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Assessing the Economic Impact of Lockdowns in Italy: A Computational Input-Output Approach*

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Abstract

We build a novel computational input-output model to estimate the economic impact of lockdowns in Italy. The key advantage of our framework is to integrate the regional and sectoral dimensions of economic production in a very parsimonious numerical simulation framework. Lockdowns are treated as shocks to available labor supply and they are calibrated on regional and sectoral employment data coupled with the prescriptions of government decrees. We show that when estimated on data from the first "hard" lockdown, our model closely reproduces the observed economic dynamics during spring 2020. In addition, we show that the model delivers a good out-of-sample forecasting performance. We also analyze the effects of the second "mild" lockdown in fall of 2020 which delivered a much more moderate negative impact on production compared to both the spring 2020 lockdown and to a hypothetical second "hard" lockdown.

Keywords: Input-output, Covid-19, Lockdown, Italy.
JEL Codes: C63, C67, D57, E17, I18, R15

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1 Introduction

Italy was the first country in Europe to be severely affected by the Covid-19 pandemic and the first western country to introduce a series of unprecedented social distancing measures to hamper the spread of the virus. During the spring of 2020 the Italian government emanated a number of comprehensive measures culminating in a national lockdown, which mandated the closure not only of *customer-facing* outlets, such as retail and hospitality services, but, for a certain period, also of *all* workplaces considered to be non-essential, in manufacturing as well as in non-customer-facing services.[1]

While the necessity of a fast response to a rapidly deteriorating epidemiological situation is evident, there is less clarity on the appropriate scope of lockdown measures and the choice of the sectors to be closed down. This calls for reliable methods that are able to evaluate both epidemiological and economic effects of different types of closures. Moreover, as far as the economic sphere is concerned, lockdown effects are likely to differ across sectors and regions, both as a direct consequence of the type of measures implemented and, indirectly, through production networks connecting firms across sectors and regions.

However, evaluating the economic impact of lockdown measures by also considering the regional and sectoral dimensions is far from trivial. This is because of the high degree of sectoral and regional heterogeneity in terms of contributions to overall activity and degrees of specialization, and because of the complex input-output interactions present in advanced economies. The situation is made even more complicated by the scarcity of suitable datasets, due either to data unavailability (given the unprecedented nature of the lockdown measures) or delays in their publication. Detailed macroeconomic models typically require long and relatively stable time series to be reliably estimated (Kenny and Morgan, 2011). Given the shortage of relevant data and the urgency of the situation, parsimony therefore represents a key asset in the challenging task of modeling the impact of lockdowns.

There already exists a rapidly growing literature examining the economic effects of Covid-19, with joint analyses of economic and epidemiological dynamics (Eichenbaum et al., 2020) as well as of the possible interconnections between supply and demand shocks originating in the pandemic (Guerrieri et al., 2020) featuring particularly prominently. Our contribution consists in proposing a simple and intuitive framework for the evaluation of the direct and indirect effects of lockdown measures both at the regional and sectoral level using a production-network approach. We employ 32-sector inter-regional Input-Output (IO) tables for Italy provided by the Istituto Regionale per la Programmazione Economica della Toscana (IRPET), and we construct a novel computational simulation model that accounts for the interconnections between productive sectors and allows for a sequential adjustment process in response to shocks to productive capacity (supply shocks) and/or to final demand (demand shocks). We estimate the parameters of the model using a small set of short, sector-level time-series on production

[1] The ACAPS Covid-19 Government Measures Dataset (`https://www.acaps.org/covid-19-government-measures-dataset`) provides a detailed timeline of all measures which were applied.

and turnover from the first Italian lockdown and subsequent re-openings. We show that our estimated model, despite its simplicity and parsimony, is capable of replicating quite closely the dynamics of sectoral and aggregate production in Italy, observed during the first lockdown. In addition, out-of-sample forecasting exercises on the dynamics of industrial production, service turnover, and GDP suggest that the model performs satisfactorily. We subsequently apply the estimated model to an analysis of the effects of the measures implemented in Italy in the fall and winter of 2020, as a response to the second wave of the pandemic. Our numerical simulation results indicate that the overall impact of this second set of milder measures is moderate and concentrated on those sectors directly affected by the closures.

We believe that our framework, despite its simplicity, can provide useful insights on the effects of different specifications of lockdown measures, both at the macroeconomic and, importantly, at the sectoral and regional levels. In addition, the computational parsimony our framework allows one to quickly obtain impact estimates using only a small amount of data. At the present stage of development, our work aims purely at providing a quantitative assessment of the economic effects of lockdown measures, leaving aside any consideration on their efficacy in minimizing the social and economic costs of the epidemic. Nevertheless we believe that a comprehensive assessment of the efficacy of alternative lockdown measures cannot ignore their epidemiological impact, which also feeds back on the need for, as well as the duration and intensity of further social distancing measures.

The paper is structured as follows: Section 2 provides a brief overview of the literature on the economic consequences of Covid-19 and on relevant aspects of IO and production-network modeling. Section 3 describes the model. The procedure used to derive the lockdown shocks is described in section 4 while section 5 discusses the estimation procedure. Section 6 presents numerical simulation runs using the estimated model. Section 7 concludes and briefly discusses the refinements planned in order to address the limitations of the model at the current stage of development. Further technical details about the model, the construction of the shocks, the estimation procedure, as well as a sensitivity analysis are contained in the appendices.

2 Related literature

The outbreak of the Covid-19 pandemic has quickly given rise to a large amount of research works investigating the short-term fallout from the pandemic and evaluating the measures taken to contain it. The macroeconomic literature includes both stand-alone analyses of the economic consequences in models wherein the pandemic is introduced as an exogenous shock, and models that couple economic and epidemiological dynamics to simultaneously simulate the progression of the epidemic and its economic fallout.

As explained in Baldwin and Weder di Mauro (2020), the epidemic is best viewed as simultaneously impacting both the supply and demand sides of the affected economies. For instance, Guerrieri et al. (2020) characterize the epidemic as a 'Keynesian supply shock', showing that, under certain conditions, supply shocks in a multi-sector economy (such as those triggered by national lockdown measures) may have impacts on aggregate demand which even exceed the size of the initial supply shocks themselves. Eichenbaum et al. (2020) combine a standard real-business-cycle type model with a canonical epidemiological SIR model to study the optimality of different containment policies. Similarly, Bethune and Korinek (2020) and Assenza et al. (2020) use economic frameworks based on trade-offs between economic and epidemiological effects, deriving optimal policies in epidemic scenarios. Turning to less canonical approaches, there exist a number of works combining an agent-based approach to both macroeconomic and epidemiological modeling. Delli Gatti and Reissl (2020) present a macroeconomic agent-based model coupled with a network-based SIR model used to analyse the consequences of the first wave of the epidemic for the Lombardy region of Italy. Basurto et al. (2020) perform a similar exercise calibrated to the German economy. Mellacher (2020) also focuses on the German case, building a detailed agent-based model of epidemiological dynamics embedded in a strongly-simplified economic model.

Another growing strand of the literature on the effects of the epidemic focuses on the role of production networks in propagating shocks. For instance, Bodenstein et al. (2020) use a growth model with a simplified production network distinguishing between core and non-core industries to investigate the impact of disruptions to production in the core sectors. Del Rio-Chanona et al. (2020) apply a sectoral perspective to investigate the first order effects (i.e. without considering propagation through feedback effects in production networks) of supply and demand shocks on industries both in terms of output and possible job losses within the US. Making use of the method developed by di Giovanni et al. (2020), Gerschel et al. (2020) analyse the impact of a decline in Chinese productivity on global value chains to quantify the possible impact of the lockdown measures taken in the Hubei province at the beginning of the pandemic. Baqaee and Farhi (2020) present a neoclassical model with a disaggregated productive structure to demonstrate how non-linearities (e.g. arising from input complementarities in production networks) may amplify the effects of negative supply shocks. Pichler et al. (2020) use a computational IO framework with a detailed distinction between essential and non-essential inputs to production to provide estimates of the effects of lockdown measures in the UK and discuss various possible scenarios for re-openings. The agent-based model developed by Poledna et al. (2020a) also includes a detailed production network and has been used to provide possible scenarios for the post-lockdown recovery in Austria (Poledna et al., 2020b). Ferraresi et al. (2020) use an IO-approach to evaluate the varying degrees of participation of the Italian regions in different supply chains, distinguishing between supply chains serving essential and non-essential needs. The authors use this framework to analyze the effects of lockdown measures both in economic and epidemiological terms, by evaluating the potential to mitigate contagion through remote working.

IO models have been widely used in research on disaster analysis (see Koks et al., 2019), a literature which has given rise to a number of distinct approaches. Interesting examples are the 'Inoperability Input Output Model' (Santos, 2006), which aims at quantifying economic losses suffered as a consequence of a demand disturbance based on a standard demand-driven

IO framework, and the 'Non-linear Programming' approach (Oosterhaven and Bouwmeester, 2016), which describes the adjustment of economic actors to a disruptive event (e.g. a stop in production in some sector or region) toward re-establishing the pre-shock level and pattern of transactions. In the literature on static IO models, supply-side shocks (in the sense of shocks to productive capacity) have been analyzed using a number of different approaches. The *hypothetical extraction method*, aims at quantifying the induced reduction in total output when a specific productive sector j is removed from the economy. A generalization of this method instead postulates an *exogenous specification of the output of a subset of sectors*. Variants of the hypothetical extraction method are still used in the literature (Dietzenbacher and Lahr, 2013; Dietzenbacher et al., 2019). The model proposed by Ghosh (1958) expresses (changes in) sectoral gross output as a function of (changes in) their primary inputs, assuming constant output allocation rather than fixed input/technological coefficients as in the traditional Leontief model. However, neither the Ghosh model nor the other methods mentioned above allow for the analysis of shocks to final demand[2] or interactions between demand and supply effects. More broadly, static IO approaches are by definition not capable of depicting the entire process of adjustment to a shock but rather focus purely on final equilibrium positions.

This paper uses a *sequential* IO model to analyze the effects of lockdown measures. Sequential IO modeling originates from the contributions of Romanoff and Levine (1986) and Cole (1988). The focus of Cole (1988) is to explicitly introduce time into IO modeling so as to allow for an analysis of post-shock adjustment processes based on the assumption of lagged responses of expenditures to shocks. Romanoff and Levine (1986) use a similar framework to account for time (e.g., transaction delays, production times and inventories) in order to analyze sequential responses to shocks to both final demand and productive capacity. In our model, lockdown measures trigger supply shocks, which consist in the closure of production sites in (parts of) certain sectors, affecting the availability of labor and hence productive capacity. They may however have repercussions on final demand to the extent that the latter is endogenized and becomes a function of output levels.[3]

3 A sequential input-output model

To illustrate the logic underlying our modeling strategy it is useful to recall the power series approximation of the Leontief inverse and its economic interpretation. The Leontief inverse is given by:

$$(\mathbf{I} - \mathbf{A})^{-1} \cong \mathbf{I} + \mathbf{A} + \mathbf{A}^2 + \mathbf{A}^3 + ... \tag{1}$$

where $\mathbf{A}$ is the matrix of technological coefficients derived from an IO table. The response of a standard Leontief system, expressed in changes of sectoral production in response to a change

[2]Of course, a specular limitation applies to the classic demand-driven IO model.

[3]In principle, our framework also allows for the simultaneous application of demand shocks, e.g. declines in or changes in the composition of consumption expenditure in response to social distancing measures. However in the present work we exclusively focus on the effects of mandated firm closures.

in final demand can be written as:

$$\Delta\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\,\Delta\mathbf{f} \cong (\mathbf{I} + \mathbf{A} + \mathbf{A}^2 + \mathbf{A}^3 + ...)\Delta\mathbf{f} = \Delta\mathbf{f} + \mathbf{A}\Delta\mathbf{f} + \mathbf{A}^2\Delta\mathbf{f} + \mathbf{A}^3\Delta\mathbf{f} + ... \quad (2)$$

where $\mathbf{x}$ is the vector of sectoral outputs and $\mathbf{f}$ is the vector of final demand. This formulation has a straightforward economic interpretation: each successive term in the power series approximation represents the magnitude of the round-by-round impact of a change in final demand on sectoral production. The first term simply states that output adapts to demand levels. The second term captures the first-order/first-round indirect effect: since sectoral output has changed, the demand for inputs also changes, inducing a further adjustment in sectors' production, and so forth. The total effect on gross production eventually converges to the analytical solution of the Leontief model.

While static IO models focus on analyzing the final equilibrium position reached by this process, we are instead interested in analyzing the adaptation to shocks over time and hence depicting the multiplicative process discussed above as a sequential phenomenon. In our model, time is discrete and one period is assumed to represent one week. Sectors hire labor and place orders of intermediate inputs based on *expectations* about demand. Moreover, they hold inventories of intermediate inputs and target a stock of inventories depending on their long-term sales expectations and a sector-specific planning horizon. Their production may be constrained by the availability of labor or other inputs needed for production. As a consequence, the system adapts gradually to (possibly overlapping and heterogeneous) shocks to supply (i.e. productive capacity) and/or final demand.

This makes our framework well-suited to an analysis of the effects of lockdown measures, as the restrictions imposed in Italy were heterogeneous across productive sectors and were both implemented and released in different stages. Lockdown measures, which we depict as shocks affecting the sectoral availability of labor, constrain the output that can be allocated to final demand and to other sectors, affecting demand for non-labor inputs and, possibly, creating bottlenecks in the production of downstream sectors.

Inventories of inputs represent a sectoral absorptive capacity that may delay, dampen, or even prevent the transmission of a supply shock from an affected sector (see Scheinkman and Woodford, 1994; Contreras and Fagiolo, 2014, for models embodying a similar idea). Since every sector holds inventories required for production over a certain future time horizon, it may take some time before a shock hitting an upstream sector constrains the production of downstream ones, and it might well be the case that a transitory shock does not propagate at all, e.g. if sectors hold sufficient inventories to face temporary shortages of inputs. The introduction of inventories in the analysis is also a requirement for obtaining a non-trivial impact of heterogeneous shocks hitting different sectors at the same time.[4]

[4]Without inventories - and because of the lack of input substitutability in the Leontief production function - the impact on downstream sectors' production would simply be proportional to the largest shock in percentage terms. This would leave no role for heterogeneous supply shocks as the final effect would always end up being proportional to the largest shock.

The next sections describe the main features of the model. Additional details are presented in appendices A and B.

3.1 Notation

The description of the model is based on the following notation. Italic letters are used for variables taking scalar values. Bold letters are used to indicate vectors. Matrices are indicated by bold capital letters. The subscripts $_t$ and $_j$ are employed to define a generic production period and a generic sector respectively. We indicate with a bar over a variable, e.g. $\overline{x}$, the (constant) value of the variable taken from the empirical input-output table that we employ. Superscripts ^{e} and ^{d} indicate the expected and demanded values of a variable respectively. When dealing with inputs, which can be accumulated as inventory, the ^{stock} superscript is employed to refer to stock values, rather than to flows. Lastly, when discussing final demand components, we use the superscripts *exo* and *end* to distinguish between exogenous and endogenous variables. Expectation superscripts can be further specified by ^{short} and ^{long} to specify whether we refer to short or long-term expectations.

