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Forecasting the propagation of pandemic shocks with a dynamic input-output model

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A B S T R A C T

We introduce a dynamic disequilibrium input-output model that was used to forecast the economics of the COVID-19 pandemic. This model was designed to understand the upstream and downstream propagation of the industry-specific demand and supply shocks caused by COVID-19, which were exceptional in their severity, suddenness and heterogeneity across industries. The model, which was inspired in part by previous work on the response to natural disasters, includes the introduction of a new functional form for production functions, which allowed us to create bespoke production functions for each industry based on a survey of industry analysts. We also introduced new elements for modeling inventories, consumption and labor. The resulting model made accurate real-time forecasts for the decline of sectoral and aggregate economic activity in the United Kingdom in the second quarter of 2020. We examine some of the theoretical implications of our model and find that the choice of production functions and inventory levels plays a key role in the propagation of pandemic shocks. Our work demonstrates that an out of equilibrium model calibrated against national accounting data can serve as a useful real time policy evaluation and forecasting tool.

1. Introduction

The social distancing measures imposed to combat the first wave of the COVID-19 pandemic created severe industry-specific disruptions to economic output. Some industries were shut down almost entirely by lack of demand, labor shortages restricted others, and many were initially largely unaffected. Feedback effects then amplified the initial shocks. The lack of demand for final goods such as restaurants or transportation propagated upstream, reducing demand for the intermediate goods that supply these industries. Supply constraints due to a lack of labor under social distancing propagated downstream, creating input scarcity that sometimes limited production even in cases where the availability of labor and demand would

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not have been an issue. The resulting supply and demand constraints interacted to create bottlenecks in production, which in turn led to unemployment, eventually decreasing consumption and causing additional amplification of shocks that further decreased final demand. The unprecedented scale and heterogeneity of the shocks caused a major disruption of the economy that presented a challenge for economic modelers.

In this paper we introduce a dynamic input-output model that addresses the unique features of the pandemic. The model, which is directly initialized from national accounts and other data sources where this is possible, has several new elements that affect production, consumption and changes in the labor force. We developed this model during March-April 2020, and used it to forecast the economic consequences of the relaxation of the lockdown in the UK in real-time, in a working paper we released in May 2020 (Pichler et al., 2020). Here we show that the model predicted aggregate economic effects very well and analyze why it succeeded. We first analyze how the model anticipated the impact of the COVID-19 pandemic on the UK economy, particularly at the sectoral level. We then show that our model accurately captures supply chain effects that explain the dynamics of related industries. Finally, we delve into specific mechanisms and theoretical implications, including the distinction between shocks and higher-order impacts and the limited usefulness of closed-form statistics, such as upstreamness or output multipliers. Overall, our work demonstrates how a data-driven, out of equilibrium model can serve as a useful real time policy evaluation and forecasting tool.

A dynamic input-output model of the COVID-19 pandemic. We introduce a dynamic macroeconomic model that simulates the dynamics of output, value added, employment and other macroeconomic variables across industries. In normal times, the model rests in a steady state that is compatible with national accounts, input-output tables and other statistics. In this steady state, demand equals supply and no hiring and firing takes place. At some point, the model economy is hit by demand and supply shocks. Industries' demand changes as other industries change their intermediate demand and consumers change their final demand. Also the supply may change, as firms may run out of intermediate inputs or labor supply and may need to stop production. As a result, large imbalances in the economy may emerge, leading to a rich endogenous dynamics that interacts with the exogenous shock processes.

Our model is inspired by previous work on the economic response to natural disasters (Hallegatte, 2008; Henriet et al., 2012; Inoue and Todo, 2019). As in these models, industry demand and production decisions are based on simple rules of thumb, rather than resulting from optimization in a dynamic general equilibrium setup. We think that the COVID-19 shock was so sudden and unexpected that agents' expectations had little time to converge to an equilibrium over the short time period that we consider (Evans and Honkapohja, 2012).[1] Compared to prior economic disaster models, our model has differences in the treatment of production, consumption and changes in the labor force.

