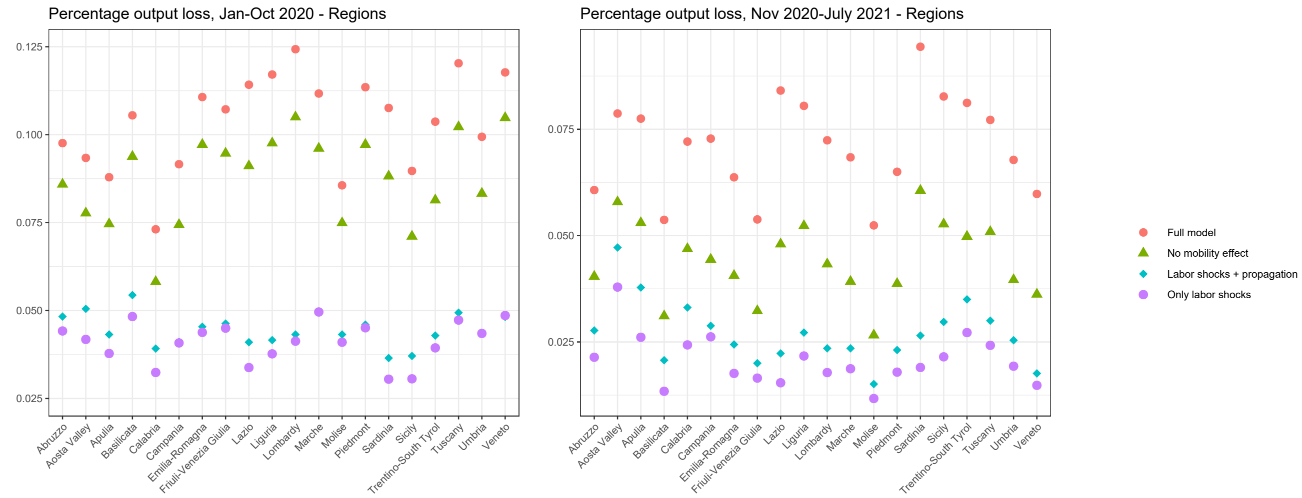

Figure 10: Percentage losses in regional gross output for the periods January to October 2020 (left panel) and November 2020 to July 2021 (right panel) predicted by the four model versions

Figure 11 plots the simulated percentage losses in gross output for the same two simulation phases at the sectoral level. In this case, the results are even more heterogeneous than at the regional level. Across both simulation phases, output losses differ very strongly between sectors. In addition, some sectors experience declines of similar magnitude across model versions while in others, the predicted losses differ widely, typically between model versions considering variations in final demand and those in which final demand is constant. Across sectors, there is also no longer a uniform order of the size of losses as was the case at the regional level.

For instance, in some sectors, such as *Hospitality* the loss predicted by the model featuring only direct effects of labor shocks exceeds that which arises from the model also considering propagation effects (during the first phase) or even that predicted by the model excluding only the mobility effect (second phase). In some other sectors the loss predicted by the full model vastly exceeds those given by any of the three other versions. This arises in particular for those sectors which are strongly liked to ‘inessential’ consumption expenditures, such as *Arts & Entertainment* (during the first phase) and *Hospitality* (during the second phase). Conversely, some sectors that are strongly connected to essential needs, such as *Food, Beverages, and Tobacco*, *Human Health & Social Work Activities*, and *Real Estate Activities*, in one or both phases experience lower losses under the full specification of the model than in the scenario with varying demand but no mobility effect as a consequence of a favorable shift in the allocation of households’ consumption as the crisis unfolds.

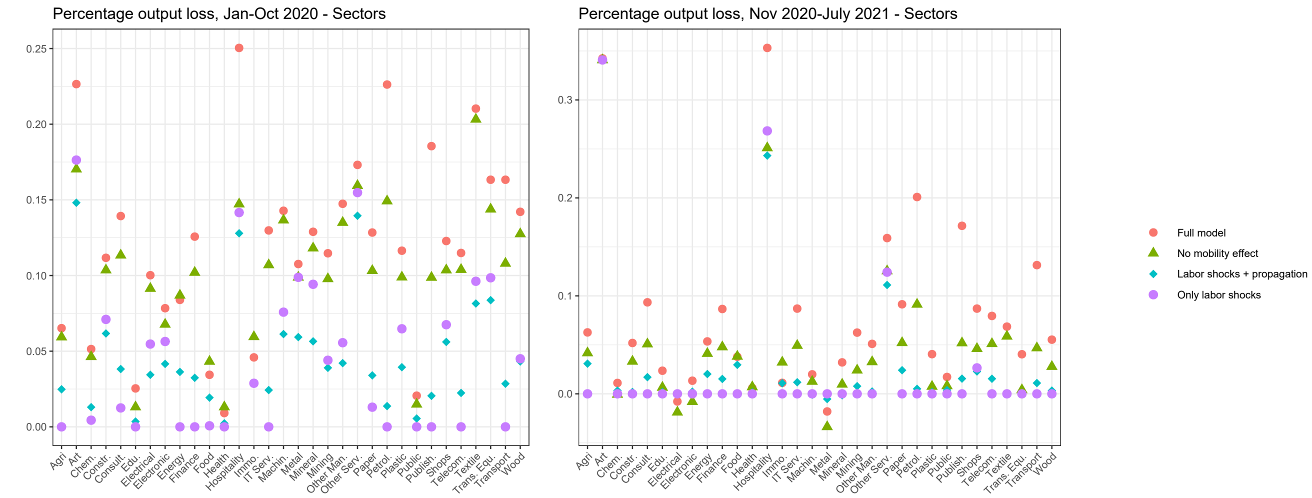

Figure 11: Percentage losses in sectoral gross output for the periods January to October 2020 (left panel) and November 2020 to July 2021 (right panel) predicted by the four model versions

A similar picture emerges when looking at the ratio between total demand and total output producible (the aggregate version of which was shown in figure 9) at the regional and sectoral levels. Instead of plotting 20 regional and 32 sectoral time-series for this ratio, we calculate the respective means for each region and sector, using the same two phases for which the percentage output losses were computed above.

At the regional level, shown in figure 12 the picture is once again quite uniform. In the two model versions excluding final demand effects, total demand on average exceeds output producible in all regions and in both parts of the simulation. The model with varying final demand but no mobility effect on consumption demand in most cases also predicts output producible to be the relevant constraint in both phases. In the full model, on the other hand, total demand is on average smaller than output producible suggesting that regional output levels were not constrained by supply in all but two regions during the first phase of the simulation, and in all regions during the second phase. Interestingly, during the second phase there are several regions in which the ratio produced by the specification with varying final demand but no mobility effect exceeds that arising from the specification considering only the direct effects of labor shocks. As was already shown for the aggregate level in figure 9, the final demand effects arising during the second lockdown in the absence of a mobility effect are quite limited, meaning that for most regions they only slightly decrease the ratio relative to the model with labor shocks and propagation effects.

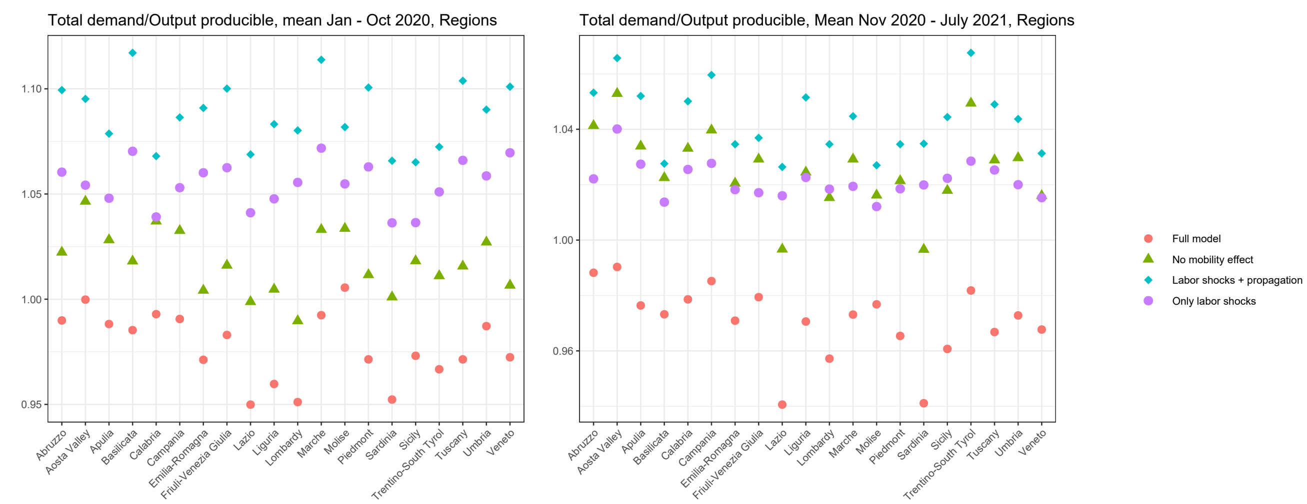

Figure 12: Ratio between total demand and total output producible for the four model versions; regional level, January-October 2020 (left panel) and November 2020 - July 2021 (right panel)

The uniformity of results found at the regional level again does not emerge when plotting the same ratio at the sectoral level, shown in figure 13. With the exception of the model with only the direct effects of labor shocks (in which demand, both final and intermediate, never changes by assumption), sectors constrained by demand and sectors constrained by supply co-exist.