3.2 Production and input-output relations

The production structure of our model is very similar to a standard IO model, but we add a spatial dimension distinguishing among regions within the national economy. Each sector in each region produces a homogeneous good with a constant returns to scale technology where all inputs are used in fixed proportions.[5] The good is then used both to satisfy final demand and the demand for inputs from other sectors. All prices are fixed. Following standard input-output notation, we indicate by $\mathbf{Z}$ the matrix of inter-industry exchanges which includes the above-mentioned sectoral and a geographical dimensions:

$$\underset{nm \times nm}{\mathbf{Z}} = \begin{array}{c} \\ \mathbf{z_1^R} \\ \vdots \\ \mathbf{z_j^R} \\ \vdots \\ \mathbf{z_{nm}^R} \end{array} \begin{array}{c} \begin{array}{ccccc} \mathbf{z_1^C} & & \mathbf{z_j^C} & & \mathbf{z_{nm}^C} \end{array} \\ \begin{pmatrix} z_{1,1} & \cdots & z_{1,j} & \cdots & z_{1,nm} \\ \vdots & \ddots & \vdots & & \vdots \\ z_{j,1} & \cdots & z_{j,j} & \cdots & z_{j,nm} \\ \vdots & & \vdots & \ddots & \vdots \\ z_{nm,1} & \cdots & z_{nm,j} & \cdots & z_{nm,nm} \end{pmatrix} \end{array} \tag{3}$$

$\mathbf{Z}$ is a square $nm \times nm$ matrix where n is the number of productive activities and m is the number of regions. Each row and column of $\mathbf{Z}$ refers to a specific productive sector located *within a specific region*. For the sake of simplicity, we will generically refer to 'sectors' in what follows and, unless stated otherwise, we shall consider the same productive activity located in

[5] Although we are aware that some degree of substitutability exists in the real world, we believe this relatively restrictive assumption to be the most suitable to describe the short-run perspective of the lockdowns and to avoid making equally arbitrary assumptions about the degree of substitutability between intermediate inputs.

two different regions as two different sectors. Each entry $z_{i,j}$ records the purchases by sector j of sector i's products. As usual, the columns of $\mathbf{Z}$, indicated by column-vectors $\mathbf{z^C}$ can be interpreted as the inputs required for the production of each sector, i.e. its 'production recipe', whereas the rows, indicated by row-vectors $\mathbf{z^R}$ show how each sector's output is allocated to the others.

We collect all the components of final demand, both domestic and foreign (i.e. exports), into a unique column vector $\mathbf{f}$ of length nm, indicating total final demand going to our nm sectors. Given standard input-output accounting, each sector's gross output can be computed by adding its final demand to the sum across the elements of the corresponding row of $\mathbf{Z}$. The matrix $\mathbf{A}$ of technical coefficients can be computed by dividing sectoral purchases of inputs as extracted from the input-output table, i.e. the columns extracted from $\overline{\mathbf{Z}}$, by the sectoral outputs as extracted from the input-output table, $\overline{\mathbf{x}}$.

$$\underset{nm \times nm}{\mathbf{A}} = \begin{pmatrix} a_{1,1} & \cdots & a_{1,j} & \cdots & a_{1,nm} \\ \vdots & \ddots & \vdots & & \vdots \\ a_{j,1} & \cdots & a_{j,j} & \cdots & a_{j,nm} \\ \vdots & & \vdots & \ddots & \vdots \\ a_{nm,1} & \cdots & a_{nm,j} & \cdots & a_{nm,nm} \end{pmatrix} = \begin{pmatrix} \frac{\overline{z}_{1,1}}{\overline{x}_1} & \cdots & \frac{\overline{z}_{1,j}}{\overline{x}_j} & \cdots & \frac{\overline{z}_{1,nm}}{\overline{x}_{nm}} \\ \vdots & \ddots & \vdots & & \vdots \\ \frac{\overline{z}_{j,1}}{\overline{x}_1} & \cdots & \frac{\overline{z}_{j,j}}{\overline{x}_j} & \cdots & \frac{\overline{z}_{j,nm}}{\overline{x}_{nm}} \\ \vdots & & \vdots & \ddots & \vdots \\ \frac{\overline{z}_{nm,1}}{\overline{x}_1} & \cdots & \frac{\overline{z}_{nm,j}}{\overline{x}_j} & \cdots & \frac{\overline{z}_{nm,nm}}{\overline{x}_{nm}} \end{pmatrix} \tag{4}$$

In addition to $\mathbf{Z}$, which records transaction flows between domestic sectors, we also define a matrix $\mathbf{Z^{stock}}$ that features the stock of input inventories accumulated by sectors over time. We aggregate the rest of the world into one large region rather than treating a subset of foreign countries individually. This rest-of-the-world region delivers a single homogeneous good to the domestic sectors, which the latter use for production, and purchases goods from domestic producers in the form of exports which are a part of final demand. We therefore define as $\mathbf{m}$ a vector of imported inputs collecting the flow of goods that productive sectors purchase from abroad in order to produce their output, and a vector $\mathbf{m^{stock}}$ indicating the corresponding stocks of imported goods. As for domestic inputs, we can compute a vector of technical coefficients for imported factors by dividing the elements of $\overline{\mathbf{m}}$ by the corresponding sector's initial gross output $\overline{\mathbf{x}}$.

$$\mathbf{a^m} = \overline{\mathbf{m}} \oslash \overline{\mathbf{x}} = \begin{pmatrix} \frac{\overline{m}_1}{\overline{x}_1} \\ \vdots \\ \frac{\overline{m}_j}{\overline{x}_j} \\ \vdots \\ \frac{\overline{m}_n m}{\overline{x}_{nm}} \end{pmatrix} \tag{5}$$

where $\oslash$ indicates element-wise division. Finally, we define by $\mathbf{l}$ an $nm \times 1$ vector tracking the quantity of workers available to each sector for production. The initial quantity of labor available to each sector of the economy within each region, indicated by vector $\overline{\mathbf{l}}$, is a numéraire and is set equal to 100 for simplicity. Based on this assumption, we can define a vector of technical coefficients for labor $\mathbf{a^l}$ by dividing $\bar{\mathbf{l}}$ by the vector of sectors' initial gross output $\overline{\mathbf{x}}$:

$$\mathbf{a^l} = \bar{\mathbf{l}} \oslash \overline{\mathbf{x}} = \begin{pmatrix} \frac{\bar{l}}{\overline{x}_1} \\ \vdots \\ \frac{\bar{l}}{\overline{x}_j} \\ \vdots \\ \frac{\bar{l}}{\overline{x}_{nm}} \end{pmatrix} \tag{6}$$

In the model estimation and simulation analyses that we carry out in sections 5 and 6, we employ the 2016 IRPET (Istituto Regionale per la Programmazione Economica della Toscana) inter-regional IO tables (Paniccià and Rosignoli, 2018), providing input-output data for Italy at the regional level (comprising all 20 Italian regions) for 32 sectors (meaning that in our analysis $n = 32$ and $m = 20$). The 2016 table is the most recent inter-regional IO table available for Italy at the time of writing. It is converted from annual to weekly frequency by dividing all entries by 53, the number of calendar weeks in 2020. An overview of the structure of our IO tables and a list of all sectors, including the abbreviations of sector names we use in the figures shown below, can be found in appendix A.

Production is carried out by employing labor along with stocks of inputs inherited from the past, according to a Leontief production function. This means that the maximum output which each sector can produce is given by:

$$\mathbf{x_t^{max}} = min\left(\mathbf{l_t} \oslash \mathbf{a^l}, colmin\left(\mathbf{Z_{t-1}^{stock}} \oslash \mathbf{A}\right), \mathbf{m_{t-1}^{stock}} \oslash \mathbf{a^m}\right) \tag{7}$$

Notice that the above production function excludes the possibility of substitution between products of different sectors, including between products of the *same sectors* from *different regions*. While this assumption may appear quite restrictive, relaxing it would imply making a large number of arbitrary assumptions about substitutability between inputs from different regions, as well as the speed with which such substitutions can take place. In our view, our approach represents a valid approximation in a short-term analysis, as it will likely take time to find new suppliers for a good if an input coming from some particular region suddenly becomes unavailable (cf. Baqaee and Farhi, 2020).

The demand for goods received by each sector, recorded in $\mathbf{x^d}$, is composed of final demand ($\mathbf{f}$, described below) and demand for inputs received from other productive sectors, $\mathbf{Z^d}$. The amount of inputs each sector demands, as well as its available labor force (in the absence of lockdown shocks) are determined by its demand expectations. We distinguish between two concepts of expected demand, namely short-term expectations and long-term expectations. Short-term expectations, $\mathbf{x^{e,short}}$ are the demand which sectors expect to receive in the current period. In the absence of shocks to labor supply, they determine both the amount of additional labor (if any), which sectors wish to hire (as described in section 4), and the amount of inputs they demand from other sectors to replace those expected to be used up in current period production. We assume that the short-term expectations of each sector are 'naive' in that they equal the respective demand received in the previous period, but we additionally assume that, when a lockdown is imposed (or lifted), sectors are aware of the consequent reduction (or increase) in the productive capacity of their customers and adjust their short-term sales expectations accordingly.

Long-term expectations instead drive a target-level of input inventories that sectors wish to hold to be able to maintain production at a level expected in the longer term over a sector-specific planning horizon. To keep things simple, long-term expectations, $\mathbf{x^{e,long}}$, are a simple average of past demand over a total of $\beta \in \mathbb{Z}^+$ periods, where β is uniform across sectors. They determine a sector-specific target-level of inventories given by $\gamma_j \in \mathbb{Z}^+$ times the amount of intermediate inputs needed to produce $\mathbf{x^{e,long}}$.[6] Sectors adjust their inventories to this target level at a speed given by $\frac{1}{\gamma_j}$. A sector's total order of inputs (both from other domestic sectors and from abroad in the form of imports) is given by the sum of input demand derived from short-term expectations and input demand derived from long-term expectations. A detailed description of expectations formation and the determination of input orders is provided in appendix B.

As indicated above, production in t is carried out using stocks of material inputs inherited from $t-1$. Together with currently available labor, which in the absence of labor shocks is determined by $\mathbf{x^{e,short}}$ (see also section 4), the maximum output currently producible by each sector, $\mathbf{x_t^{max}}$, is determined by equation (7). Actual gross output is given by the minimum between $\mathbf{x_t^{max}}$ and total demand for each sector's products $\mathbf{x_t^d}$.

$$\mathbf{x_t} = min\left(\mathbf{x_t^{max}}, \mathbf{x_t^d}\right) \tag{8}$$

It follows that gross output may be lower than demand if a constraint in labor or in other inputs is binding.[7] In this case, we assume the amounts delivered by sector j to its downstream sectors and to final demand to be reduced by the same fraction[8], given by $\frac{x_{j,t}}{x_{j,t}^d}$.

[6] Note that this implies the assumption of all intermediate inputs, including *services*, being equally storable. While this may appear unrealistic, the assumption of storable inputs is essential to avoid that any shock to the productive capacity of any sector is immediately and entirely transmitted to all its downstream sectors. Given the fixed proportions hypothesis of the Leontief technology and the very dense structure of Input Output networks, a complete closure of a sector which brings its productive capacity close to 0, would then be sufficient to trigger an immediate collapse of the entire economy, no matter how small or arguably inessential the sector originally hit was for the rest of the economy. In our model, input inventories provide sectors with an absorptive capacity which prevents this from happening. We deem this solution preferable to the alternative of making a large range of arbitrary assumptions regarding which intermediate inputs are essential or inessential to the production of every individual sector.

[7] The stock of domestic and imported inputs available to each sector, recorded in the matrix $\mathbf{Z^{stock}}$ and the vector $\mathbf{m^{stock}}$ respectively, are updated by subtracting the amount consumed in the production process and by adding the ordered inputs received at the end of the period. Differently from domestic inputs, we assume there are no supply constraints arising from the rest of the world in the sense that demand for imported inputs is always satisfied.

[8] This assumption is coherent with the constancy of allocation parameters in the Ghosh model.

3.3 Final demand

Final demand is the sum of an endogenous component, $\mathbf{f_t^{end}}$, and of an exogenous one $\mathbf{f_t^{exo}}$ (see also figure A1 in appendix A).

$$\mathbf{f_t} = \mathbf{f_t^{end}} + \mathbf{f_t^{exo}} \tag{9}$$

Endogenous final demand is determined as the sum of an endogenous component of consumption, $\mathbf{c_t^{end}}$, and investment, $\mathbf{i_t}$.

$$\mathbf{f_t^{end}} = \mathbf{c_t^{end}} + \mathbf{i_t} \tag{10}$$

Endogenous consumption is determined by

$$\mathbf{c_t^{end}} = \mathbf{H}\ \mathbf{x_{t-1}} \tag{11}$$

where $\mathbf{H}$ is a 'bridge matrix' that links the vector of gross output $\mathbf{x_{t-1}}$ to the part of final consumption induced by the compensation of employees, which in the case of our model is the only endogenous component of consumption.[9] The remaining consumption demand is exogenous and constant and reads:

$$\mathbf{c^{exo}} = \overline{\mathbf{c}} - \mathbf{H}\ \overline{\mathbf{x}} \tag{12}$$

This ensures that if $\mathbf{x_t} = \overline{\mathbf{x}}$, then $\mathbf{c_t^{end}} + \mathbf{c^{exo}} = \overline{\mathbf{c}}$. Differently from consumption, investment is fully endogenous in the model and it is a function of the deviation of total gross output $\mathbf{x_{t-1}}$ from its baseline level $\overline{\mathbf{x}}$. More precisely, denote by $\mathbf{i_t}$ the vector of final demand for investment purposes received by each sector. Investment demand is determined according to:

$$\mathbf{i_t} = \overline{\mathbf{i}} + \alpha\ \frac{\overline{\mathbf{i}}}{\iota'\overline{\mathbf{i}}}\,(\iota'\mathbf{x_{t-1}} - \iota'\overline{\mathbf{x}}) \tag{13}$$

where $\overline{\mathbf{i}}$ is the vector of investment demand taken from the IO table, α is a parameter determining the magnitude of the reaction of investment demand to changes in output and ι is a sum-vector with all elements equal to one. Changes in aggregate investment demand, given by

[9] The $\mathbf{H}$ matrix is derived empirically by researchers at IRPET following an approach proposed by Miyazawa (1976) and summarises a number of steps: gross labor compensation per unit of output is estimated for each sector (primary distribution), and this wage income is then distributed into distinct income groups (secondary distribution) and converted into disposable incomes. These disposable incomes are then multiplied by average consumption propensities for the respective income groups as well as a matrix distributing the consumption demand of each income group thus generated to the sectors and regions in the model. These operations result in the matrix $\mathbf{H}$ which, when multiplied by the vector of outputs $\mathbf{x}$ gives rise to a vector representing the consumption demand received by each sector which is induced by the compensation of employees resulting from the production of output.

$\alpha \; (\iota'\mathbf{x_{t-1}} - \iota'\overline{\mathbf{x}})$ are hence distributed among sectors according to the sectoral shares in investment demand taken from the IO table. This formulation ensures that when $\mathbf{x_t} = \overline{\mathbf{x}}$, $\mathbf{i_t} = \overline{\mathbf{i}}$.