A key innovation in our economic model is the introduction of an industry-specific production function with a new concept of substitution between intermediate inputs. Standard production functions used in models that study the economic effects of the COVID-19 pandemic assume (i) no possibility of subsitution, as in the Leontief production function typically used in Input-Output analysis; (ii) an infinite elasticity of substitution (linear production function, Richiardi et al. 2020); an elasticity of substitution of 1 (Cobb-Douglas production function, Fadinger and Schymik 2020); and a generic value for the elasticity of substitution, as in the Constant Elasticity of Substitution (CES) production function.[2] While nested CES production functions in principle can accommodate a wide range of technologies, the more detailed the nested structure is, the more difficult they are to calibrate empirically, and as a result they may be used in theoretical work but remain scarcely used when bringing the models to data, particularly in studies of the economic impact of the pandemic. To solve this problem we introduce a new production function that distinguishes between critical and non-critical inputs at the level of the 55 industries in the World Input-Output tables. The Partially Binding Leontief (PBL) production function that we introduce here allows firms to keep producing as long as they have the inputs that are absolutely necessary, which we call *critical inputs*. To determine which inputs are critical and which are not, we use a survey performed by industry analysts of IHS Markit at our request. We show that a realistic specification of the production function is a key ingredient with strong effects on model accuracy.

Another key element of our modeling approach is a detailed representation of industry-specific input inventories. Inventories act as buffers in the presence of supply chain disruptions or demand shocks and thus can play an important role in shock propagation dynamics. Here, we use a survey by the UK Office for National Statistics (ONS) on industry-level inventories to initialize our model so that each industry has different initial inventory levels.[3]

We introduce a COVID-19-specific treatment of consumption. Most models do not incorporate the demand shocks that are caused by changes in consumer preferences in order to minimize risk of infection (Guan et al., 2020). We consider demand shocks to consumption due to "fear of infection", and also consider the effect of the drop in current income due to unemployment and reduced expectations of permanent income due to pessimism about the end of the pandemic.

[1] In this sense our dynamic input-output model is closer to some agent-based models (ABMs) of the COVID-19 pandemic (Basurto et al., 2020; Delli Gatti and Reissl, 2022; Sharma et al., 2021) than to general equilibrium models. While our model does not consider individual households and firms, it is simulated forward in time, rather than "solved" for some set of prices and quantities that clear the market.

[2] Typical calibration for short term analysis uses an elasticity of substitution between intermediates less than 1 and often close to 0 (Barrot et al., 2021; Bonadio et al., 2021; Mandel and Veetil, 2020).

[3] Inventory levels in economic disaster models are frequently assumed to be homogeneous across industries (e.g. Wenz and Levermann, 2016 and Inoue and Todo, 2019) or calibrated such that they yield good model results (e.g. Reissl et al., 2021).

Finally, compared to other economic disaster models, our model explicitly considers labor. Industries adjust their labor force depending on supply constraints due to lockdown, lack of demand or lack of intermediate inputs. Adjustment is sluggish, so firms cannot instantly increase production if they lack workers, as hiring takes time.

Economic forecasting in real-time. We released our results for the UK economy online on May 21, 2020, not long after social distancing measures first began to take effect in March. Our central scenario considered a government policy for reopening that was very close to what the UK government decided. In that scenario, we predicted a 21.5% contraction of GDP in the UK economy in the second quarter of 2020 with respect to the last quarter of 2019. This forecast was remarkably close to the actual contraction of 22.1% estimated by the ONS. (The forecast by the Bank of England was roughly 30%, and the median forecast by several institutions and financial firms for Q2/Q1 was -16.6% (the ONS early estimate for Q1/Q4 was -2%)).[4]

In this substantially revised version relative to our original paper released in May 2020, we take advantage of the fact that we now know what actually happened to do a “postmortem” of our model and analyze the factors that influenced its performance. We introduce an updated version of the model that incorporates some small changes, which are documented in detail in Section S8 of the Supplementary Information. The changes are: the use of UK rather than US inventory data, slight modifications of a few shocks, a slight modification of the consumption function, and a small modification in the form of the production function. The aggregate performance of the updated model is essentially the same as that of the original model, while the sectoral performance is about 13% better.[5]

We show that our model not only predicts value added, but also correctly predicts reductions in the various components of expenditure and income accounts. For instance, it correctly predicts stronger reductions in private consumption and investment than in government consumption and inventories, and weaker reductions in wages and salaries than in profits (due to government furlough support schemes). At the sectoral level, the correlation between output reductions in the model and in the data is generally high (the Pearson correlation coefficient weighted by industry size is 0.75), although the dynamics of a few specific industries have not been captured well by our model (e.g. vehicle manufacturing, air transport). We conjecture that this is due to idiosyncratic features of these industries that our model could not anticipate. Conversely, we provide examples where our model predicts sectoral outcomes correctly through time, even though these depend on complex inter-industry relationships.