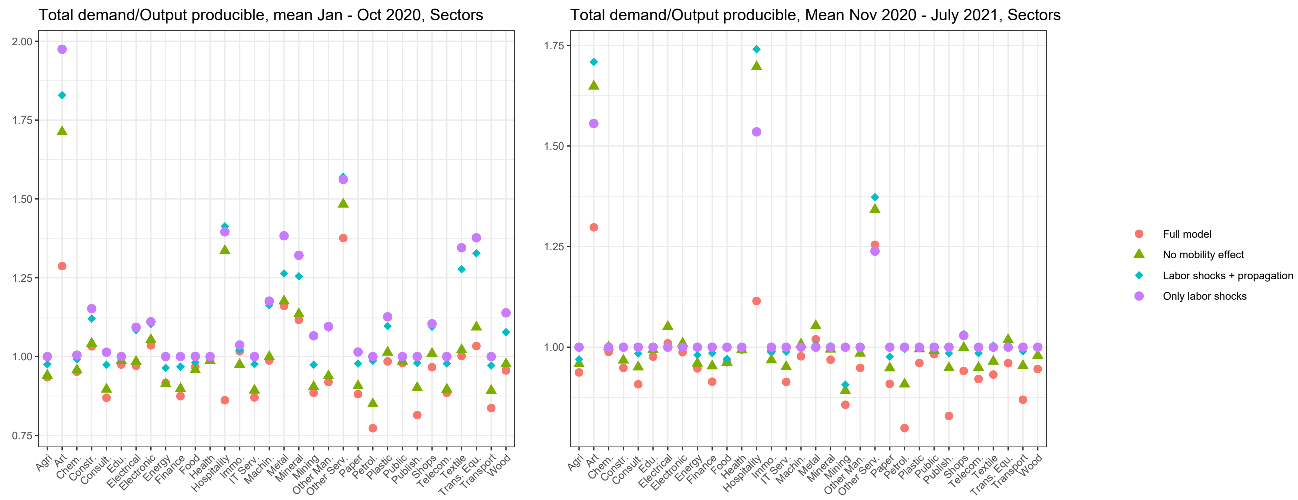

Figure 13: Ratio between total demand and total output producible for the four model versions; sectoral level, January-October 2020 (left panel) and November 2020 - July 2021 (right panel)

Supply constraints are most severe in those sectors which were more frequently targeted by government's order to close in both phases of the simulation, such as *Arts & Entertainment* and *Other Services*. In the full version of the model, the *Hospitality* sector switches from being demand driven during the first phase of the simulation, when hotels were formally open but people stayed at their home, to being supply driven during the second. On average however, 23 out 32 sectors result to be demand-driven in the period between January 2020 and October 2020, while the number grows to 27 for the second phase of the simulation, from November 2020 to July 2021.

Finally, using simulation output from the full model, we calculate the ratio between consumption demand given by the mobility effect and consumption demand given by the output effect, the aggregate of which was plotted in figure 8, at the regional and sectoral levels. As in the previous figures, we calculate means over the two previously defined phases of the simulation for each sector and each region.

At the regional level, figure 14 demonstrates that the mobility effect dominates the dynamics in every region across both phases of the simulation. In addition, the values of the ratios are fairly uniform across regions.

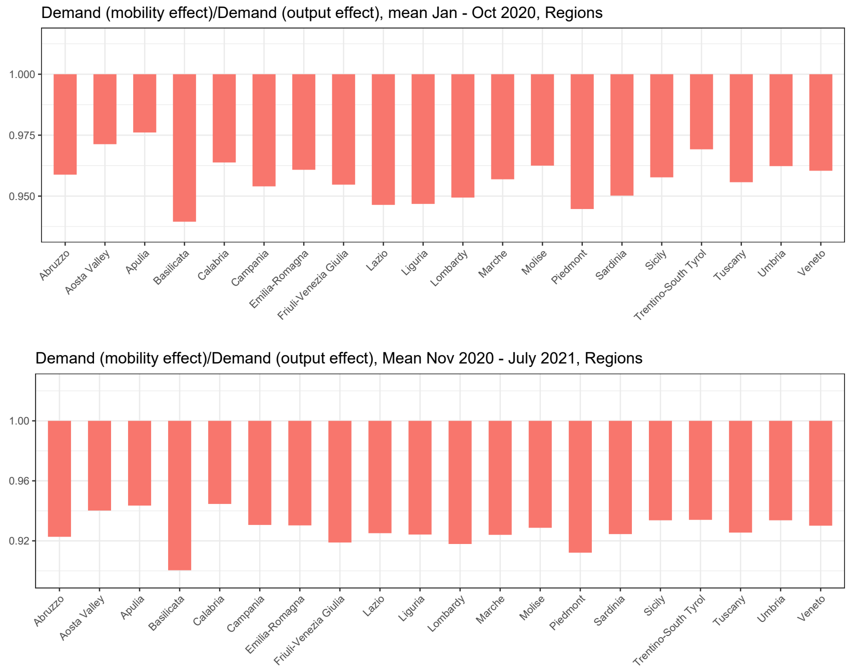

Figure 14: Ratio between total consumption demand given by the mobility effect and total consumption demand given by the output effect for the full model; regional level, January-October 2020 (top panel) and November 2020 - July 2021 (bottom panel)

The picture is more heterogeneous at the sectoral level (shown in figure 15), with consumption demand implied by the mobility effect being much lower than the one given by the output effect for sectors such as *Arts & Entertainment*, *Hospitality*, but also *Transport Equipment* and *Publishing & Broadcasting*. Furthermore, there are some sectors in which the output effect on consumption demand is stronger than the mobility effect. Typically, these are those sectors more connected the expenditure functions gathered in the 'essential' macro-group, for which the mobility effect, due to the negative value taken by ρ_e in equation 7, predicts a favorable shift in final consumption demand when mobility drops, e.g. *Agriculture*, *Chemistry*, *Construction*, *Real Estate* (which includes demand for residential housing services) *Energy*, *Health*, *Food*, manufacture of basic *Metals* and of non-metallic *Mineral* products non-machinery, and *Telecommunications*. In addition, the prevalence of the output effect over the mobility effect in steering demand is more frequent during the first phase of the simulation, which includes the implementation of the national lockdown when output declines much more strongly due to the pervasiveness of closures, enhancing the output effect on demand.

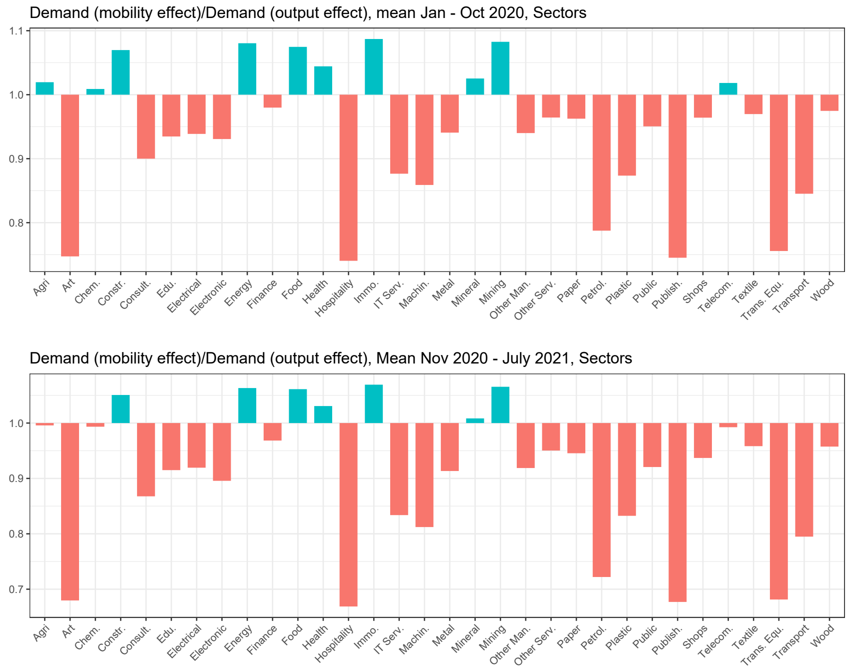

Figure 15: Ratio between total consumption demand given by the mobility effect and total consumption demand given by the output effect for the full model; sectoral level, , January-October 2020 (top panel) and November 2020 - July 2021 (bottom panel)