The overall level of exogenous *domestic* final demand (which is constant) can be calculated as $\overline{\mathbf{f^{domestic}}} - \mathbf{H}\;\overline{\mathbf{x}} - \overline{\mathbf{i}}$, where, again, the bar over a variable denotes values taken from the empirical IO table. To obtain *total* exogenous demand, we add a foreign component, given by $\overline{\mathbf{exp}}\; exp_t$, where $\overline{\mathbf{exp}}$ is export demand taken from the IO table and $0 \leq exp_t \leq 1$ is a *time-varying* index of export demand. Given that Italy is small compared to the world economy and because of the assumption of constant prices, it is reasonable to consider Italian exports as exogenous to the model. We therefore use available monthly exports data for Italy in order to set the values of exp_t.

3.4 Sequence of events

In each period the following sequence of events and decisions takes place in our model.

1. Shocks to available labor and/or final demand are determined.
2. Short and long-term demand expectations are formed within each sector.
3. Feasible production is determined given the amount of workers and other productive factors available. Workers can be hired if needed, provided that there is no external constraint limiting the availability of workers.
4. Orders of domestic and imported inputs are placed based on short and long term expectations.
5. Total demand for each sector is computed and production takes place.
6. Orders are delivered and inputs consumed in the production process are replenished with the delivered goods, determining the productive capacity in terms of available inputs for the next period.

The period then ends and a new one begins.

4 Lockdown shocks

We use the model outlined in the previous sections to evaluate the impact of lockdown measures introduced in Italy in 2020. We assume that a lockdown affects the productive capacity of sectors by reducing the amount of workers available. This reduction in capacity is likely to also trigger decreases in actual output, in which case it will also endogenously feed back on final demand (see equations (11) and (13)). For the sake of simplicity, we assume that there are no labor force constraints on production in addition to those implied by lockdowns. In particular, we posit that unless there is a lockdown in place for a given sector, that sector is free to temporarily hire additional workers beyond $\bar{l}$ based on its demand expectations, if they are needed to increase productive capacity in the current period. We also assume that such additional hiring is done only for one period. Accordingly, all sectors that are not in lockdown begin every period with a labor force equal to $\bar{l}$.

Since the initial labor force $\bar{l}$ of each sector is normalized to 100, shocks induced by a lockdown are defined as percentage deviations from that baseline level. For example, a 30.5% negative shock for a sector implies an absolute reduction of 30.5 labor units in the sector when the lockdown is implemented. Employment of the sector is then constant at 69.5 units for the duration of the lockdown and returns to 100 when the lockdown is lifted.

More formally, let $\mathbf{l_t}$ denote the quantity of labor available to each sector of the economy in each Italian region at period t and $\mathbf{shock_t}$ the shock to their labor supply occurring in that period, expressed as a percentage deviation from $\bar{\mathbf{l}}$. We then define a vector v of length nm the element of which corresponding to sector j will be equal to 1 if, having considered the possible application of a shock in the current period, labor is below the initial level $\bar{l}$, that is: $v_j = 1$ if $l_{j,t-1} + \bar{l}\frac{shock_{j,t}}{100} < \bar{l}$, $v_j = 0$ otherwise. $\mathbf{l_t}$ will then be given by:

$$\mathbf{l_t} = v \otimes \left(\mathbf{l_{t-1}} + \bar{\mathbf{l}} \otimes \frac{\mathbf{shock_t}}{100} \right) + (1 - v) \otimes max\left(\bar{\mathbf{l}}, \mathbf{x_t^{e,short}} \otimes \mathbf{a^l} \right) \tag{14}$$

where $\otimes$ indicates element-wise multiplication.

To evaluate the magnitude of the labor shocks associated with the lockdown measures implemented in Italy we construct a measure of the share of labor input, for each of our 32 sectors in the 20 Italian regions, which becomes unavailable as a consequence of the government-mandated closures of specific (sub-)sectors. For this purpose, we consult the series of decrees issued by the Italian prime minister during the first wave of the pandemic, which determine the timing of closures and subsequent re-openings of productive sectors in terms of the ATECO classification of economic activities at the 5 digit level of disaggregation.[10]

Combining this information with data on employees at the regional and 5 digit ATECO sectoral level (a more disaggregated sectoral classification than the one used in our model) we are able, as also discussed in appendix C, to derive the share of the workforce in each of the 32 sectors contained in our model which is affected by a given decree. We assume that during lockdown, workers whose task cannot be performed from home become unavailable to their sector whilst those who can work from home are still available as labor input. We therefore construct an index of tele-workability (described in detail in appendix C). This index measures the share of workers in each sector who *cannot* work from home. Multiplying this by the respective shares of workers affected by the decrees we obtain a vector of labor shocks specified both at the regional and sectoral level for each simulation period, giving the share of labor input which is unavailable due to lockdown measures at any point during the simulation.

[10] The ATECO classification is the Italian national version of the statistical classification of economic activities in the European Community (NACE Rev. 2). It is identical to NACE Rev. 2 up to the 4 digit level but also includes a 5 and 6 digit level of disaggregation.

As a final step, we multiply the labor shocks (expressed as percentage variations) by the vector $\bar{\mathbf{l}}$ so as to obtain the vectors of labor shocks expressed in absolute values for each point in time, $\mathbf{shock_t}$. These shocks are then imposed on the model in the periods corresponding to the calendar weeks in which the respective decrees were implemented.
The same procedure is employed to construct the labor shocks applied during the second wave of the pandemic in fall and winter 2020. In this case, the Italian government adopted a different strategy, assigning different colors - yellow, orange and red - to individual regions according to the severity of the epidemic within their borders. As a region moves from yellow to orange and red, the measures adopted become tighter, implying the closure of a higher number of sub-sectors (and vice-versa in the case of a shift in the opposite direction).
Table 1 presents an overview of the lockdown measures taken during the first wave as far as closures of productive sectors are concerned. As a full list of all ATECO codes together with an open/closed indicator would be far too lengthy[11], the table gives a broad characterization of the measures taken at each stage.

Table 1: First wave lockdown measures

Calendar week	**Measures**
11	Closure of hospitality services, non-essential retail, gyms, hairdressers etc.
13	Wide-ranging closures in 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

Table 2 provides a similar summary for the measures taken during the second wave. As above, the descriptions are not exhaustive but rather aimed at giving a broad characterization of the closures taking place in the different zones. In addition, table C1 in appendix C provides the list of regions along with their classifications from calendar week 46 onward.

Table 2: Second wave lockdown measures

Zone	**Measures**
Yellow	Closure of gyms, museums and other leisure facilities
Orange	Yellow + closure of restaurants, bars etc.
Red	Orange + closure of non-essential retail & personal services

5 Model Estimation

Recall that in making its orders for input inventory accumulation based on long-term expectation, sector j uses the sector-specific parameter $\gamma_j \in \mathbb{Z}^+$ to determine the amount of inputs (in terms of periods of future production) it wishes to hold (see section 3.2 and equation (24) in appendix B). To reduce the dimensionality of the parameter space in the estimation procedure

[11]Two spreadsheets containing these data for both the first and second Italian lockdown are available at `https://github.com/SReissl/CovidIO`.

described below, we constrain γ_j to be uniform across all sectors which are part of the manufacturing industry (sectors 3 to 16). In addition, we also assume that all service sectors (sectors 19 to 32) have a uniform γ_j. This means that there are 6 distinct γ_j inventory parameters to be estimated; one each for agriculture, mining, manufacturing, electricity generation, construction and services. The remaining parameters are α (see equation (13)) which gives the degree to which investment reacts to changes in production, and β (see section 3.2 and equation (23) in appendix B), which identifies the number of past observations included in the computation of long-term demand expectations, meaning that we have to estimate a total of 8 parameters.

In order to determine the values of these parameters we use an algorithm inspired by the method of simulated moments (MSM, see Gilli and Winker, 2003; Adda and Cooper, 2003), which has extensively been applied in various research fields (Duffie and Singleton, 1993; Franke and Westerhoff, 2012; Schmitt, 2020; Guerini et al., 2020). The objective of this method is to find a vector of parameters such that the (weighted) distance between a set of chosen moments or statistics calculated from empirical and simulated data is minimized. MSM is typically used in order to find the parameter combination at which a given model is best able to reproduce the general characteristics of one or more (possibly filtered) empirical time series in terms of their moments, such as the standard deviation or auto- and cross-correlation structures. Moments are typically assumed to reflect the cyclical features of the observed times series. Here we employ a slightly different logic. Indeed, we do not aim at replicating the general cyclical properties of a time series, but rather at finding the parameter combination under which our model is best able to reproduce the dynamics observed during a specific and unprecedented historical episode, namely the strict lockdown measures implemented across Italy during the first wave of the Covid-19 pandemic.

To achieve the above objective we make use of the following empirical data, obtained from the Italian National Statistical Institute (ISTAT):

- Monthly indexes of production for 16 of our 32 sectors (namely sectors 3-16 and 18) from *January to August* 2020.
- Quarterly indexes of *revenue* for 4 of our 32 sectors (namely sectors 19-22) for *Q1 and Q2* 2020.

These data[12] allow us to calculate production/turnover indexes over the period considered for 20 out of the 32 sectors depicted in the model (see also appendix D for further details).[13] These empirical time series are then used to calculate the following 40 statistics, which are employed as ‘moments’ in the estimation procedure:

1. The maximum decline relative to January 2020 (=100) in each of the monthly production indexes up to August 2020 (=16 statistics).
2. The changes in the 4 indexes for revenue in the service sectors relative to Q4 2019 (=100) in Q1 and Q2 2020 (=8 statistics).

[12]All series employed are seasonally adjusted and calendar effects are removed.
[13]Only partial or no empirical data are available for the remaining 12 sectors contained in our model.

3. 16 statistics calculated by applying the *GSL-div* algorithm developed by Lamperti (2018b), giving a measure of the similarity of the shape of two time-series (see appendix D), to the 16 empirical time series for industrial production and their simulated counterparts.

This choice of statistics allows us to closely evaluate the models' ability to reproduce the observed dynamics during the first lockdown. Items 1 and 2 above capture the depth of the lockdown- and pandemic-induced downturn for each sector for which data are available. Item 3 instead provides a synthetic quantitative assessment of the overall similarity between the empirical and simulated time series for monthly production, hence evaluating the model's ability to match the speed of decline and the partial post-lockdown recovery.[14]
Given the extreme, unprecedented and transitory character of the events our model aims to describe, the estimation algorithm should be purely interpreted as a tool to identify the parameter combination under which the model is best able to reproduce the observed sectoral dynamics over a relatively short and specific historical phase. As the nature of the chosen statistics and the brevity of the used time series makes clear, it will not be possible to apply any of the existing asymptotic theory for MSM to our procedure, as the former assumes that the chosen moments are a function of time (this is not the case for statistics 1 and 2) and that sufficiently long time-series are available, which clashes with our objective of explaining a particular and brief historical episode rather than the general characteristics of a set of long time-series. We therefore refrain from making any claims about the consistency or efficiency of the obtained parameter estimates but maintain that our approach makes the best possible use of the available data given the specific nature of the modelled phenomena. Although the brevity of the times series employed implies the limitations just discussed, having an estimation procedure and a parsimonious model that can approximate the effects of lockdown measures using very few data points is a significant asset to inform the decisions of policy makers, which must be taken promptly. Obviously, matching the data employed for the estimation is not sufficient. Below we therefore also carry out an out-of-sample exercise to examine the model's ability to reproduce data-points which were not included in the estimation. Formally, the estimation procedure has the goal of minimizing the loss function:

$$\mathcal{L}(\Theta) = \ell(\Theta)'\mathbf{W}\ell(\Theta), \tag{15}$$

where Θ is a vector of parameters. ℓ is an error vector which for each parameter combination Θ contains the following elements:

- Elements 1-16: the difference between the empirical and simulated maximum declines in the 16 production indexes for which empirical data are available,

[14] GSL-div also takes into account the depth of the downturn, in the sense that, if there are two otherwise identical simulated time-series, the one which more closely matches the empirical observation representing the maximum decline will be judged to be more similar to the empirical one. More generally, however, the GSL-div measure is determined by the *overall* similarity between two time-series and hence only partly depends on whether or not the maximum decline is matched.

- Elements 17-24: the difference between the empirical and simulated changes in the service sector revenue indexes during Q1 and Q2 2020,
- Elements 25-40: the $GSL - div$ measures obtained from comparing the simulated industrial production series to their simulated counterparts.

$\mathbf{W}$ is a weighting matrix which in our case is given by a diagonal matrix with each entry on the diagonal giving the share of the sector to which the corresponding element of ℓ refers in total gross output as given by the IO table. This pre-specified matrix is used in order to give a higher weight to statistics derived from larger sectors in the estimation (see Cochrane, 2005, as well as appendix D for a discussion). We aim to find:

$$\Theta^* = \arg\min_{\Theta} \mathcal{L}(\Theta). \tag{16}$$

Using latin hypercube sampling (Salle and Yildizoglu, 2014), we obtain a total of 200000 sample points (i.e. vectors of parameter values) from the parameter space detailed in appendix D. Exploring such a large set of combinations is possible thanks to the parsimony of the model and to its deterministic character. The model is then simulated using each of these parameter combinations and, for each of them, the resulting error vector is calculated. Since the $GSL - div$ algorithm allows for different degrees of precision but the computational burden of running it increases exponentially with its precision, we follow a two step procedure. First, we employ a coarser specification of the $GSL - div$ to select, from the 200000 original parameter combinations, a small subset for which the value of the loss function is below an arbitrary threshold. After this first selection, we subject the surviving combinations to a further round of estimation in which we double the $GSL - div$ precision parameter relative to the first step, enabling it to distinguish more finely between simulated time series which already look fairly similar to the empirical ones.

Table 3 gives the parameter values of the winning combination of this second round estimation. Although remaining below the upper bound of the range, β takes a high value, suggesting that, in order to match the lockdown-induced downturn and the ensuing recovery, long-term expectations must be fairly stable and, differently from the naive short-term expectations, not react strongly to transitory changes in sales.[15] The inventory parameters take diverse values although all of them, except for γ_5, imply a fairly long planning horizon and a low speed of inventory adjustment. Tables 4 and 5 provide an overview of the fit by comparing the empirical and simulated characteristics of the downturn.

[15] Such a high value can be interpreted as the result of sectors assigning a transitory character to the lockdown, leading them to expect that their output will return relatively quickly toward the previous level after the measures are lifted. For many sectors included in our estimation this belief appears well-grounded, as is confirmed by the plots showing empirical monthly industrial production in figure 1.

Table 3: Parameter values

Symbol	Description	Value
α	Investment adjustment parameter	0.02138
β	Observations used for long-term expectation	51
γ_1	Desired inventories agriculture	16
γ_2	Desired inventories mining	23
γ_3	Desired inventories manufacturing	18
γ_4	Desired inventories electricity	19
γ_5	Desired inventories construction	5
γ_6	Desired inventories services	14

Table 4 shows the empirical and simulated maximum declines (as compared to Jan 2020 and the baseline taken from the IO table respectively) in the monthly sectoral production series. Table 5 gives the empirical and simulated changes (relative to Q4 2019 and the baseline taken from the IO table respectively) in the service sector revenue indexes. It can be seen that, despite its parsimony, the model does a surprisingly good job at reproducing the empirically observed declines in sectoral output.

Table 4: Empirical and simulated maximum declines in monthly production series in %

Label	Weight	Empirical	Simulated
Mining And Quarrying	0.45	-25.88	-44.13
Food, Beverages And Tobacco	7.73	-6.34	-26.56
Textiles, Wearing Apparel And Leather	4.63	-70.16	-72.14
Wood And Products Of Wood And Cork	0.82	-61.03	-48.62
Paper & Paper Products, Printing & Rep. Of Rec. Media	1.93	-17.66	-34.78
Coke And Refined Petroleum Products	2.01	-19.70	-26.62
Chemicals And Pharmaceutical Products	4.27	-12.67	-31.00
Rubber And Plastic Products	2.39	-46.59	-49.32
Other Non-Metallic Mineral Products	1.68	-74.73	-70.65
Basic Metals, Fabricated Metal Products	7.46	-52.46	-73.89
Computer, Electronic And Optical Products	1.23	-38.14	-43.73
Electrical Equipment	2.24	-50.71	-42.34
Machinery And Equipment N.E.C.	6.60	-52.21	-56.88
Transport Equipment	5.06	-74.22	-73.86
Manufacturing N.E.C, Repair & Inst. Of Mach. & Equip.	3.49	-60.21	-42.08
Construction	10.52	-70.84	-53.20

Table 5: Empirical and simulated changes in quarterly service sector revenue in %

Label	Weight	Empirical	Simulated
Q1 Wholesale & Retail Trade; Repair Of Motor Vehicles	19.12	-5.81	-5.87
Q2 Wholesale & Retail Trade; Repair Of Motor Vehicles	19.12	-19.49	-21.55
Q1 Transportation & Storage	10.75	-5.89	-2.65
Q2 Transportation & Storage	10.75	-31.22	-21.21
Q1 Accommodation & Food Services	6.21	-23.97	-14.37
Q2 Accommodation & Food Services	6.21	-71.53	-35.15
Q1 Publishing, Motion Picture, Video, Sound & Broadcasting	1.41	-1.00	-2.15
Q2 Publishing, Motion Picture, Video, Sound & Broadcasting	1.41	-8.26	-17.07

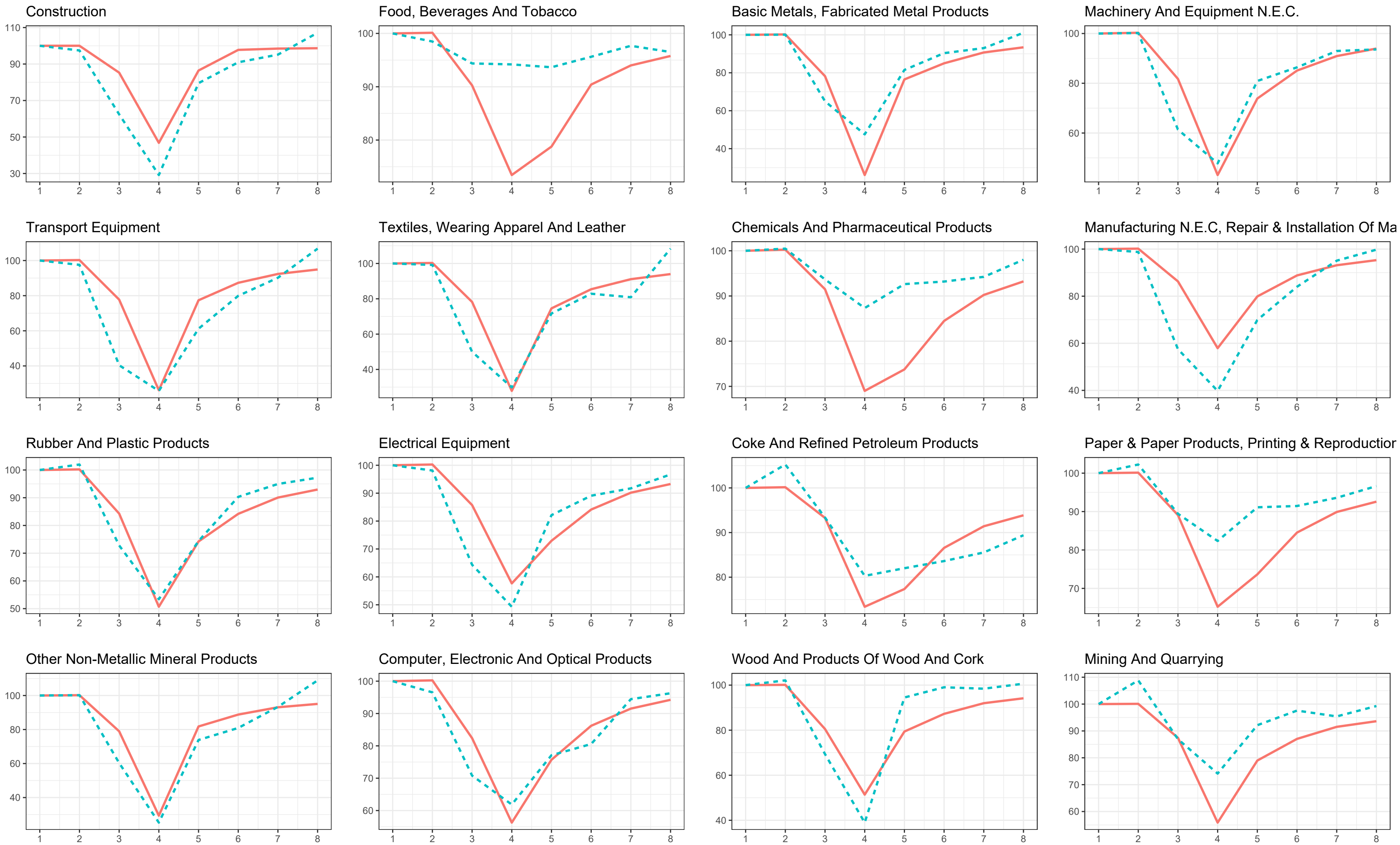

Figure 1: Empirical (dashed) and simulated (solid) monthly production

The good performance of the model is also revealed by figure 1, which plots the empirical and simulated monthly series for industrial production, showing that in most cases, the model is able to quite closely reproduce not only the downturn in production but also the subsequent recovery. The same figure, however, also shows instances in which our model fails to reproduce the observed dynamics even approximately. This is because the model, due to its simplicity, is unable to capture some specific characteristics of epidemic and lockdown-induced downturns. Mandatory and voluntary limitations to consumers' mobility likely prevented or discouraged the consumption of certain types of goods and services. For instance, considerable parts of the Accommodation & Food Service sector in Italy, especially hotels, were in fact not closed by decree during the first lockdown. Nevertheless, limitations to mobility caused a large drop in the demand for these services, something which cannot be reproduced by our model. As a result, empirical revenues for this sector dropped much more than they do in the simulated model. A reverse effect is likely to be at work in the Food, Beverage & Tobacco sector, which was far less affected as compared to other sectors, since consumers may have shifted some of their spending toward this sector over the course of the lockdown. Finally, given the pandemic situation, parts of the Chemical & Pharmaceutical sector likely experienced a positive shock in final demand which could explain the absence of a severe downturn as predicted by the model. Overall, figure 1 indicates a high correlation between the outputs of different sectors both in the empirical and simulated data. This is indeed the case, with the correlation being equal to 0.87 in the empirical data and 0.93 in the corresponding simulated industrial production series.

6 Evaluating the impact of lockdowns in Italy

In the present section, we utilize simulation runs of our estimated model to evaluate the impacts of the first and second set of lockdown measures implemented in Italy during 2020. We begin by analyzing the impact of the first lockdown and subsequently assess the additional effects generated by the second set of lockdown measures.

6.1 First lockdown

To isolate the economic consequences of the first national lockdown, we analyze the annualized decline in production and GDP under the assumption that the lockdown implemented in March 2020 was the only one (i.e. as if there was no second wave lockdown from the beginning of November onward). The annualized decline, whether of a sector's/region's gross output or of GDP, is calculated relative to the respective figure taken from the IO table. For a sector j, the decline is thus given by:

$$\frac{\sum_{t=1}^{53} x_t^j}{53\overline{x^j}}, \tag{17}$$

and equivalently for regions and for aggregate GDP.

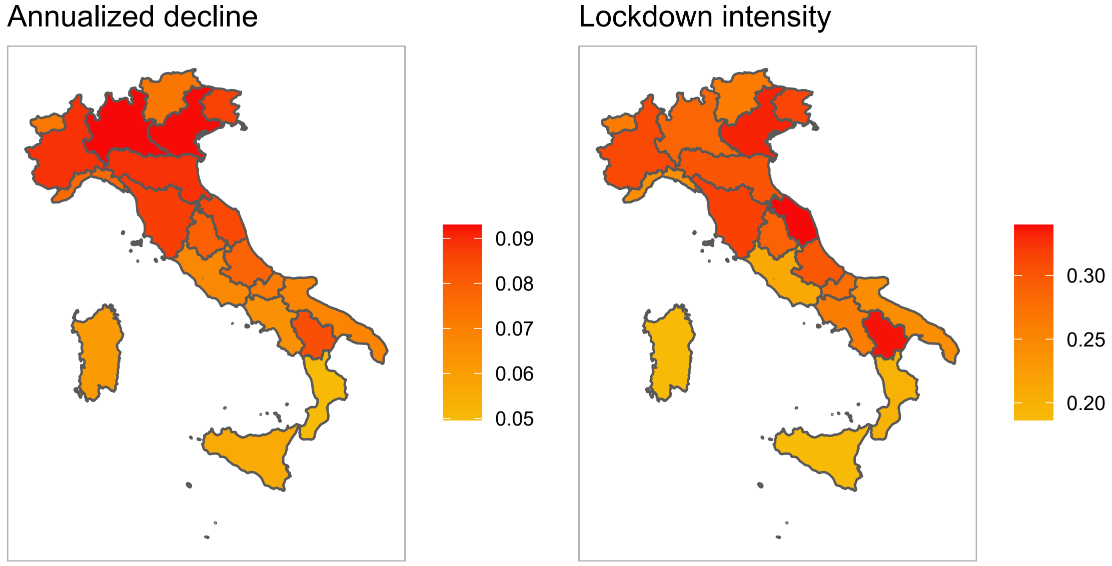

Figure 2: Annualized decline in production (simulated), calculated according to equation (17) and lockdown intensity, calculated according to equation (18) by region (first lockdown only)

The left panel of figure 2 shows the annualized decline in total production by region resulting from the simulation incorporating only the first lockdown. The figure reveals the presence of a clear north-south divide in the severity of the decline in production, with the northern regions of Italy like Lombardy, Piedmont and Veneto being hit particularly hard. Furthermore, the right panel of figure 2 indicates that regional declines are strongly but not perfectly correlated with the intensity of the first lockdown at the regional level. Whilst the first lockdown was applied uniformly across the country in terms of the sub-sectors which were ordered to close, the intensity of the lockdown in each region was different as a consequence of their differing productive structures, i.e. of the fact that, across regions, the same sectors account for differing portions of regional total production. Accordingly, we define the 'lockdown intensity' within a given region j as:

$$\sum_{i=1}^{32} \tilde{l}_i^j \frac{\overline{x}_i^j}{\overline{x}^j} \tag{18}$$

where $\tilde{l}_i^j$ is the *maximum* share of the labor force of sector i in region j that is in lockdown at any point during the simulation and $\frac{x_i^j}{x^j}$ is the ratio of sector i's output relative to the total output produced in region j according to our IO table. The presence of a positive relationship between lockdown intensity and regional decline in production is also illustrated in figure 3, with output declines ranging from around $5-6\%$ for some southern regions up to more than 9% for the most strongly affected regions in the North.

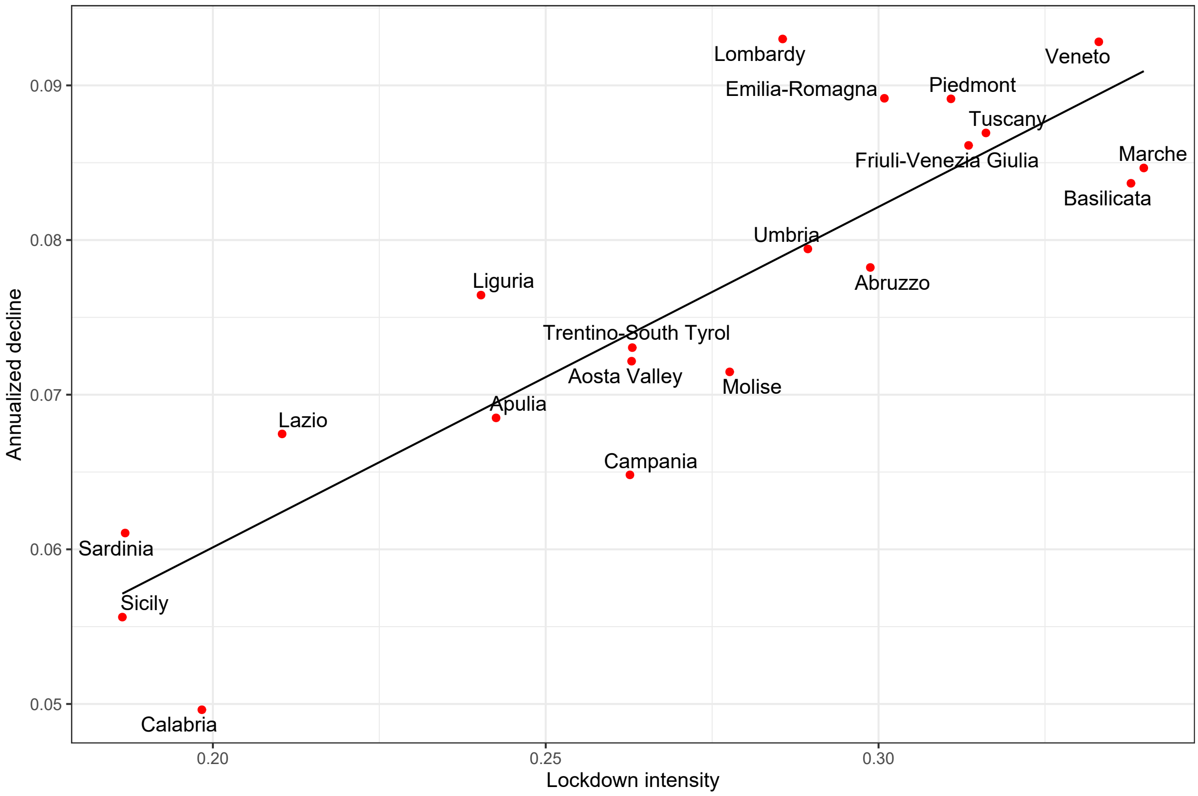

Figure 3: Annualized decline in production by region (simulated, first lockdown only), calculated according to equation (17) vs. intensity of first lockdown, calculated according to equation (18)

A similar positive relationship also holds between sectoral production (aggregated across regions) and lockdown intensity, as Figure 4 suggests. The lockdown intensity of a sector i defined as:

$$\sum_{j=1}^{20} \tilde{l}_i^j \frac{\overline{x}_i^j}{\overline{x}_i}, \tag{19}$$

meaning that the maximum share of the labor force of sector i in region j that is in lockdown is weighted by the output of sector i in region j relative to the overall output of sector i across Italy, $\overline{x}_i$, both taken from the IO table. Interestingly, Figure 4 also reveals the presence of considerable heterogeneity in output declines across sectors that did not experience any mandated closure, and for which the lockdown intensity is thus equal to zero. In addition, some of these sectors (e.g. Energy, or Paper and Chemical products) experienced a fall in output that was similar to the one of sectors with high lockdown intensity. This result shows the importance of feedback effects at work through the chain of input-output relations during the lockdown.