Overall, our results suggest that labor shocks and their propagation through the Input-Output network were responsible for most of decline in output experienced in the immediate aftermath of the Covid-19 outbreak, in particular during the enforcement of the nation-wide lockdown of Spring 2020. During this phase, output is constrained by the decline in sectoral productive capacities originating with the closures of all productive facilities regarded as non-essential. From the beginning of May onwards, however, with a few exceptions at sectoral level, production appears to no longer be constrained by supply factors but instead by demand, which dropped partly as a consequence of the decline in output and income levels caused by the closures themselves. Demand is the most important driver of output at the aggregate, regional and sectoral levels both for much of the first phase of the epidemic, i.e. from the outbreak of the first wave to the start of the second one in October 2020, and, to an even greater extent, during the second phase in which the zone-based regional system of closures was implemented.

This observation provides some support for putting the implementation of policies designed to counteract the decline in demand by sustaining the income of households affected by closures, such as income support through direct payments, layoff bans, tax deferrals or postponements of utility bills for laid-off workers and the self-employed, at the core of fiscal policy interventions.[16] However, our results also highlight a critical issue in that, for all regions and for many sectors, demand levels appear to be mostly driven by the mobility effect, rather than the output/income effect. The same occurs for aggregate consumption demand for long phases of the simulation. As a consequence, income support for households may fail to translate into increases in consumption demand, hampering the efficacy of fiscal policy.

While our analysis points to the relevance of the mobility effect, it remains agnostic about the determinants of mobility, the latter being treated as exogenous and calibrated on actual data that are the result of both mandatory restrictions on personal mobility and voluntary reductions to avoid infection. While mandatory restrictions and voluntary choices may indeed be correlated, since different degrees of restrictions to personal mobility were enforced depending on the state of the epidemic[17], which should affect individuals' fear of being infected and thus their voluntary mobility, the question remains whether the observed declines in average levels of mobility would have been present even in absence of government-mandated restrictions.[18] Besides difficulties in separating mandated and voluntary effects on personal mobility, the picture is further complicated by the fact that infections and mobility influence one another. As such, imposing prompt and tight restrictions, causing mobility to fall, may have a bigger impact on demand in the short run but, if effective in keeping infections low, bring advantages in the medium term, allowing

[16] Incidentally, since the model is estimated using sectoral production and turnover data, which also embed the effects of policies implemented by the government, it may be the case that the decline in demand and its relative importance in steering output, compared to reductions in productive capacity caused by closures, would have been even greater in the absence of any intervention.

[17] In particular, under the zone-based regional system, different extents of restrictions were automatically enforced at the regional level depending on a precisely defined set of epidemiological indicators.

[18] Golsbee and Syverson (2021), studying the US, compare consumer behavior during the crisis within the same commuting zones but across state and county boundaries with different policy regimes to separate the effects of legal constraints and voluntary choices on consumer behavior, finding that most of the effect was driven by voluntary choices. This decomposition is far more problematic in the case of the Italian regions as they have been subject to a uniform set of legal rules throughout the pandemic.

mobility to recover sooner. Conversely, milder forms of restrictions might have lower impacts in the short term, but cause larger and long-lasting economic losses if mobility declines due to voluntary choices as a consequence of higher infections. If instead looser restrictions are enough to keep infections low, or if voluntary mobility is less sensitive to the spread of the contagion, these might bring lower economic losses. To conclude, our analysis points to the prevalence of demand factors over supply bottlenecks in driving the economic losses experienced in Italy between January 2020 and July 2021. At the same time, we identify a possible threat to the efficacy of policies aiming to stimulate demand, in that declines in mobility may prevent households' from spending. To correctly investigate the characters of this threat, our analysis thus urges studies to assess the effects and mutual influence of voluntary mobility choices, imposed mobility restrictions, and the epidemiological dynamics.

6 Conclusion

This paper presented an inter-regional computational input-output model for Italy, building on the framework developed in Reissl et al. (2021). The model was applied to an analysis of the economic effects of the first and second sets of lockdown measures implemented in Italy to contain the spread of Covid-19. The main innovation to the model is the addition of a block which depicts household consumption demand for different categories of goods and services as a function of changes in average mobility at the regional level, taken as a proxy of both mandated mobility restrictions and the perceived severity of the epidemic. Modelled in this way, household consumption demand may change both in terms of level and composition in response to the epidemic, allowing us to capture an important factor which was absent in the previous version of the model. It was shown that the model, once estimated, does a good job at reproducing empirical time-series on sector level activity and household consumption expenditure both in-sample (2020) and out-of-sample (the first half of 2021). In addition, it was demonstrated that the model is also able to closely reproduce empirical data for Italian GDP which were not included in the estimation. Additionally, regional GDP indices produced by the model were compared to a quarterly proxy of regional Italian GDP provided by the Bank of Italy, showing that the two metrics predict very similar dynamics. The model hence appears to perform well also at the regional level, the modelling of which is an important advantage of our framework with respect to other IO approaches which have been applied to analyses of the pandemic.

The estimated model was applied to an in-depth analysis of the relative importance of demand and supply-side factors in driving simulation dynamics, using a succession of scenarios in which various elements of the model were switched off. This analysis showed that supply and demand-side effects play diverse roles over the course of the simulation; while the collapse of output during the first lockdown can very largely be explained by supply shocks and their propagation through the production network, demand factors play a much more central role in shaping the slow recovery following the first lockdown and the renewed downturn during the second wave of the epidemic in Italy. At the sectoral level, it was shown that, while in most sectors output is driven by demand, demand and supply-constrained sectors co-exist throughout the simulation. Furthermore, the impact of changes in sectoral final consumption demand as a reaction to both mandated restrictions and the perceived severity of the epidemic (captured by changes in average mobility), is highly heterogeneous across sectors, depending on the depending on the category of consumption demand to which they chiefly cater. In addition, as was the case in Reissl et al. (2021), the economic loss predicted by the model differs strongly across regions, as a result not only of the measures imposed but also, and to a great extent, of their different productive structures.

The regional level of analysis incorporated into our model allows for an ex-ante evaluation showing which regions are likely to be the most strongly affected by a lockdown - information which can in turn be used in targeting policy measures aimed at supporting incomes and employment. At the sectoral level, the model provides estimates not only regarding the impact of lockdowns on sectors directly targeted by restrictions, but also regarding indirect feedback effects on other sectors. In addition, it gives an indication of whether a particular sector is more likely to face demand or supply-side constraints. Such information is crucial in designing and targeting policy support measures aimed at the firm sector. For instance, policies aimed at boosting demand are unlikely to aid a sector which is primarily constrained by supply-side factors, while they may benefit sectors suffering from a low demand, as seems to be the case for most of the sectors considered in our analysis for most of our simulation horizon. However, our experiments show that these policies may be lacking in efficacy if their support to income levels does not translate into higher demand due to a decline in mobility, either induced by restrictions or by voluntary choices. Therefore, our framework also stresses the need to unravel the relationship between voluntary mobility choices, imposed restrictions, and the dynamics of infections.

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Appendix

A Additional tables and figures

Table A1 lists the 32 sectors of our IO table and the respective abbreviations which are at times used in the main text. Figure A1 gives a schematic overview of our inter-regional IO table.