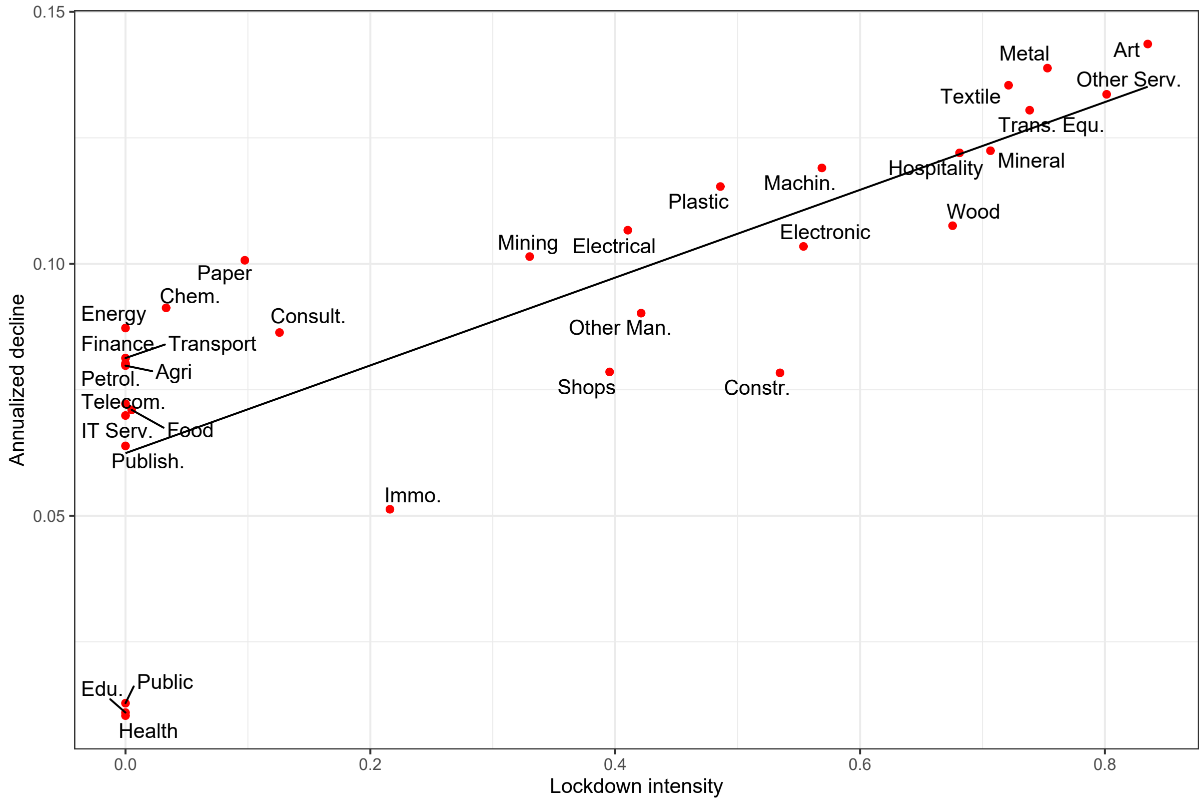

Figure 4: Annualised decline in production by sector (simulated, first lockdown only), calculated according to equation (17) vs. intensity of first lockdown, calculated according to equation (19)

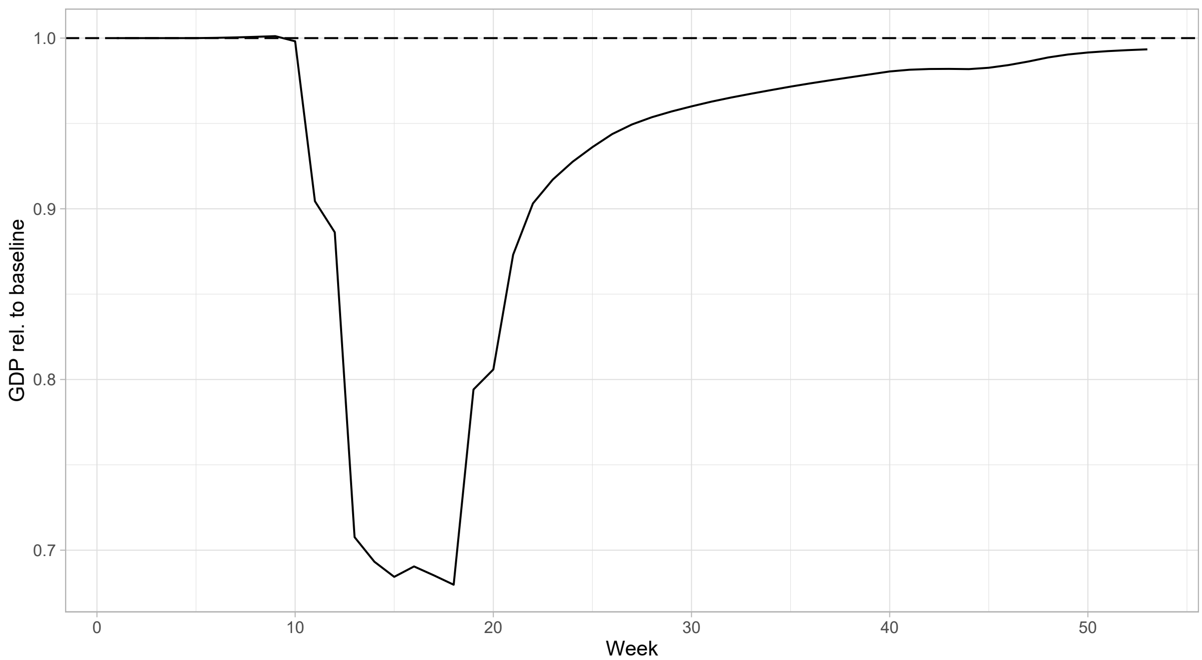

Figure 5: GDP (simulated) relative to baseline (first lockdown only)

Finally, Figure 5 plots simulated GDP as a fraction of the baseline value taken from the IO table (shown as a dashed horizontal line with intercept 1). The lockdown measures implemented in

March 2020 caused a steep decline in GDP, followed by a swift recovery once the lockdown is lifted. During the downturn GDP declines as a a direct consequence of the lockdown, of the ensuing reduction in orders of inputs by productive sectors and of the endogenous final demand effects. The fast recovery[16] that follows is however *partial* and, after an initial steep increase, GDP only slowly converges back to its baseline level. Overall, under the assumption of only a single lockdown, the model predicts an annual loss of GDP equal to around 6.8%. Appendix E presents the results of a sensitivity analysis on the estimated parameter combination, showing how the GDP loss in this scenario (which was also the one used for estimation) varies when parameter values are varied in a neighborhood of the estimated ones.

6.2 Second lockdown

The second impact analysis we perform focuses on the second set of lockdown measures, which were implemented in early November 2020 in the wake of the second wave of the epidemic. As outlined in section 4, these measures classified regions into different zones (yellow, orange, and red), according to the value of various epidemiological indicators, with each zone corresponding to a different extent of business closures as well as other containment measures. Regions could change zones depending on the development of the epidemiological indicators.

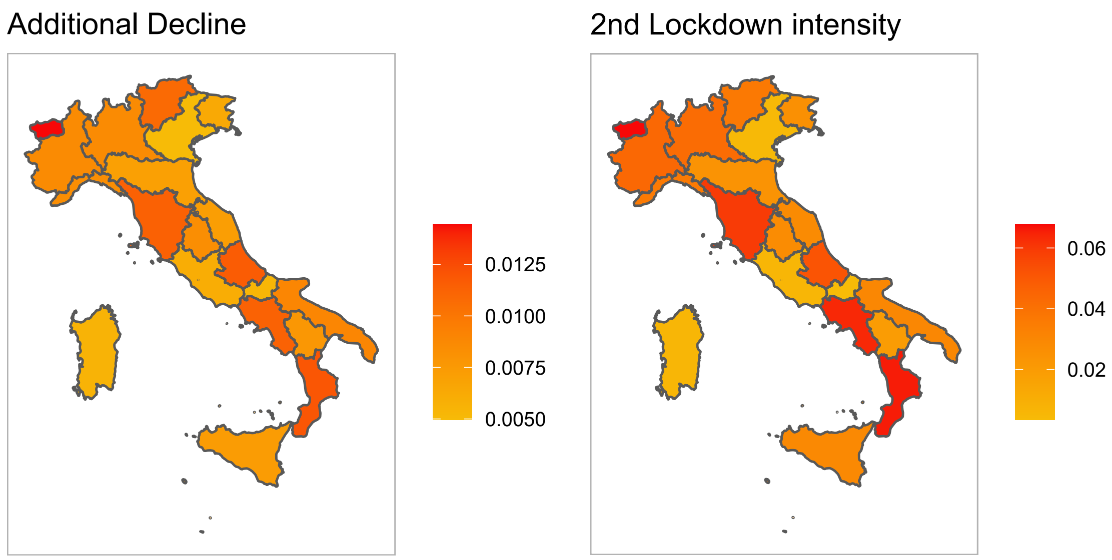

Figure 6: Additional decline in production (simulated), calculated as difference between loss in production with and without second lockdown and lockdown intensity, calculated according to equation (18), by region (second lockdown)

[16]The fast recovery can be explained by the fact that in the model short-term expectations take into account the effect that negative and positive shocks to available labor will exert on sectors' demand for inputs

To evaluate the effects of these measures, we compare the annualized declines in overall production and GDP both in the presence and absence of a second lockdown. This produces a measure of the additional decline caused purely by the second lockdown. Figure 6 illustrates the effects of the second lockdown on a regional basis. The left panel gives a regional overview of the additional decline in production caused by the second lockdown. The right panel shows the intensity of the implemented measures across regions, defined as in equation (18) but where the maximum decline in the labor force is taken only for the period during which the second lockdown was in effect (calendar week 46 onward). Interestingly, the second lockdown has somewhat more severe effects in some southern regions than in the north (with the exception of the Aosta Valley), despite northern regions (e.g. Lombardy) also spending long periods in the red zone. This result may be explained by the differing configurations of the first and second set of lockdown measures. While during spring mandated closures affected a significant fraction of manufacturing and a broad set of services, the second lockdown was targeted toward the retail, hospitality and leisure industries, which have a higher weight in the output of southern regions compared to northern ones.

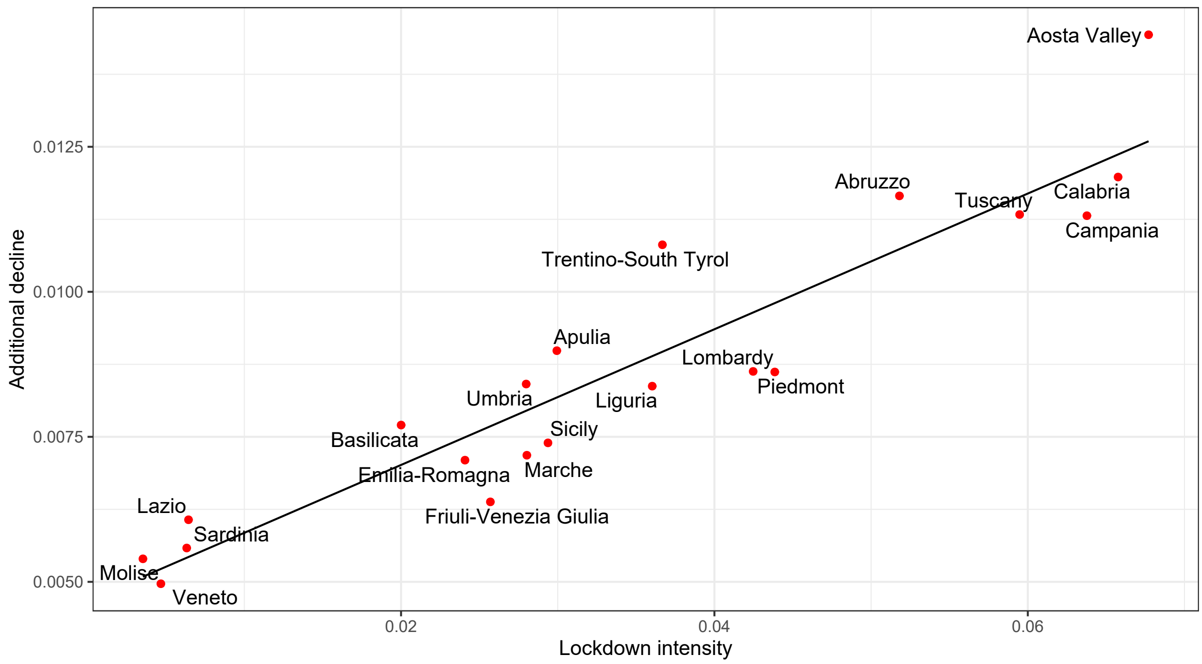

Figure 7: Additional in production by region (simulated) during second lockdown, calculated as difference between loss in production with and without second lockdown vs. intensity of second lockdown, calculated according to equation (18)

Figure 7 shows that a positive relationship between lockdown intensity and regional decline in production emerges also during the second lockdown. However, the simulated effects of the second lockdown are much less severe than those of the first, with the most strongly affected regions experiencing an additional loss in overall production of around 1%. Figure 8 provides a sectoral perspective, showing the declines in production during the second lockdown for all 32 sectors in the model. As expected, sectors that were directly targeted by the closures (like

Hospitality, Accommodation & Food Service Activities, or Arts, Entertainment & Recreation) are also those affected the most. In addition, the construction sector (which was not directly targeted by lockdown measures) is impacted fairly strongly. In contrast, the output loss in retail outlets (which were affected by closures in the red zone) is more moderate and does not exceed the loss experienced by some sectors which were not subject to closures during the second lockdown.