Table A1: IRPET Sectors

#	Description	Abbreviation
1	Agriculture, Forestry & fishing	Agri.
2	Mining & Quarrying	Mining
3	Manufacture of Food, Beverages & Tobacco	Food
4	Manufacture of Textiles, Wearing Apparel & Leather	Textile
5	Manufacture of Wood & of Products of Wood & Cork, except Furniture	Wood
6	Manufacture of Paper & Paper Products, Printing & Reproduction of Recorded Media	Paper
7	Manufacture of Coke & Refined Petroleum Products	Petrol.
8	Manufacture of Chemicals & Pharmaceutical Products	Chem.
9	Manufacture of Rubber & Plastic Products	Plastic
10	Manufacture of other Non-Metallic Mineral Products	Mineral
11	Manufacture of Basic Metals, Fabricated Metal Products, except Machinery & Equipment	Metal
12	Manufacture of Computer, Electronic & Optical Products	Electronic
13	Manufacture of Electrical Equipment	Electrical
14	Manufacture of Machinery & Equipment n.e.c.	Machin.
15	Manufacture of Transport Equipment	Trans. Equ.
16	Manufacturing n.e.c., Repair & Installation of Machinery & Equipment	Other Man.
17	Electricity, Gas, Water Supply, Sewerage, Waste & Remediation Services	Energy
18	Construction	Constr.
19	Wholesale & Retail Trade; Repair of Motor Vehicles & Motorcycles	Shops
20	Transportation & Storage	Transport
21	Accommodation & Food Service Activities	Hospitality
22	Publishing, Motion Picture, Video, Sound & Broadcasting Activities	Publish.
23	Telecommunications Activities	Telecom.
24	Computer Programming, Consultancy & Related Activities; Information Activities	IT Serv.
25	Financial & Insurance Activities	Finance
26	Real Estate Activities	Immo.
27	Legal & Accounting Consulting, Architectural & Engineering Activities; Technical Testing & Analysis Services	Consult.
28	Public Administration & Defence; Compulsory Social Security	Public
29	Education	Edu.
30	Human Health & Social Work Activities	Health
31	Arts, Entertainment & Recreation	Art
32	Other Services	Other Serv.

Figure A1: Structure of the inter-regional IO table

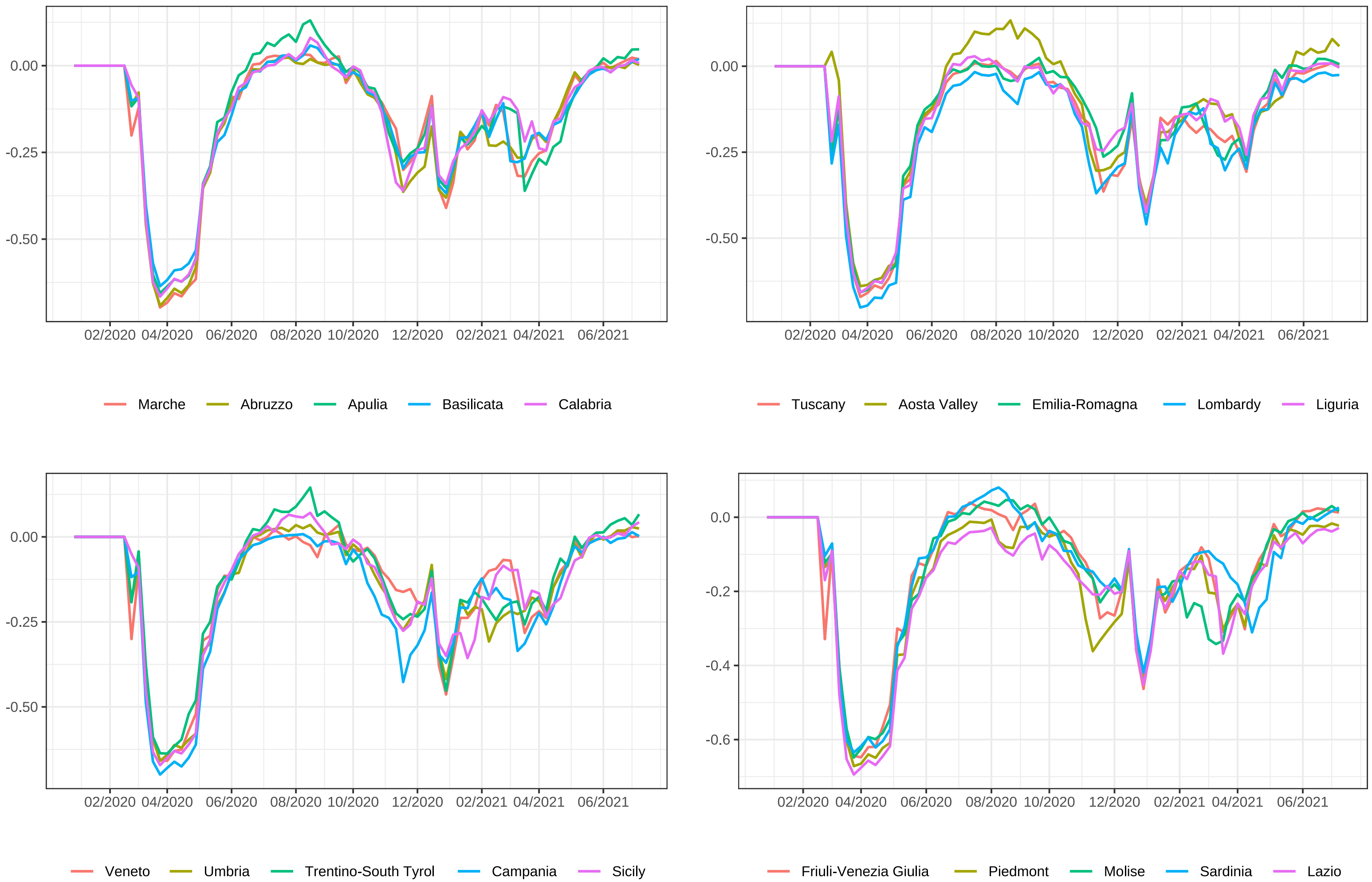

Figure A2: Regional mobility indexes

In figure A2 we plot the Facebook mobility indexes for the Italian regions, converted to weekly frequency, which are used to model the impact of changes in mobility on consumption demand. As mentioned in the main text, these are calculated relative to a baseline of February 2020, with a value smaller than zero indicating that mobility is lower than the baseline. The available data begin on March 1 2020 and we consequently set all observations prior to this date to 0. As can be seen, the mobility patterns are quite similar across regions, although some differences emerge during summer 2020 and in particular during the second lockdown in which restrictions were regionally differentiated.

B Construction of labor shocks

The two main exogenous factors affecting the dynamics of our model are the empirical mobility indices which feed back on the final consumption demand of households, and the lockdown shocks affecting sectoral productive capacity. In the present section, we outline the construction of the latter. As indicated in the main text, lockdowns in our model are depicted as (negative) shocks to the amount of labor input available to a particular set of sectors. If a sector is affected by a lockdown, the maximum amount of labor it can employ in production is temporarily limited to a level below the baseline. Its productive capacity is consequently reduced, which in turn may also translate into decreases in *actual* output, unless the demand for that sector's output is already lower than the now reduced productive capacity. Reductions in actual output will themselves feed back further on the model, both through the endogenous components of final demand tied to output (investment and consumption induced by the compensation of employees) and the demand of the constrained sector for intermediate inputs.

In order to focus in on the effects of constraints induced directly by lockdown measures, we assume that unless a sector is subject to a lockdown, it does not face any labor constraints, i.e. that that sector is always able to hire additional labor as required to increase its productive capacity beyond a baseline level implied by the amount of labor $\bar{l}$, with which every sector starts out in every period. This initial labor force $\bar{l}$ is normalized to 100 for each sector, and lockdown shocks are formulated in terms of percentage deviations from this level such that, for instance, a 20% negative lockdown shock to some sector implies that for the duration of the lockdown in question, that sector will have a maximum of 80 units of labor available.

In formal terms, let the vector $\mathbf{l_t}$ denote the amount of labor available to each sector of the economy in every region in period t. The vector $\mathbf{shock_t}$ contains the shocks to their labor supply which occur in that period. Next, let υ denote a vector of length $n \cdot m$ in which, for each element j, $\upsilon_j = 1$ if $\bar{l}\frac{shock_{j,t}}{100} < \bar{l}$ and $\upsilon_j = 0$ otherwise. $\mathbf{l_t}$ is then calculated as

$$\mathbf{l_t} = \upsilon \otimes \left(\bar{\mathbf{l}} \otimes \frac{\mathbf{shock_t}}{100} \right) + (1 - \upsilon) \otimes max \left(\bar{\mathbf{l}}, \mathbf{x_t^{e,short}} \otimes \mathbf{a^l} \right) \tag{12}$$

with $\otimes$ indicating element-wise multiplication.