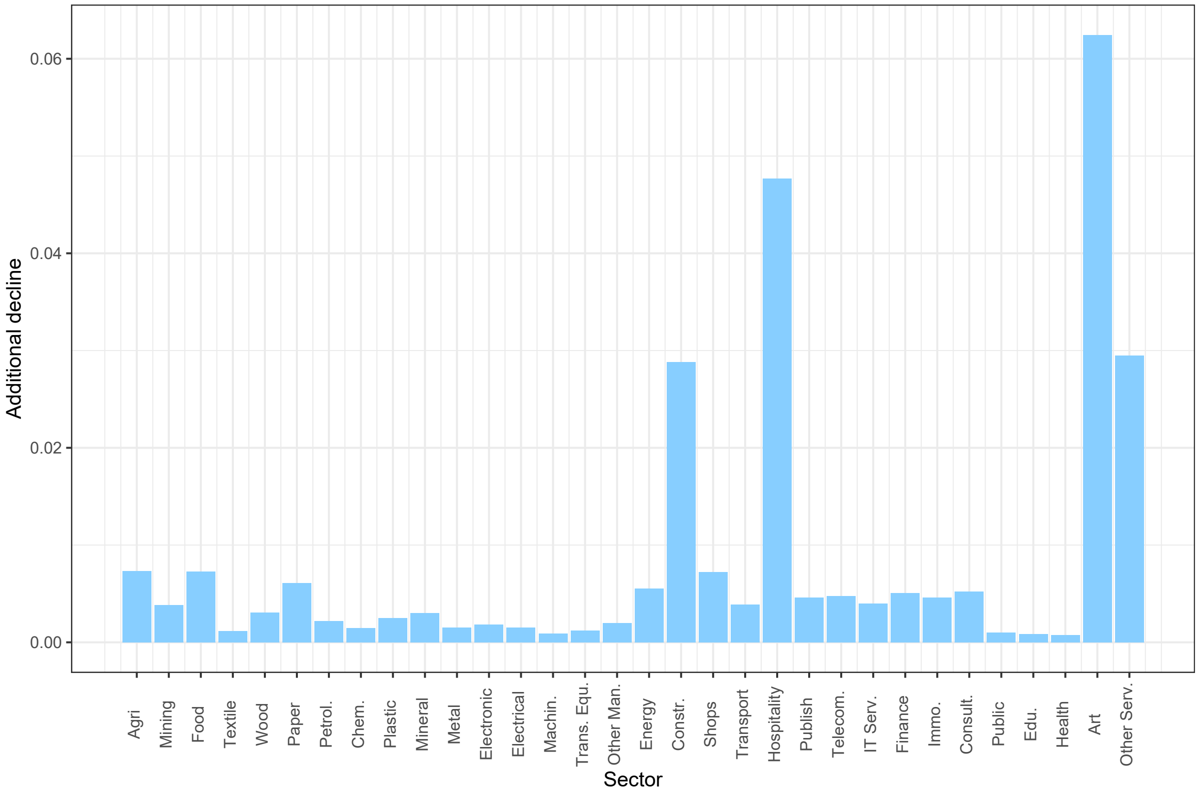

Figure 8: Additional decline in production by sector (simulated) during second lockdown, calculated as difference between loss in production with and without second lockdown

The results discussed so far are obtained from the model estimated on industrial production indexes from January to August 2020 and the service turnover indexes for Q1 and Q2 2020 (see Section 5). For this reason, we carry out an out-of-sample forecasting exercise to evaluate the performance of our model in reproducing observations outside this sample. Table 6 compares the empirical industrial production indexes for *September to December* 2020, the most recent available empirical data-points at the time of writing, to their simulated counterparts. Table 7 does the same for the change in the service sector revenue indexes in *Q3* 2020. The tables indicate that, especially as far as industrial production is concerned, the out-of-sample forecasting performance appears fairly acceptable although it deteriorates toward the end of the year.

Table 6: Empirical & simulated values of production indexes post Aug. 2020 (out of sample)

	September		**October**		**November**		**December**	
Label	Empirical	Simulated	Empirical	Simulated	Empirical	Simulated	Empirical	Simulated
Mining And Quarrying	94.20	94.99	93.95	96.02	93.23	95.19	90.33	95.11
Food, Beverages And Tobacco	97.14	96.93	96.78	97.63	95.26	94.23	94.82	94.74
Textiles, Wearing Apparel And Leather	82.75	95.91	82.98	96.86	76.57	97.58	75.87	98.62
Wood And Products Of Wood And Cork	100.00	95.60	100.63	96.58	102.01	96.20	96.83	96.21
Paper & Paper Products, Printing & Rep. Of Rec. Media	92.35	94.32	94.26	95.57	90.21	93.70	90.78	93.76
Coke And Refined Petroleum Products	88.76	95.47	85.44	96.48	83.08	96.59	81.26	97.01
Chemicals And Pharmaceutical Products	94.42	95.21	96.69	96.30	97.07	96.96	97.64	97.90
Rubber And Plastic Products	101.29	94.88	104.15	96.05	102.97	96.12	104.65	96.85
Other Non-Metallic Mineral Products	95.16	96.43	94.58	97.20	96.90	96.94	97.58	96.83
Basic Metals, Fabricated Metal Products	95.67	95.26	98.03	96.35	98.62	96.80	100.79	97.75
Computer, Electronic And Optical Products	96.35	96.02	97.90	96.93	93.80	97.32	94.80	98.03
Electrical Equipment	96.14	95.34	100.66	96.41	101.03	97.13	100.28	98.05
Machinery And Equipment N.E.C.	91.36	95.95	93.61	96.88	92.89	97.89	92.35	98.91
Transport Equipment	95.49	96.59	99.90	97.37	99.22	97.97	94.31	98.79
Manufacturing N.E.C, Repair & Inst. Of Mach. & Equip.	98.61	96.73	99.34	97.47	97.29	97.55	98.03	97.97
Construction[17]	98.17	98.89	96.25	99.11	97.90	98.08		

Table 7: Empirical and simulated changes in quarterly service sector revenue indexes in Q3 2020 in % (out of sample)

Label	Empirical	Simulated
Wholesale & Retail Trade; Repair Of Motor Vehicles	4.8	-3.23
Transportation And Storage	-9.7	-6.32
Accommodation And Food Services	-18.8	-0.09
Publishing, Motion Picture, Video, Sound & Broadcasting	0.9	-4.71

[17] Data for December were not yet available at the time of writing.

Table 8: Empirical and simulated index of GDP across quarters of 2020

	Empirical	Simulated
Q1	94.4	96.1
Q2	82.2	81.0
Q3	95.1	96.6
Q4	93.3	95.8

Furthermore, Table 8 presents the results of a similar exercise which compares the empirical and simulated dynamics of Italian GDP. It shows that our model is able to predict the observed dynamics fairly well in the first 3 quarters of 2020, despite not being directly estimated on GDP. The performance declines in Q4 of 2020, suggesting that our model has a tendency to under-estimate the negative effects of the second set of lockdown measures. This is likely due to the relatively under-developed modeling of the demand side of our model, which only endogenizes part of the income effect due to the mandated closures. While during the first lockdown, declines in production and GDP can largely be explained as a consequence of the very stringent closures across a wide variety of sectors, closures were much more limited during the second lockdown. Negative shocks to final demand (and their propagation through production networks), especially due to consumer confidence and psychological effects (e.g. voluntary abstention, on a precautionary basis, from attending potentially crowded neighborhoods and facilities) as well as to restrictions on mobility, likely played a relatively more important role than mandated business closures during the second lockdown. These factors appear to have played an important role in determining the contraction of US GDP, as confirmed empirically by Goolsbee and Syverson (2021).

Figure 9 compares the dynamics of simulated GDP in the presence and absence of the second lockdown, showing that the second set of lockdown measures leads to an additional moderate decline in GDP at the end of 2020. Specifically, our model predicts that the second lockdown increases the annual loss of GDP by around 0.7%, leading to an annualized total loss of around 7.5%. This is in contrast to the result of a counterfactual experiment in which the second lockdown replicates the features of the first, 'hard' lockdown by implementing the prime-ministerial decree of 22^{nd} March, which mandated the broadest set of closures, in week 46 of the simulation and then assuming the same timing and stages as in spring for the following re-openings. In this scenario, which is also depicted in figure 9, the second lockdown leads to an additional GDP loss of around 3.7% instead of 0.7%, increasing the total loss to 10.5%. While the set of lockdown measures actually implemented during fall hence implied a lower economic loss than a hypothetical second 'hard' lockdown, this should not be interpreted as a judgment in favor of the 'milder' lockdown, for which an assessment of epidemiological impacts would also be required.

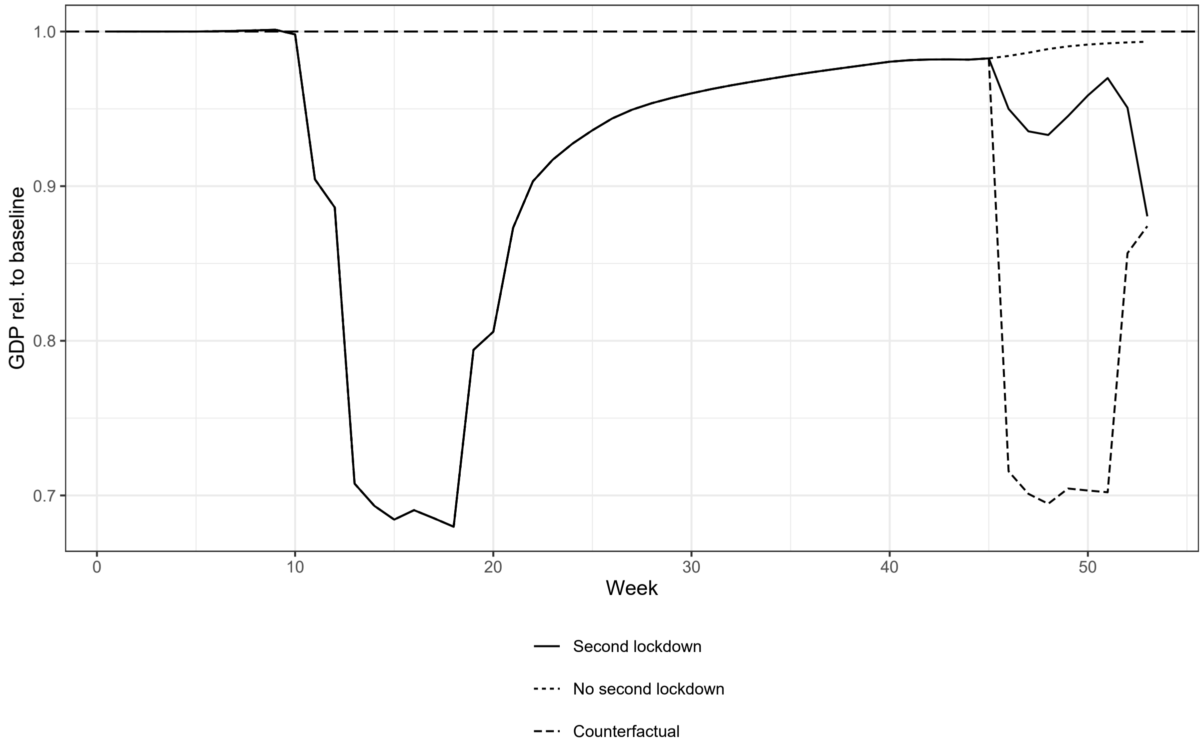

Figure 9: GDP relative to baseline for actual, counterfactual and no second lockdown

7 Conclusions

The pandemic presented policymakers with enormous challenges which led to unprecedented measures, such as the decision to put entire branches of economies into lockdown. The absence of tools to assess the possible economic impact of different types of closures, both for the overall economy, and especially for specific regions and sectors makes the task of designing lockdown measures (as well as policies to alleviate their negative economic effects) even more difficult. Providing such an assessment is not trivial, also since data which can inform economic models in such unprecedented scenarios become available only with a delay, which may be incompatible with the short time span within which governments must act.

The purpose of this paper was to present a simple and parsimonious computational input-output model to analyze the regional and sectoral effects of different lockdown measures, which can be estimated with relatively little data, over a relatively short time span. We employed the model to analyze of the effects of epidemic-induced lockdowns in Italy. We showed that, despite its simplicity, an empirically estimated version of the model is able to reproduce the downturn and recovery following the lockdown implemented in Italy during the spring of 2020 fairly accurately both at the sectoral and aggregate levels. Thanks to its regionally disaggregated nature, we showed that the model is also able to provide a picture of the heterogeneous impact of lockdown measures at the sub-national level, which adds an important perspective that cannot be obtained from aggregate models.

In addition, we analyzed the effects of the second lockdown in fall and winter of 2020, based on the division of the country into different zones depending on the regional evolution of the epidemic. Unsurprisingly, our numerical simulations suggest that this second, 'soft' lockdown was much less costly in terms of economic loss when compared to a hypothetical second 'hard' lockdown. A full evaluation of the desirability of either approach would however also have to consider the respective epidemiological implications which our framework at present does not depict. For the scenario including the empirically-observed second lockdown, our model predicts an annual loss in GDP equal to around 7.5%. This estimate is below those previously produced by institutions such as the European Commission (9.9%; European Commission 2020), Istat (8.9%; Istat 2020), the Bank of Italy (9.2%; Banca d'Italia 2021) and the IMF (10.6%; IMF 2020). As indicated above, this is likely to be due to the presently under-developed demand side of the model, which gives it a tendency to under-estimate the impact of the second lockdown.

In the present paper we decided to avoid adding any further assumptions to our model in the interest of simplicity. We focused purely on the shocks to productive capacity implied by the lockdown measures as well as their propagation and feedback effects on final demand. However, we believe that the structure of the model makes it possible to refine the analysis by including more realistic features. A planned refinement is the inclusion of the the demand effects induced by mobility constraints and by voluntary abstention for precautionary reasons, which reduced or prevented the consumption of certain types of services (e.g. hotel accommodation). As discussed above, we believe that these amendments will lead to a substantial improvement in the explanatory power of the model, in particular for milder lokdown measures, without greatly compromising its parsimony and would likely bring the estimate of GDP loss closer to those cited above. More sophisticated behavioral specifications can also be included. For example, one might consider a relaxation of the assumption of constant technological coefficients, e.g. by allowing sectors to shift their demand for inputs from other sectors between regions. Once again, however, we believe parsimony to be one the key benefits or our framework vis à vis more elaborate ones, given the challenges and time-constraints posed by the analysis of lockdown measures. Together with studies focusing on other aspects of the effects of lockdown measures, such as impacts on inequality as analysed e.g. by Palomino et al. (2020) and Hacıoğlu-Hoke et al. (2021), our framework can provide useful insights to aid in the evaluation of containment measures to combat the pandemic. Finally, while in the present work we abstained from any consideration regarding the desirability of alternative lockdown configurations, we are currently working to an augmented version of the framework proposed including a similarly parsimonious epidemiological model to evaluate the impact of lockdown measures on the reproduction number of the virus. This will enable us to investigate the possible trade-off between economic and epidemiological outcomes and to assess the efficacy/desirability of alternative social distancing schemes based on both empirical experience and an extensive exploration of counterfactual scenarios.

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Appendix

A Input-Output tables

Table A1 gives a list of the 32 sectors contained in our model and the corresponding abbreviations used in figures in the main text. Figure A1 below provides an overview of the structure of the 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

B Expectations and orders

Demand expectations play an important role in the model, both in determining productive capacity in terms of available labor and in driving sectors' orders of inputs (see also section 3.2). We distinguish between short and long term expectations: the former are relevant to determine the amount of inputs required for production in the next period. The latter instead drive a target level of inventories required for production over the entire future planning horizon of a sector.

To model short term expectations we assume naive expectations, meaning that expected sales in the current period are equal to the orders received in the previous period. However, we slightly amend this otherwise fully backward looking scheme by assuming that, when a lockdown is implemented, firms within each sector know which type of activities are targeted by the measure and are able to assess the direct impact that the lockdown will exert on their customers' level of activity. Hence, they correct their naive expectations accordingly. This assumption appears plausible given the public character and high resonance of information regarding the sectors targeted by the lockdown,[18] and the existence of stable business relationships and partnerships between upstream and downstream enterprises along supply chains.