In order to determine the magnitudes of the lockdown shocks affecting the 32 sectors in the 20 regions in each period, we begin by consulting the various decrees mandating the temporary closure of specific (sub-)sectors issued by the Italian government. These decrees specify both the timing of closures and re-openings and the sectors affected in terms of the ATECO classification of economic activities at the 5 digit level of disaggregation.[19] These decrees may be divided into two sets. The first set comprises the decrees issued during the first wave of the epidemic in spring and early summer of 2020, the contents of which applied uniformly across the country. The second set comprises those decrees issued to combat the second wave beginning in fall of 2020. They instituted a system whereby a given region could move between different 'zones' (red, orange and yellow), implying differing levels of firm closures and other restrictions, depending on the evolution of epidemiological indicators within that region. These decrees, together with a time series indicating how regions moved between the different zones during the second wave, enables us to construct a dataset showing, for each calendar week of 2020 and the first half of 2021, which 5-digit sectors were closed in each region.

We then combine this dataset with another which provides data on the number of em-

[19] ATECO is the Italian version of the classification of economic activities established by the European Community (NACE Rev. 2). It is identical to the latter up to the 4 digit level but also includes a 5 and 6 digit level of disaggregation.

ployees in each 5-digit sector at the regional level, which in turn enables us to derive the share of the workforce in each of the (more aggregated) sectors of our model which was affected by lockdown measures in any given calendar week. We assume that those workers subject to a lockdown whose tasks cannot be performed from home become unavailable for the duration of the measure, whilst the rest are still available to the respective sector. We assess tele-workability using the procedure proposed in Cetrulo et al. (2020), drawing on survey data on the characteristics of occupations to determine which tasks can be performed from home and how many workers are employed in each of these occupations across sectors. We are thus able to compute a ratio between the number of workers whose occupation is *not* tele-workable and the total number of workers for 18 NACE macro-sectors. The 18 indexes we obtain are linked to the 32 model sectors via table C2. [20]. Finally, we multiply the sectoral shares of workers affected by lockdown measures in each week by the sector-specific tele-workability indexes which take values between 0 and 1, with 0 meaning that all workers can work from home and 1 meaning that none can. In this fashion, we obtain for each calendar week a vector of sector- and region-specific labor shocks.

In order to provide a broad overview of the sectoral closures which were implemented in Italy, table C1, reproduced from Reissl et al. (2021), very briefly summarises the decrees which were issued during the first wave of the epidemic.

Table C1: First wave lockdown measures

Calendar week	**Measures**
11	Closure of hospitality services, non-essential retail, gyms, barbers, etc.
13	Extensive closures of manufacturing & non-customer-facing services
16	Limited re-openings in manufacturing, services & retail
19	Re-opening of manufacturing, retail & most services
21	Complete re-opening

The treatment of the second lockdown is complicated by the fact that the definition of the zones, in terms of the sectors ordered to close, changed somewhat over time. For instance, museums were initially closed in red, orange as well as yellow zone regions but in early

[20]For additional details on the construction of the indices see Cetrulo et al. (2020) and Reissl et al. (2021)

2021 were allowed to re-open in the yellow zone regime. In addition, a 'white zone' was introduced during spring 2021, which initially did not differ from the yellow zone in terms of sectoral closures but which eventually evolved into a regime in which only very limited closures in leisure facilities were in place. We provide a brief summary of the closures implied by the different zone regimes and, where applicable, how they changed over time in table C2.[21]

Table C2: Second wave lockdown measures

Zone	**Closures**
White	Introduced March 2021, initially identical to yellow From June 2021 only night clubs, dance halls etc. closed
Yellow	Closure of gyms, museums and other leisure facilities Museums open from mid-January 2021 Theaters and concert halls open from May 2021 Sea- and lakeside beach facilities open from mid-May 2021 Gyms & swimming pools open from end May 2021
Orange	original Yellow + closure of restaurants, bars etc.
Red	Orange + closure of non-essential retail & personal services; Book shops open from March

In modelling the first lockdown, the following simplifying assumptions are made:

- Since the time-unit of the model is a week, lockdown measures and relaxations are always implemented at the beginning of the calendar week in which they were implemented in the real world.
- For the first lockdown in 2020, we assume a full re-opening in the 21st calendar week for simplicity, whilst in the real world some sub-sectors such as theaters and cinemas were closed slightly longer.

In our depiction of the second lockdown, we implement the following simplifying assumptions:

- During the second wave of the epidemic, lockdown measures were implemented separately for the autonomous provinces of Bolzano and Trento, which together

[21]Spreadsheets containing exhaustive data on which sectors were closed at which points during the first and the different phases of the second set of lockdown measures can be found at `https://github.com/SReissl/CovidIO2`.

make up the region of Trentino-South Tyrol, such that two different zone regimes could apply to the two provinces at any given time. Our inter-regional IO table, on the other hand, aggregates the two provinces into the aforementioned region. For every sector, we make use of labor force data at the provincial level to discern the number of workers affected by lockdown measures, but then express this as a share of the overall employment in every sector at the *regional* level in order to construct a regional shock. This allows us to roughly translate shocks at the provincial level to regional ones.

- During the last week of 2020 and the first week of 2021 the entirety of Italy was placed under uniform restrictions, moving back and forth between the red and orange zones at higher than weekly frequency. Since our model runs at weekly frequency, we place the entire country into red zone restrictions in the 53rd calendar week of 2020 and the first calendar week of 2021.

- From the 3rd to the 5th of April 2021, i.e. the Easter weekend including Easter Monday, the entire country was placed under red zone restrictions, followed by a return to regionalized classifications on the 6th of April. Due to the model running at a weekly frequency, and given that two of the aforementioned days are public holidays, we do not model these very short-term measures, instead assuming that no change took place on the 3rd and 4th of April and that the classifications coming into force on the 6th of April already applied on the 5th.

The classification into the different zones over the period which we model is given in C3, with letters denoting the respective colors of the zones (**R**ed, **O**range, **Y**ellow, **W**hite). To give a better idea of the magnitude of the labor shocks imposed on the model over the course of the simulation, we plot them as time-series in figures C1 and C2. Figure C1 gives a regional perspective, showing the share of the labor force of each region which is unavailable due to a labor shock in every simulation period. Figure C2 shows the equivalent time-series at the sectoral level, but only showing the sectors which were in fact at some point subject to lockdown measures.

Table C3: Second wave lockdown measures by region

	2020								2021																										
Calendar week:	**46**	**47**	**48**	**49**	**50**	**51**	**52**	**53**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**
Piedmont	R	R	R	O	O	Y	Y	R	R	Y	O	O	Y	Y	Y	Y	O	O	R	R	R	R	O	O	Y	Y	Y	Y	Y	Y	Y	W	W	W	W
Aosta Valley	R	R	R	R	O	O	Y	R	R	Y	O	O	Y	Y	Y	Y	Y	Y	O	O	R	R	R	R	O	R	O	O	Y	Y	Y	Y	Y	W	W
Lombardy	R	R	R	O	O	Y	Y	R	R	O	R	O	Y	Y	Y	Y	O	O	R	R	R	R	O	O	Y	Y	Y	Y	Y	Y	Y	W	W	W	W
Trento	Y	Y	Y	Y	Y	Y	Y	R	R	Y	Y	Y	Y	Y	O	O	O	O	R	R	R	O	O	O	Y	Y	Y	Y	Y	Y	Y	W	W	W	W
Bolzano	R	R	R	R	O	O	Y	R	R	Y	R	R	O	R	R	R	R	O	O	O	O	O	O	O	Y	Y	Y	Y	Y	Y	Y	Y	W	W	W
Veneto	Y	Y	Y	Y	Y	Y	Y	R	R	O	O	O	Y	Y	Y	Y	Y	O	R	R	R	O	O	O	Y	Y	Y	Y	Y	Y	W	W	W	W	W
Friuli-Venezia Giulia	Y	O	O	O	Y	Y	Y	R	R	Y	O	O	Y	Y	Y	Y	Y	O	R	R	R	R	O	O	Y	Y	Y	Y	Y	W	W	W	W	W	W
Liguria	O	O	O	Y	Y	Y	Y	R	R	Y	O	O	Y	Y	O	O	O	Y	O	O	O	O	O	O	Y	Y	Y	Y	Y	Y	W	W	W	W	W
Emilia-Romagna	Y	O	O	O	Y	Y	Y	R	R	O	O	O	Y	Y	Y	O	O	O	R	R	R	R	O	O	Y	Y	Y	Y	Y	Y	Y	W	W	W	W
Tuscany	O	R	R	R	O	O	Y	R	R	Y	Y	Y	Y	Y	O	O	O	O	O	O	R	R	O	O	Y	Y	Y	Y	Y	Y	Y	Y	W	W	W
Umbria	O	O	O	O	Y	Y	Y	R	R	Y	O	O	O	O	O	O	O	O	O	O	O	O	O	O	Y	Y	Y	Y	Y	Y	W	W	W	W	W
Marche	Y	O	O	O	Y	Y	Y	R	R	Y	O	O	Y	Y	Y	Y	O	O	R	R	R	O	O	O	Y	Y	Y	Y	Y	Y	Y	Y	W	W	W
Lazio	Y	Y	Y	Y	Y	Y	Y	R	R	Y	O	O	Y	Y	Y	Y	Y	Y	R	R	O	O	O	O	Y	Y	Y	Y	Y	Y	Y	W	W	W	W
Abruzzo	O	O	R	R	R	O	O	R	R	Y	O	O	Y	Y	O	O	O	O	O	O	O	O	O	O	Y	Y	Y	Y	Y	Y	W	W	W	W	W
Molise	Y	Y	Y	Y	Y	Y	Y	R	R	Y	Y	Y	Y	Y	Y	O	R	R	R	O	O	O	O	O	Y	Y	Y	Y	Y	W	W	W	W	W	W
Campania	Y	R	R	R	O	O	Y	R	R	Y	Y	Y	Y	Y	Y	O	O	R	R	R	R	R	R	O	Y	Y	Y	Y	Y	Y	Y	Y	W	W	W
Apulia	O	O	O	O	Y	Y	Y	R	R	Y	O	O	O	O	O	O	O	Y	R	R	R	R	R	R	O	O	Y	Y	Y	Y	Y	W	W	W	W
Basilicata	O	O	O	O	O	Y	Y	R	R	Y	Y	Y	Y	Y	Y	Y	R	R	O	O	O	O	O	O	O	O	Y	Y	Y	Y	Y	Y	W	W	W
Calabria	R	R	R	O	O	Y	Y	R	R	O	O	O	Y	Y	Y	Y	Y	Y	O	O	R	R	O	O	O	O	Y	Y	Y	Y	Y	Y	W	W	W
Sicily	O	O	O	Y	Y	Y	Y	R	R	O	R	R	O	O	Y	Y	Y	Y	O	O	O	O	O	O	O	O	O	Y	Y	Y	Y	Y	W	W	W
Sardinia	Y	Y	Y	Y	Y	Y	Y	R	R	Y	Y	O	Y	Y	Y	Y	Y	Y	Y	O	O	O	R	R	R	O	O	Y	Y	W	W	W	W	W	W

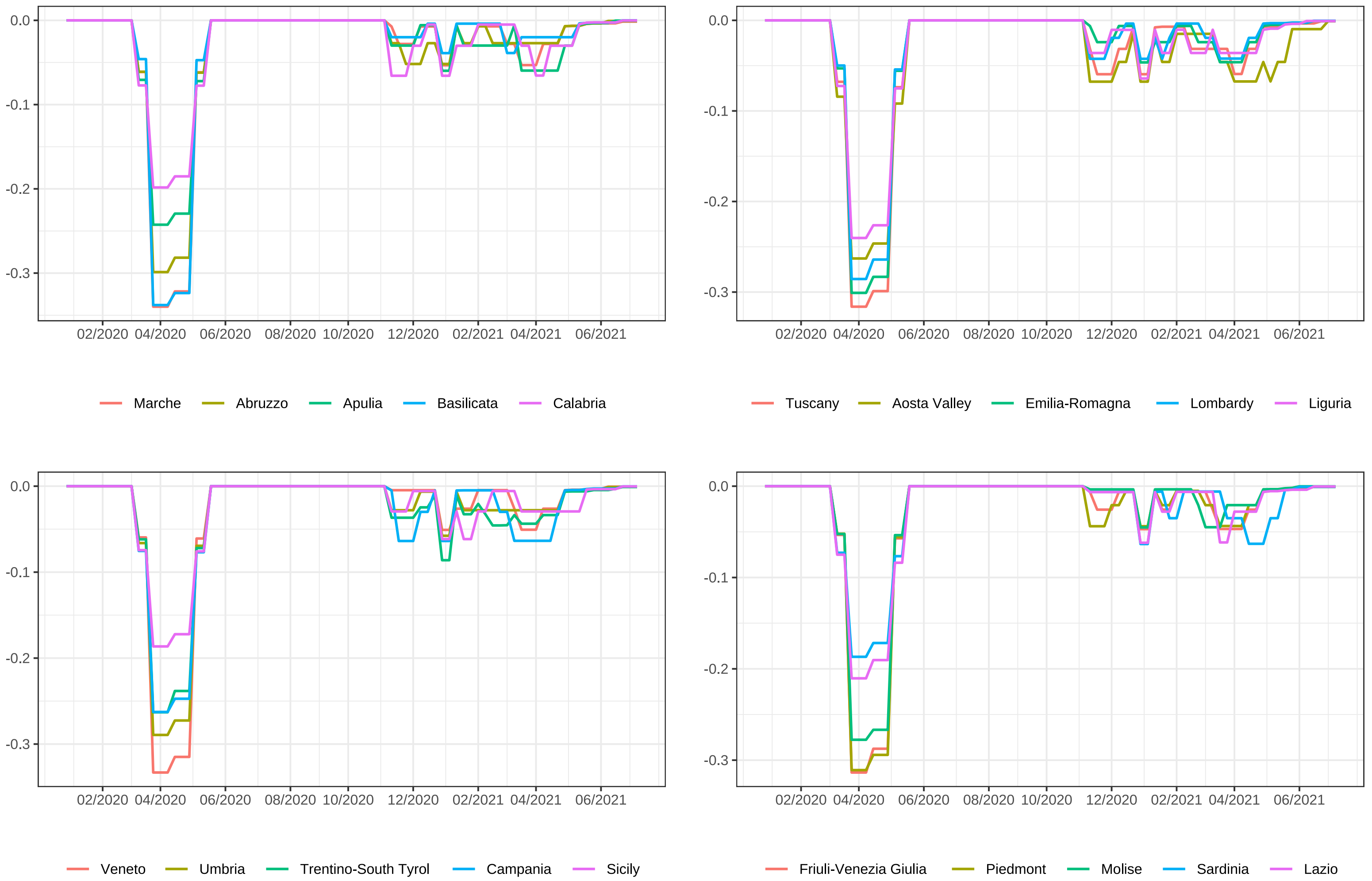

Figure C1: Labor shocks at regional level

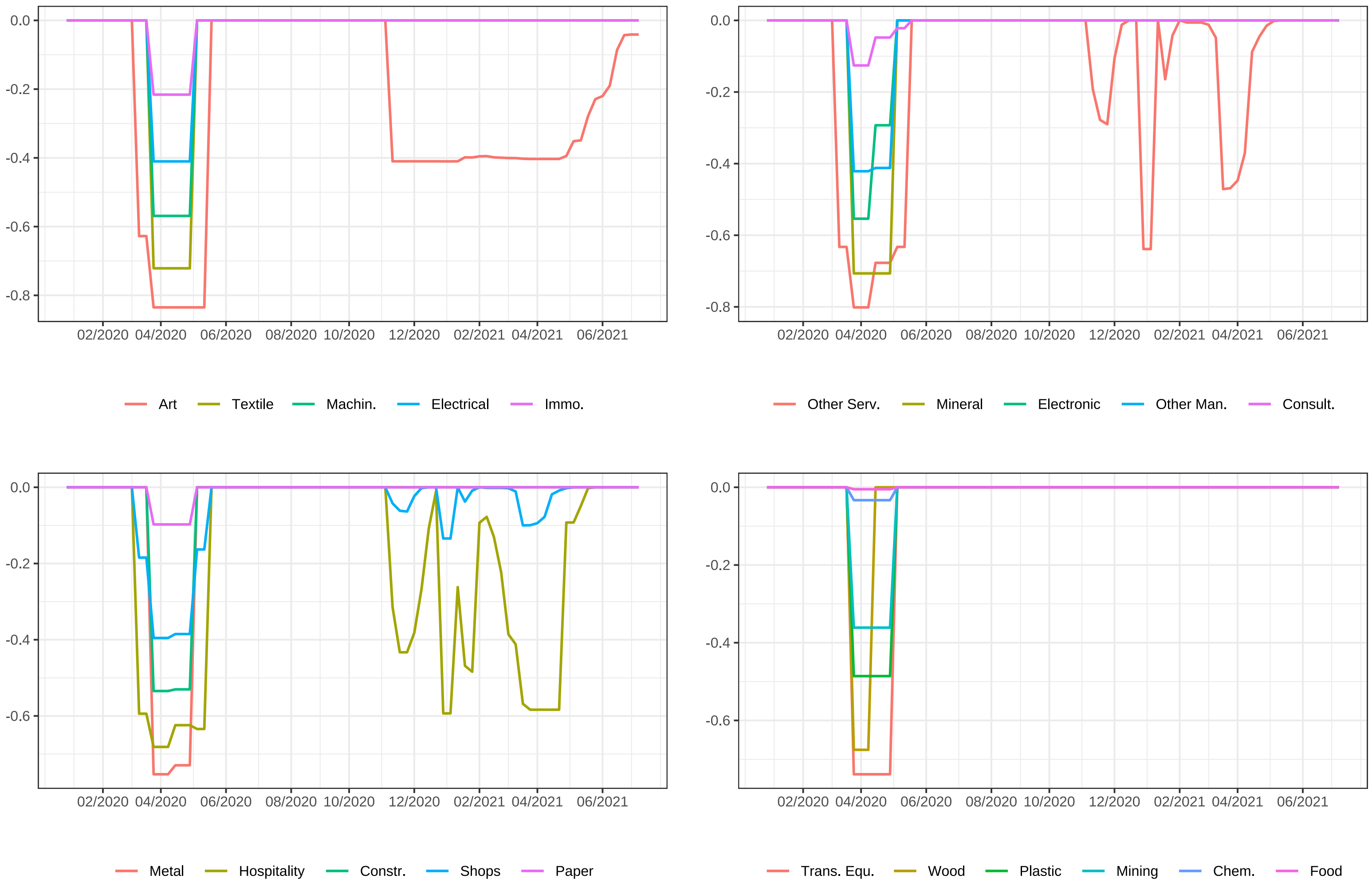

Figure C2: Labor shocks at sectoral level

C Expectations

Demand expectations play a crucial role in the model, since they drive sectors' orders of intermediate inputs and are thereby also an important determinant of sectoral productive capacity. As indicated in the main text, the model distinguishes between short and long term expectations: the former are used to derive the amount of inputs required for production in the next period, while the latter determine a target inventory stock of inputs which sectors wish to hold.

Short-term expectations are assumed to be naive, i.e. the short-term demand expectations of each sector are given by orders received in the previous period. This simple heuristic is however amended by assuming that, in case of a lockdown, the firms making up the sectors are aware of the contents of the lockdown decrees and are able to assess the extent to which the productive capacity of their customers will be reduced (or increased in case of a re-opening) by the announced measures. They then use this knowledge in order to adjust their short-term demand expectations. This assumption appears reasonable under the existence of stable relationships between firms along supply chains and given that in Italy, lockdown decrees publicly reported the precise sectoral codes of the (sub-)sectors to be closed or re-opened.

The direct impact of a lockdown on productive capacity due to the reduction in sectors' availability of labor is given by $\mathbf{\Delta l_t^{lock}} \oslash \mathbf{a^l}$, where $\mathbf{\Delta l_t^{lock}}$ is the change in sectoral labor forces implied by the lockdown regime in place in t. By pre-multiplying this vector with the matrix of technical coefficients $\mathbf{A}$ we obtain the expected reduction in the orders of inputs received by each productive sector which is implied by this reduction in productive capacity. Short term expectations are then computed as:

$$\mathbf{x_t^{e,short}} = \nu \otimes \mathbf{x_{t-1}^d} + (1-\nu) \otimes \mathbf{x_{t-1}^d} + \mathbf{A}\left[\mathbf{\Delta l_t^{lock}} \oslash \mathbf{a^l}\right] \tag{13}$$

whereby ν is a vector the $j-th$ element of which is 0 if sector j is subject to a labor shock in t and 1 otherwise. These short-term demand expectations are then used by sectors in order to formulate their own orders of intermediate inputs for the purpose of current production as described in the main text.

Long term expectations, instead of being based only on orders received in the previous period, are assumed to be calculated as a simple average over the past β periods:

$$\mathbf{x_t^{e,long}} = \frac{\sum_{i=1}^{\beta} \mathbf{x_{t-i}^{d}}}{\beta}. \tag{14}$$

As stated in the main text, these long-term expectations are used to calculate a target stock of input inventories for each sector, towards which sectors aim to gradually adjust.

D Estimation

D.1 Parameter space

The estimation procedure aims to minimise the loss function given in equation (11) by using Latin Hypercube sampling from the parameter space summarised in table D1.

Table D1: Parameter space

Symbol	**Description**	**Range**
α	Investment adjustment parameter	$0.037; 0.061$
β	Observations used for long-term expectation	$38; 64$
γ_1	Desired inventories agriculture	$14; 22$
γ_2	Desired inventories mining	$12; 20$
γ_3	Desired inventories manufacturing	$10; 16$
γ_4	Desired inventories electricity	$19; 31$
γ_5	Desired inventories construction	$19; 31$
γ_6	Desired inventories services	$8; 14$
ρ_e	Consumption demand essential	$-3; 3$
ρ_m	Consumption demand intermediate	$-3; 3$
ρ_i	Consumption demand inessential	$-3; 3$

For the first 8 parameters we set the parameter space as an interval of $\pm 25\%$ around the values estimated in Reissl et al. (2021) (rounded in the case of parameters taking discrete values) while choosing a uniform and fairly wide interval for the three expenditure function parameters added in the present version of the model. This wide parameter space allows for the hyperbolic tangents incorporated in equation (7) to take a wide range of shapes from almost linear to highly non-linear within the domain defined by the range of variation of the empirical mobility statistics. We sample a total of 100000 combinations from this parameter space, simulate the model for each of them, and record the corresponding values of the loss function.