The direct impact of a lockdown on productive capacity due to the reduction in sectors' availability of labor is given by $(\mathbf{l_t} - \mathbf{l_{t-1}}) \oslash \mathbf{a^l}$. By pre-multiplying this vector with the matrix of technical coefficients $\mathbf{A}$ we obtain the consequent reduction in the orders of inputs received by each productive sector. Short term expectations are then computed as:

$$\mathbf{x_t^{e,short}} = \nu \otimes \mathbf{x_{t-1}^d} + (1-\nu) \otimes \mathbf{x_{t-1}^d} + \mathbf{A}\left\{\left[(\mathbf{l_t} - \mathbf{l_{t-1}}) \oslash \mathbf{a^l}\right]\right\} \tag{20}$$

where ν is a vector the element of which corresponding to sector j is equal to 0 if in the current period a labor shock, either positive or negative, hits the sector, and 1 otherwise. Each sector j then computes the amount of inputs it needs for production based on these short-term expectations. However, they abstain from purchasing inputs in excess compared to the amount they can actually employ given the number of workers currently available. Therefore, they place orders of domestic inputs for short-term production purposes according to:

$$\mathbf{z_{j,t}^{d,short,C}} = \mathbf{a_j^C} min\left(x_{j,t}^{e,short}, l_{j,t}a_j^l\right) \tag{21}$$

Similarly, they place orders of imported inputs for short-term production purposes following:

$$m_{j,t}^{d,short} = \mathbf{a_j^m} min\left(x_{j,t}^{e,short}, l_{j,t}a_j^l\right) \tag{22}$$

Long term expectations are assumed to be the simple average over a time span of the past β

[18] In Italy, the Decrees of the President of the Council of Ministers (DPCM) establishing the lockdown in March 2020 reported the precise ATECO codes of the sectors involved.

periods.

$$\mathbf{x_t^{e,long}} = \frac{\sum_{i=1}^{\beta} \mathbf{x_{t-i}^{d}}}{\beta} \tag{23}$$

We assume sectors have a target stock of inputs equal to the amount required for the production of $x_t^{e,long}$ over a time span of γ_j periods, which represents the sector's future planning horizon. The stock of inventories is adapted from period to period by a fraction $\frac{1}{\gamma_j}$ of the difference between targeted and actual levels. This implies that sectors will all converge asymptotically to their targets but the adjustment will be fast for sectors having short planning horizons and slow for sector having long ones. Formally, sector j's demand for domestic inputs required for long-term production planning is given by:

$$\mathbf{z_{j,t}^{d,long,C}} = \frac{1}{\gamma_j}\left(\gamma_j \mathbf{a_j^C} x_{j,t}^{e,long} - \mathbf{z_{j,t}^{stock,C}}\right) \tag{24}$$

Total orders of domestic inputs are then given by:

$$\mathbf{z_{j,t}^{d,C}} = max\left(\mathbf{0}, \mathbf{z_{j,t}^{d,short,C}} + \mathbf{z_{j,t}^{d,long,C}}\right) \tag{25}$$

Following the same logic, the stock of imported inputs is managed according to:

$$m_{j,t}^{d,long} = \frac{1}{\gamma_j}\left(\gamma_j \mathbf{a_j^m} x_{j,t}^{e,long} - m_{j,t}^{stock}\right) \tag{26}$$

The total demand for imported inputs is then:

$$m_{j,t}^{d} = m_{j,t}^{d,short} + m_{j,t}^{d,long} \tag{27}$$

C Construction of labor shocks

As mentioned in the main text, the lockdown decrees mandating the closure of particular productive sectors make use of the ATECO classification of economic activities to specify which sectors may remain open and which must close. We convert the decrees into a dataset consisting of flags indicating whether a given 5-digit sector was open or closed at a particular point in time and we map each 5-digit sector into the 32 sectors of our IO table. Combining this dataset with data on the number of employees in each Italian region, disaggregated at the level of 5-digit ATECO classification available from the Italian Statistical Institute (ISTAT), we calculate the share of workers in each of our 32 sectors in the 20 Italian regions directly affected by each of the decrees. We assume however that the labor supply coming from these affected workers becomes unavailable only if their work cannot not be performed from home, thus becoming infeasible once the physical facilities of their work-place are closed. For this purpose, we construct an index of tele-workability for each of our 32 sectors. The index for each sector is bounded between 0 and 1, with 0 meaning that all workers in a sector can work from home and 1 meaning that none of them can. We multiply the share of workers affected by the lockdown in the each sector and region by the corresponding tele-workability index, thereby obtaining a vector of labor shocks specified both at the regional and sectoral levels for each simulation period, giving the share of labor input which is unavailable due to lockdown measures.

Tele-workability is assessed through the same procedure applied in Cetrulo et al. (2020a) who extend the exercise by Dingel and Neiman (2020) and adapt it to the European case. First, we retrieve information on tasks and activities performed in workplaces from the ICP-INAPP (Indagine Campionaria delle Professioni [Sample Survey of Professions]) dataset, which contains data from interviews with 16,000 Italian workers ensuring statistical representativeness of sectoral, occupational and geographical heterogeneity.[19] We focus on thirty questions belonging to the 'generalized activities' (G) and 'work context' (H) sections of the dataset and construct an indicator function that specifies whether a given occupation can be performed from home or not. In order for an occupation to be classified as non-tele-workable, most of the respondents involved in that occupation must either indicate (i) that they spend a large fraction of their working time in external environments, or (ii) that they frequently use equipment, machinery and tools, or (iii) that they need continuous physical contact with other people, or any combination of (i), (ii) and (iii). More details about the procedure can be found in Cetrulo et al. (2020a). After classifying occupational categories at the 4-digit level, these are aggregated at the 1-digit level according to the International Standard Classification of Occupations (ISCO) and linked to the ISTAT 2016 Labor Force Survey to gather information about the number of workers across occupations and sectors. At this point, we are able to estimate the number of workers that cannot work from home for each occupation within each sector. Our tele-workability index is computed as the ratio between the number of workers whose occupation is not tele-workable and the total number of workers for each of the 18 NACE macrosectors. The use of the 18 macrosectors instead of a finer sectoral disaggregation allows for a precise matching of occupations to productive sectors. The 18 tele-workability indexes thus constructed are then linked to the 32 sectors in our model using table C2 that shows which sector(s) out of the 32 contained in our model correspond to each of the 18 NACE macrosectors (implying that tele-workability will be uniform across some of our 32 sectors).
In implementing the lockdown in our model, we make the following simplifying assumptions:

- As our model runs at weekly frequency, lockdown measures are always implemented for multiples of full weeks (i.e. closures and re-openings always take place at the beginning of a week).
- For simplicity, we assume that all sectors fully re-open in the 21st calendar week. In reality, very few sub-sectors such as theaters and cinemas were closed slightly longer, but the effects of this on overall simulation outcomes are very minor.

[19]The ICP-INAPP dataset represents the only European source of information comparable to the American O*NET database, the latter being a comprehensive database reporting qualitative and quantitative information on tasks, skills, work contexts and organizational characteristics at the 5-digit level of observation (Cetrulo et al., 2020b). Currently, two waves of the ICP dataset are available (2007 and 2012) with a spectrum covering 797 occupational codes. We make use of the 2012 wave.

In modeling the second lockdown based on the division of the country into different zones, we make the following additional assumptions:

- In the Italian regional IO table available to us, the autonomous provinces of Bolzano and Trento are aggregated into the region of Trentino-South Tyrol (which consists only of these two provinces). During the second wave, however, lockdown measures were implemented separately for the two provinces. We address this problem by using labor force data for the individual provinces to determine the number of workers affected by the closure of a given sector in these provinces, and express it as a share of the overall regional employment in that sector, using this as a measure of the regional shock. For instance, in calendar week 46, Bolzano was in the red zone, meaning (inter alia) that non-essential retail was closed, whereas Trento was in the yellow zone. The shock hitting the retail sector in Trentino-South Tyrol in our model would in this case be given by the number of workers in non-essential retail in Bolzano divided by the number of workers in the retail and wholesale sector (sector 19 in our model) *in the entire region* (multiplied by the corresponding tele-workability index). This procedure to translate province-level shocks into regional ones clearly allows to provide a more precise estimation of regional shocks, compared to the alternative simplifying assumption that applies the same regime, either red or yellow, to the entire region.
- During the Christmas holiday period, a plan was enacted whereby the entire country moved back and forth between being under red and orange zone restrictions. Red zone rules were in force from the 24th to the 27th and on the 31st of December while the orange zone rules were implemented on the 28th, 29th and 30th. As our model runs at weekly frequency, we decided to treat the entire 53rd calendar week as red.

The resulting classification into zones over time is shown in table C1.

Table C1: Second wave lockdown measures by region

Calendar week:	**46**	**47**	**48**	**49**	**50**	**51**	**52**	**53**
Piedmont	Red	Red	Red	Orange	Orange	Yellow	Yellow	Red
Aosta Valley	Red	Red	Red	Red	Orange	Orange	Yellow	Red
Lombardy	Red	Red	Red	Orange	Orange	Yellow	Yellow	Red
Trento	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow	Red
Bolzano	Red	Red	Red	Red	Orange	Orange	Yellow	Red
Veneto	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow	Red
Friuli-Venezia Giulia	Yellow	Orange	Orange	Orange	Yellow	Yellow	Yellow	Red
Liguria	Orange	Orange	Orange	Yellow	Yellow	Yellow	Yellow	Red
Emilia-Romagna	Yellow	Orange	Orange	Orange	Yellow	Yellow	Yellow	Red
Tuscany	Orange	Red	Red	Red	Orange	Orange	Yellow	Red
Umbria	Orange	Orange	Orange	Orange	Yellow	Yellow	Yellow	Red
Marche	Yellow	Orange	Orange	Orange	Yellow	Yellow	Yellow	Red
Lazio	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow	Red
Abruzzo	Orange	Orange	Red	Red	Red	Orange	Orange	Red
Molise	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow	Red
Campania	Orange	Red	Red	Red	Orange	Orange	Yellow	Red

Table C1 – continued from previous page

Calendar week:	46	47	48	49	50	51	52	53
Apulia	Orange	Orange	Orange	Orange	Yellow	Yellow	Yellow	Red
Basilicata	Orange	Orange	Orange	Orange	Orange	Yellow	Yellow	Red
Calabria	Red	Red	Red	Orange	Orange	Yellow	Yellow	Red
Sicily	Orange	Orange	Orange	Yellow	Yellow	Yellow	Yellow	Red
Sardinia	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow	Red

Table C2: Correspondence table among sectoral classifications

NACE rev. 2	Description	NACE 18	IRPET
01	Crop & animal production, hunting & related service activities	1	1
02	Forestry & logging	1	1
03	Fishing & aquaculture	1	1
05	Mining of coal & lignite	2	2
06	Extraction of crude petroleum & natural gas	2	2
07	Mining of metal ores	2	2
08	Other mining & quarrying	2	2
09	Mining support service activities	2	2
10	Manufacture of food products	3	3
11	Manufacture of beverages	3	3
12	Manufacture of tobacco products	3	3
13	Manufacture of textiles	4	4
14	Manufacture of wearing apparel	4	4
15	Manufacture of leather & related products	4	4
16	Manufacture of wood & products of wood & cork, except furniture; manufacture of articles of straw & plaiting materials	4	5
17	Manufacture of paper & paper products	4	6
18	Printing & reproduction of recorded media	4	6
19	Manufacture of coke & refined petroleum products	5	7
20	Manufacture of chemicals & chemical products	5	8
21	Manufacture of basic pharmaceutical products & pharmaceutical preparations	5	8
22	Manufacture of rubber & plastic products	6	9
23	Manufacture of other non-metallic mineral products	6	10
24	Manufacture of basic metals	6	11
25	Manufacture of fabricated metal products, except machinery & equipment	6	11
26	Manufacture of computer, electronic & optical products	7	12
27	Manufacture of electrical equipment & of non-electric domestic appliances	7	13
28	Manufacture of machinery & equipment n.e.c.	7	14
29	Manufacture of motor vehicles, trailers & semi-trailers	8	15
30	Manufacture of other transport equipment	8	15
31	Manufacture of furniture	9	16
32	Other manufacturing	9	16
33	Repair & installation of machinery & equipment	9	16
35	Electricity, gas, steam & air conditioning supply	10	17
36	Water collection, treatment & supply	10	17
37	Sewerage	10	17

Table C2 – continued from previous page

NACE rev. 2	Description	NACE 18	IRPET
38	Waste collection, treatment & disposal activities, materials recovery	10	17
39	Remediation activities & other waste management services	10	17
41	Construction of buildings	11	18
42	Civil engineering	11	18
43	Specialised construction activities	11	18
45	Wholesale & retail trade & repair of motor vehicles & motorcycles	12	19
46	Wholesale trade, except of motor vehicles & motorcycles	12	19
47	Retail trade, except of motor vehicles & motorcycles	12	19
49	Land transport & transport via pipelines	12	20
50	Water transport	12	20
51	Air transport	12	20
52	Warehousing & support activities for transportation	12	20
53	Postal & courier activities	12	20
55	Accommodation	12	21
56	Food service activities	12	21
58	Publishing activities	13	22
59	Motion picture, video & television programme production, sound recording & music publishing activities	13	22
60	Programming & broadcasting activities	13	22
61	Telecommunications	13	23
62	Computer programming, consultancy & related activities	13	24
63	Information service activities	13	24
64	Financial service activities, except insurance & pension funding	14	25
65	Insurance, reinsurance & pension funding, except compulsory social security	14	25
66	Activities auxiliary to financial services & insurance activities	14	25
68	Real estate activities	15	26
69	Legal & accounting activities	16	27
70	Activities of head offices, management consultancy activities	16	27
71	Architectural & engineering activities, technical testing & analysis	16	27
72	Scientific research & development	16	27
73	Advertising & market research	16	27
74	Other professional, scientific & technical activities	16	27
75	Veterinary activities	16	27
77	Rental & leasing activities	16	27
78	Employment activities	16	27
79	Travel agency, tour operator & other reservation service & related activities	16	27
80	Security & investigation activities	16	27
81	Services to buildings & landscape activities	16	27
82	Office administrative, office support & other business support activities	16	27
84	Public administration & defence; compulsory social security	17	28
85	Education	17	29
86	Human health activities	17	30
87	Residential care activities	17	30

Table C2 – continued from previous page

NACE rev. 2	Description	NACE 18	IRPET
88	Social work activities without accommodation	17	30
90	Creative, arts & entertainment activities	18	31
91	Libraries, archives, museums & other cultural activities	18	31
92	Gambling & betting activities	18	31
93	Sports activities & amusement & recreation activities	18	31
95	Repair of computers & personal & household goods	18	32
96	Other personal service activities	18	32

D Estimation procedure

As mentioned in the main text, we use revenue rather than production data from the four service sectors for which such data are available in order to estimate the model. The choice of revenue rather than production data is clearly sub-optimal as our model does not take price changes into account (meaning that in our model, changes in output and changes in revenue are always equal) whereas an empirical index of revenue can change both as a consequence of changes in prices and in the volume of production. Unfortunately, data on production (or even deflated revenue) at the sectoral level are unavailable for service sectors in Italy. However it appears reasonable to assume prices to be relatively stable, given the short time-span characterizing the historical episode considered and the existence of lags in price reactions to changes in market conditions. In addition, a tentative analysis of monthly data on producer prices in the service sectors shows that changes in service sector revenues far outweigh changes in their respective prices during the period considered, suggesting that turnover is indeed a suitable proxy for changes in the service sectors' real output.
Additionally it must be pointed out that 3 of the time-series employed in the estimation had to be constructed from more disaggregated data since sectors in our IO table are in some cases more aggregated than those for which production/revenue indexes are available. More precisely:

- Sector 6 (Manufacture of Paper & Paper Products, Printing & Reproduction of Recorded Media) consists of ATECO sectors 17 (Manufacture of Paper & Paper Products) and 18 (Reproduction of Recorded Media) and production indexes are only available for these sub-sectors separately.

- Sector 8 (Manufacture of Chemicals & Pharmaceutical Products) consists of ATECO sectors 20 (Manufacture of Chemicals) and 21 (Manufacture of Pharmaceutical Products) and production indexes are only available for these sub-sectors separately.

- Sector 19 (Wholesale & Retail Trade; Repair of Motor Vehicles & Motorcycles) consists 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), and revenue indexes are only available for these sub-sectors separately.

In all these cases, the production/revenue indexes for the sectors appearing in our model are constructed as a weighted average of the correspondent indexes for their sub-sectors, with weights given by the share of the aggregate sectors' employment attributable to each sub-sector. Employment data for this purpose are taken from ISTAT.
Recall that one of the subsets of 'moments' we use in our estimation procedure is given by a comparison of the empirical and simulated industrial production time series using the *GSL-div* algorithm developed by Lamperti (2018b). *GSL-div* is an algorithm capable of evaluating the similarity between two time-series (e.g. an empirical and a simulated one) by discretizing and simbolizing their range and subsequently comparing the frequencies of all possible sequences of symbols contained in sub-sections of both time-series. A lower *GSL-div* value signifies a stronger similarity between two time series, i.e. if two simulated time series are compared to an empirical one, the one which is more similar to the empirical one will receive a lower *GSL-div* value. The algorithm takes two parameters, namely the maximum length of the window of time-series observations considered in calculating the frequency of sequences of symbols and the 'precision', given by the number of discrete symbols into which the range of values taken by the time series is converted. Increasing both parameters increases the computational burden of running the algorithm, especially so in the case of of the precision parameter. As detailed in Lamperti (2018b), *GSL-div* possesses the advantage of not relying on stationarity assumptions and likelihood functions, and is able to outperform alternative metrics such as the mean squared error or the Akaike Information Criterion. Its ability to reliably summarise the similarity of the shapes of two time series in a single statistic makes it very suitable for our objective of matching the shape of the lockdown-induced downturn and the subsequent recovery. For an application of *GSL-div* to the well-known model proposed by Brock and Hommes (1998), see Lamperti (2018a).

Table D1: Parameter space

Symbol	**Description**	**Range**
α	Investment adjustment parameter	$0.02 - 0.05$
β	Observations used for long-term expectation	$1 - 52$
γ_1	Desired inventories agriculture	$2 - 26$
γ_2	Desired inventories mining	$2 - 26$
γ_3	Desired inventories manufacturing	$2 - 26$
γ_4	Desired inventories electricity	$2 - 26$
γ_5	Desired inventories construction	$2 - 26$
γ_6	Desired inventories services	$2 - 26$

The parameter space used for the estimation procedure is defined as shown in table D1, which gives the range of values we consider for each individual parameter. While parameter α is continuous, parameter β as well as the γ's are discrete and take positive integer values since they are defined as numbers of weeks. The range for α is set so as to exclude regions of the parameter space which would give rise to unrealistically volatile or unresponsive investment dynamics. The range for β is set such that the maximum number of past observations which can be used in forming long-term expectations are 52, corresponding to one year. The upper bound for the γ's, i.e. the maximum number of weeks for which sectors want to hold inventories of inputs, based on their long-term demand expectations, is set to half a year.

In order to compute the value of the loss function given by equation 15, we need to characterize the weighting matrix **W**. Common choices for the weighting matrix in the literature include the identity matrix (Grazzini and Richiardi, 2015), as well as the inverse of the variance-covariance matrix of the empirical moments (Franke and Westerhoff, 2012). Given the sectoral character of the statistics employed we follow instead the practice of using a pre-specified weighting matrix as described e.g. by Cochrane (2005). In particular, we weigh the statistics employed to compute the loss function by the dimension of the sectors to which they refer, by choosing a diagonal matrix where diagonal elements express the contribution to (i.e. the share of) total gross output of the corresponding sectors, as implied by our IO table. For instance, since the first element of the error vector is the difference between the simulated and empirical maximum declines in sector 3, then first element on the diagonal of **W** will be the share of sector 3 in total output, and so on. As argued by (Cochrane, 2005, p. 215) in his discussion of the generalized method of moments, "the optimal weighting matrix makes GMM pay close attention to linear combinations of moments with small sampling error in both estimation and evaluation. One may want to force the estimation and evaluation to pay attention to economically interesting moments instead." This is precisely what our weighting matrix aims to do by giving more weight to the minimization of errors emanating from sectors contributing more to the aggregate output of the Italian economy. As a consequence, our procedure tends to assign a lower loss to those parameter combinations which more closely match dynamics in the most important sectors included in the estimation procedure.

E Sensitivity Analysis

We carry out a sensitivity analysis in a neighborhood of the estimated parameter values for the scenario which only considers the spring lockdown (which was also the scenario used for the estimation). We choose the simulated annual GDP loss relative to the baseline without shocks (taken from the 2016 IO table which, as stated above, is the most recent one available at the time of writing) as the output variable to analyze, investigating both how this GDP loss varies for different values of the parameters and, using estimated Shapley values (Shapley, 1953), to which degree variations in the different parameters contribute to explaining the variance of this GDP loss across the parameter space.

We begin by defining a neighborhood of the estimated parameter combination. The range of variation for each parameter is shown in table E1[20]. In computing the Shapley values we follow the method proposed by Song et al. (2016)[21], which allows for an estimation of Shapley values using random samples from a parameter space.

[20]The range is constructed by defining a neighborhood of ±20% (rounded in the case of discrete parameters) around the estimated value of each parameter.

[21]This algorithm is implemented in the *shapleyPermRand* function of the R package *sensitivity* (`https://cran.r-project.org/web/packages/sensitivity/sensitivity.pdf`).

We set the algorithm to run a total of 210000 different parameter combinations sampled from the neighborhood defined above and record both the estimated Shapley values for each individual parameter and the simulated GDP loss for each of the 210000 combinations.[22]

Table E1: Parameter space (sensitivity)

Symbol	**Estimated**	**Range**
α	0.02138	0.01710 – 0.02566
β	51	41 – 61
γ_1	16	13 – 19
γ_2	23	18 – 28
γ_3	18	14 – 22
γ_4	19	15 – 23
γ_5	5	4 – 6
γ_6	14	11 – 17

The recorded values for the simulated GDP loss are used below to illustrate how the latter varies in terms of level across the parameter space. The Shapley values, by contrast, provide a *variance-based* global sensitivity analysis decomposing the variance of the output variable (simulated GDP loss) arising from uncertainty about model inputs (the parameters of the model), into variance components associated with the contribution of each parameter. Song et al. (2016) show that the two standard variance-based sensitivity measures adopted for this purpose, namely the first-order effects and the total effects, both based on Sobol indices (Homma and Saltelli, 1996), may produce conflicting results and fail to appropriately measure how sensitive the model output is to variations in each parameter when there are structural interactions between parameters, as the two measures focus on different sets of interactions between inputs. Shapley effects instead allow to take proper account of all interactions between inputs and hence appear more well suited when there are structural interactions among model inputs, as is likely the case for the parameters of our model.

We present the results of our sensitivity analysis in figures E1 and E2. Figure E1 aims to give an intuitive overview of how the level of the simulated GDP loss changes across the values for any given parameter contained in our parameter space. For the purpose of plotting, parameter α, which is continuous, is discretized by dividing the range shown in table E1 into 10 equally-sized intervals. The red lines in E1 show the median value of the GDP loss across all runs performed for a given parameter value displayed on the horizontal axis. The light blue ribbons show the first and third quartiles of the distribution of results for each parameter value. The plots demonstrate that in the neighborhood of the estimated parameter combination, the GDP loss produced by the simulated model is most strongly affected by the value of β, followed by γ_3, γ_5 and γ_6, while the other parameters have a negligible or non-existent impact. The

[22] Such a thorough exploration of the parameter space (recall that a similarly large sample was also used for the estimation of the model) is made possible by some specific advantages of our framework. First, since the model is very parsimonious, individual runs take only a few seconds. Second, being completely deterministic, there is no need to perform Monte Carlo repetitions for each configuration tested in order to wash out purely stochastic factors which may affect individual runs. Third, the fact that we assume each manufacturing sector as well as each service sector to have common inventory parameters greatly reduces the dimensionality of the parameter space.

GDP loss generated by the model in the neighborhood of the estimated parameter combination hence appears to strongly depend on the degree of stability of long-term expectations, and to a somewhat lesser extent on the inventory planning and adjustment of manufacturing, services and construction. This is consistent with the fact that these macro-sectors account for the majority of production taking place in the model.

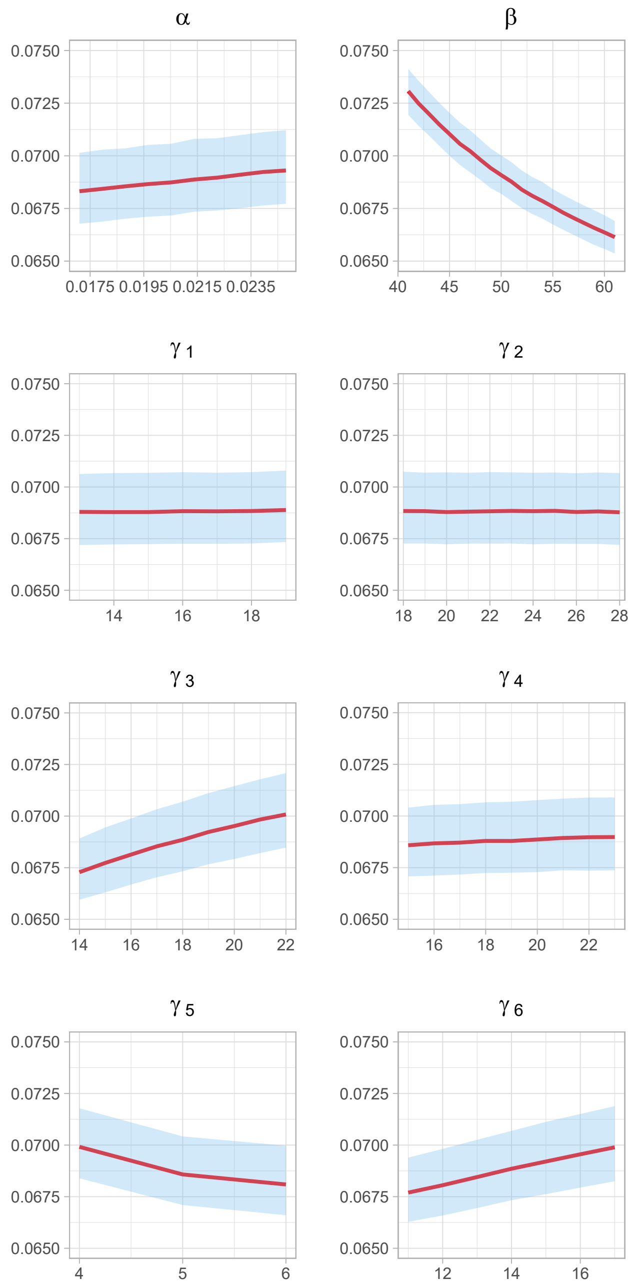

Figure E1: Median GDP loss across parameter values

The results displayed in figure E1 are also confirmed by the Shapley values generated by the analysis, shown in figure E2, where the bars above and below the points represent 95% confidence intervals. β appears to play by far the most important role in explaining the variance of GDP loss, followed by γ_3, γ_5 and γ_6, while the remaining Shapley values do not significantly differ from zero.[23] The importance of β in determining the size of the GDP loss can be explained by considering the role of long term expectations in driving sectors' long-term target for inventories of inputs. A lower value of β, implies that long-term expectations are more strongly influenced by short-term variations in demand, making them more pro-cyclical. Considering the strong impact and relatively short duration of the lockdown, lower values of β cause long-term expectations to decline more strongly and remain low for longer after the lockdown is lifted, reducing sectors' long-term inventory targets. By further reducing sectors' orders of inputs, this ends up exacerbating the decline of GDP. High values of β, by contrast, will keep long-term expectations relatively constant over the duration of the lockdown, thus contributing to a quicker recovery once sectors are no longer constrained by available labor.

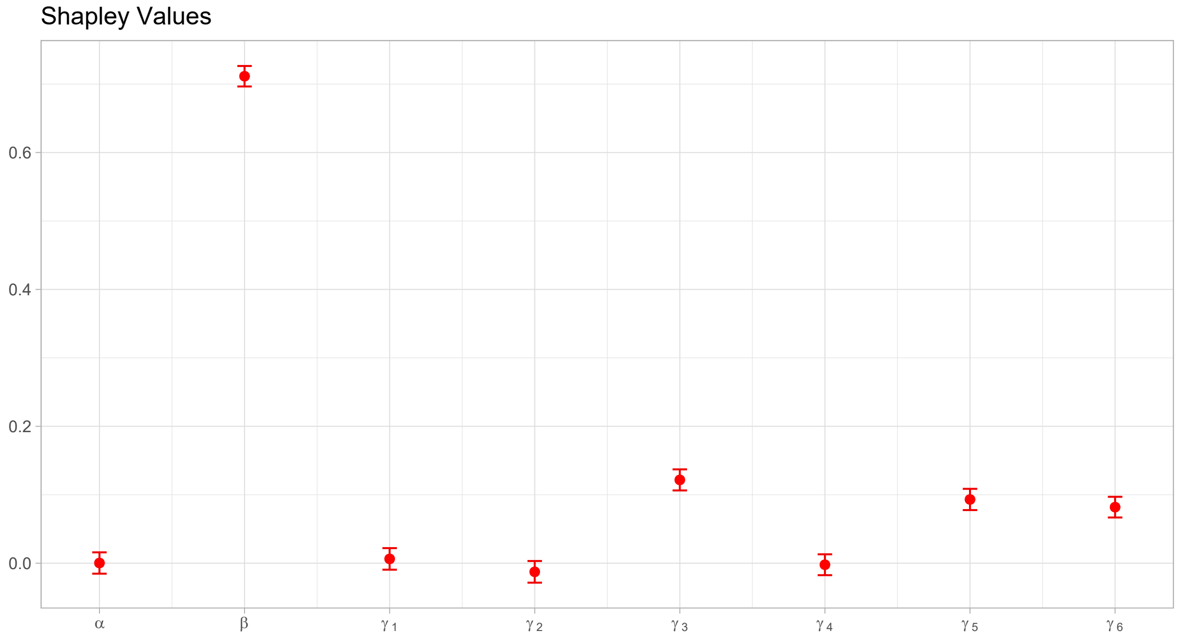

Figure E2: Shapley values for GDP loss

[23]Note that the Shapley values produced by the algorithm and displayed in the plot, are *estimated* (hence the confidence intervals). As a consequence, even though Shapley values should in theory be ≥ 0, point estimates arising from the algorithm may be slightly negative (as for γ_2 in the plot), though in these cases they are never significantly different from zero, as the confidence intervals make clear.