D.2 Additional details

As explained in section 4, in estimating the model we rely on revenue rather than output data for the four service sectors for which such data are available. While one would of course ideally want to use production or at least *deflated* revenue data, these are not available for any service sector in Italy and, as indicated, even nominal revenue data can be found only for the four sectors included in our empirical dataset. Since our model assumes constant prices, and since we assume that all goods produced are sold, changes in production and changes in revenue for a sector always coincide in simulated data. Empirically, of course, changes in revenue may also be driven by variations in prices. Unfortunately, data on service prices suitable for testing whether variations in prices can account for a large part of the observed variation in revenue are not available. When looking at producer prices in the manufacturing sectors, however, it does turn out that these have been much less volatile than industrial production during the period considered in this paper, and also that in many cases their volatility declined relative to 2019 whereas the volatility in production generally increased strongly. At best, we can extrapolate to the service sectors from this result, in which case revenue should be a reasonable proxy for output for our purposes.

In addition to this, it was also necessary to reconstruct three of the time-series used in our estimation procedure from more disaggregated data. In particular this concerns:

- Sector 6 (Manufacture of Paper & Paper Products, Printing & Reproduction of Recorded Media), which is made up of ATECO sectors 17 (Manufacture of Paper & Paper Products) and 18 (Reproduction of Recorded Media), with data on production being available only for the individual sub-sectors.

- Sector 8 (Manufacture of Chemicals & Pharmaceutical Products) which is made up of ATECO sectors 20 (Manufacture of Chemicals) and 21 (Manufacture of Pharmaceutical Products), with data on production being available only for the individual sub-sectors.

- Sector 19 (Wholesale & Retail Trade; Repair of Motor Vehicles & Motorcycles) which is made up of ATECO sectors 45 (wolesale and retail trade and repair of motor vehicles and motorcycles), 46 (wholesale trade excluding motor vehicles) and 47 (retail trade excluding motor vehicles), with revenue data being available only for the individual sub-sectors.

For the three model sectors listed above, the output/revenue series needed for our estimation procedure are constructed by taking weighted averages of the series for the corresponding sub-sectors, with the weights being given by the shares of the sub-sectors in total employment of the respective aggregate sectors.

E Sensitivity analysis

We carry out a sensitivity analysis on the model in order to improve our understanding of the impact of individual model parameters on simulation outcomes. To carry out the sensitivity analysis we define a parameter space around the estimated combination, which is given in table D2. To ensure that each parameter is allowed to vary along a reasonable range, we apply the following rules in defining the parameter space:

- α, governing the reaction of investment demand to changes in output, varies by ± 0.01 around the estimated value.

- β, which gives the number of past observations used in calculating long-term demand expectations, varies by ± 10 around the estimated value.

- The γ parameters, which determine the target input inventory stocks and inventory adjustment speeds of sectors, vary by $\pm 20\%$ around their estimated values, rounded to the closest integer.

- The ρ parameters, which govern the reactions of the different categories of household consumption demand to changes in mobility, vary by ± 0.25 around their estimated values.

Table D2: Parameter space (sensitivity)

Symbol	**Estimated**	**Range**
α	0.044	0.034 : 0.054
β	58	48 : 68
γ_1	17	14 : 20
γ_2	20	16 : 24
γ_3	11	9 : 13
γ_4	30	24 : 36
γ_5	23	18 : 28
γ_6	12	10 : 14
ρ_e	-0.2	-0.45 : 0.05
ρ_m	0.4	0.15 : 0.65
ρ_i	2.4	2.15 : 2.65

As in Reissl et al. (2021), use estimated Shapley values (Shapley, 1953) to discern the degree of influence of variations of parameter values on the observed variations in a simulated variable. We choose the simulated annual loss in GDP for 2020 predicted by the full model, relative to GDP taken from our IO table (i.e. GDP in the absence of any labor shocks or variations in final demand, including exports) as the output variable to analyze. As was done in Reissl et al. (2021) we use the algorithm proposed by Song et al. (2016),[22] which samples randomly from a parameter space, simulates the model, records the chosen output variable and estimates the resulting Shapley values. Based on our parametrization of the algorithm, the model is simulated 211000 times with different parameter combinations, recording each combination and the associated GDP loss.

We begin by using these simulation results to evaluate how the GDP loss changes in level terms as each parameter is varied along the range defined in table D2. The results of this exercise are shown in figure D1. The individual panels of the figure are constructed using the distribution of GDP losses[23] resulting at each individual value of the respective

[22]This method has been implemented in the R package *sensitivity* (`https://cran.r-project.org/web/packages/sensitivity/sensitivity.eps`). In particular, we make use of the *shapleyPermRand* function.

[23]The results are given as distributions not because the model is stochastic (which is not the case),

parameter[24]. The red lines plot the median values while the blue ribbons show the first and third quartiles of the respective distributions. The figure suggests that the parameters governing the reaction of consumption demand to changes in mobility, above all ρ_e, are the most important drivers of the aggregate GDP loss generated by the model. In addition, β and, to a somewhat smaller extent, α also play a role. The impact of the inventory parameters, on the other hand, is much more limited, with only γ_3 (manufacturing) and γ_6 (services) having a slight impact, which makes sense insofar as these two parameters govern the behavior of a vast majority of our model sectors.

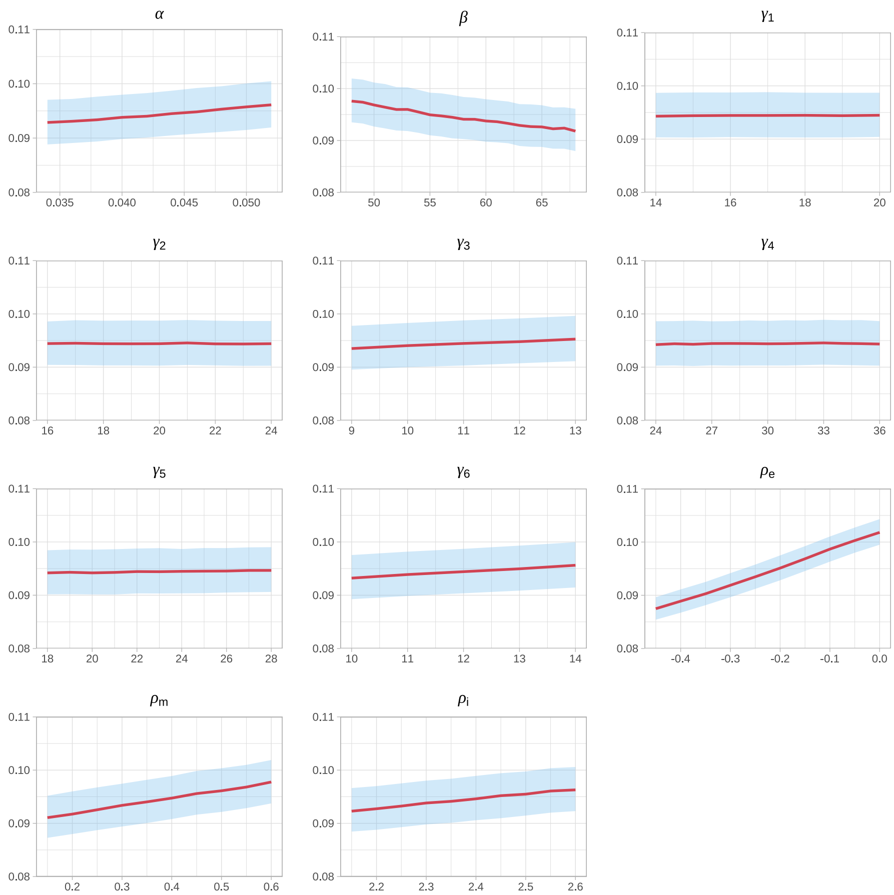

Figure D1: Sensitivity of median GDP loss to parameter variations

In contrast to the results reported in figure D1, the estimated Shapley values shown in

but because the algorithm simultaneously varies *all* parameters rather than changing them one by one. In order to analyze the results for, e.g., $\beta = 55$, we hence select all those simulations for which $\beta = 55$ but for which all other parameters may take any value within the defined intervals, resulting in a distribution of simulated GDP losses.

[24] α as well as the ρ's, which are continuous, are each discretized into 10 equally sized intervals for this purpose.

figure D2 give a *variance-based* measure of sensitivity by decomposing the variance of the simulated GDP loss across parameter combinations into components which give the contribution of each individual parameter. Figure D2, in which the bars above and below the point-estimates of the respective Shapley values represent 95% confidence intervals, largely confirms the analysis arising from D1. The ρ parameters turn out to play the largest role by far in explaining the variance of GDP loss, with α and β also making statistically significant contributions. By contrast, none of the Shapley values associated with the γ parameters are significantly different from zero.[25]

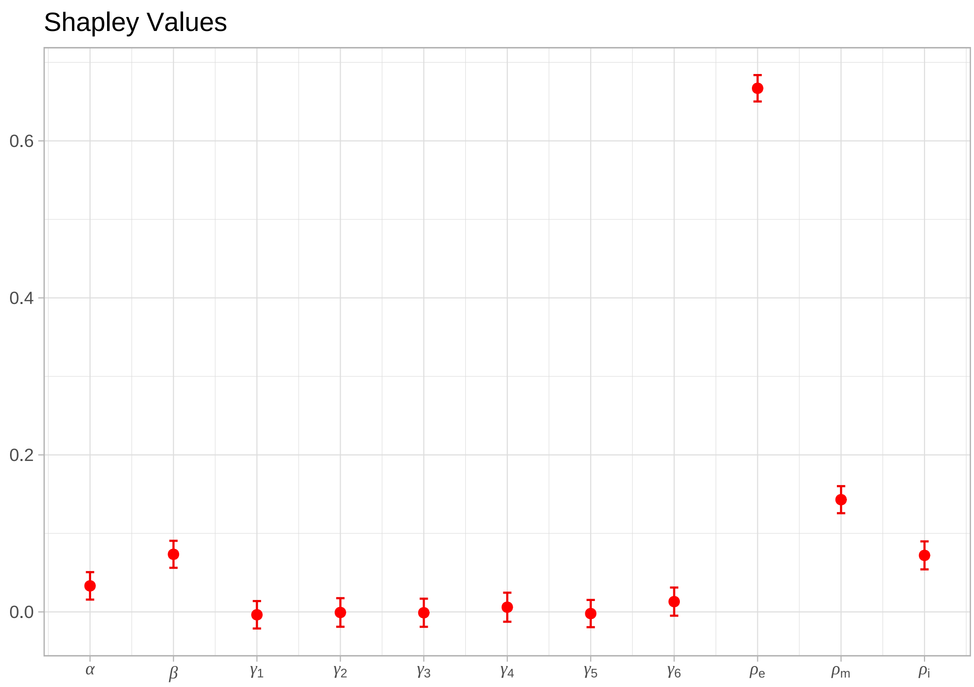

Figure D2: Shapley values

As demonstrated in section 5, the mobility effect on consumption demand is an important driver of output losses during the partial recovery following the first lockdown and in particular during the second lockdown. The strength of this mobility effect, of course, depends directly on the ρ parameters, making it unsurprising that they turn out to have by far the largest weight in explaining the simulated GDP losses generated by the model.

[25]Recall that the Shapley values are *estimates*, which also explains the presence of confidence intervals. Although Shapley values should in theory always be positive, point estimates produced by the algorithm may be slightly negative. Note however that none of the point estimates for which this is the case differ significantly from zero.