We further use our model to separate industry-specific impacts into first-order shocks and higher-order effects. Our results indicate that industries that face relatively small direct shocks tend to suffer more from indirect adverse effects induced by the production network, and vice versa. Only considering first-order shocks would lead to underestimating the economic impacts of the pandemic.

Our work belongs to the very recent effort of developing agent-based, out of equilibrium models for macroeconomic predictions. Macroeconomic agent-based models frequently involve many free parameters and are often used for qualitative analysis. Only recently have agent-based models begun to be calibrated on detailed economic data and used for economic forecasting. For example, Poledna et al. (2019) benchmark the forecasts of their agent-based model for the Austrian economy against those of time series models and dynamic stochastic equilibrium models. In the context of the COVID-19 pandemic, Reissl et al. (2021) calibrate the parameters of their dynamic input-output model and test it against data, showing that it reproduces sectoral output dynamics very well from the first lockdown through September 2020. As far as we know, our work here is the first example where an out-of-equilibrium model in this tradition has made successful economic forecasts in real-time, i.e by making predictions prior to outcomes. This insures that the match between predictions and outcomes is not due to overfitting.

Theoretical implications. By running counterfactual scenarios, we investigate the role of different model features, leading to several interesting theoretical insights.

First, our analysis shows that the inventory levels of industries strongly influence the propagation of shocks. Input inventories allow firms to continue production even in the case of bottlenecks of critical inputs, and thus can temporarily mitigate upstream shocks. We find strong interactions between inventory levels and production functions that affect overall economic impacts. This highlights the importance of a careful initialization of inventory levels and choice of production function.

Second, we compare our results on shock amplification with those that would be obtained using popular metrics of centrality, such as upstreamness and output multipliers. We find that static measures are only partially able to explain our modeling results. Nevertheless, an industry's upstreamness is a strong indicator of its potential to amplify shocks. This is true for supply shocks, as expected, but it is also true for demand shocks, which is more surprising.

[4] Sources: ONS early estimates for Q1 (13 May) https://www.ons.gov.uk/economy/grossdomesticproductgdp/bulletins/gdpfirstquarterlyestimateuk/januarytomarch2020 and Q2 (12 August) https://www.ons.gov.uk/economy/grossdomesticproductgdp/bulletins/gdpfirstquarterlyestimateuk/apriltojune2020; Median forecast of institutions and financial firms (in May): https://www.gov.uk/government/statistics/forecasts-for-the-uk-economy-may-2020; Forecast by the Bank of England (in May): https://www.bankofengland.co.uk/-/media/boe/files/monetary-policy-report/2020/may/monetary-policy-report-may-2020.

[5] The Absolute Mean Sectoral Error, defined in Eq. (2) of the Supplementary Information, was 13.5% for the original model vs. 11.8% for the updated model, i.e. the fractional change is $11.8/13.5 \approx 0.87$, i.e. about a 13% decrease in the sectoral prediction error. The aggregate errors are roughly the same in both cases.

Third, we demonstrate that network effects can strongly inhibit recovery and can cause counter-intuitive results, such as situations in which reopening a few industries can actually depress economic output. This is because the industries that are not reopened remain constrained and competition for the scarce inputs that these industries produce increases, resulting in stronger bottlenecks for reopened industries.

Overall, these results suggest that a properly tuned partially binding Leontief production function can strike the right balance between too much shock propagation and too little shock propagation. They also suggest that a dynamic input-output model like ours is warranted over simple input-output metrics and comparative statics in general equilibrium models, as it makes it possible to deal with simultaneous supply and demand shocks and non-linear effects of closing and reopening groups of industries.

Roadmap. The paper is organized as follows. We present the model details in Section 2 and show how the model has been calibrated and initialized with direct pandemic shocks in Section 3. In Section 4 we discuss the empirical impact of the COVID-19 pandemic in the UK economy and evaluate the model predictions. We present theoretical results and counterfactual runs of our model in Section 5 and conclude in Section 6.

2. A dynamic input-output model

Our model combines elements of the input-output models developed by Battiston et al. (2007), Hallegatte (2008), Henriet et al. (2012) and Inoue and Todo (2019), together with new features that make the model more realistic in the context of a pandemic-induced lockdown.

We provide the model source code, further replication files and all relevant data in an online repository.[6] In the Supplementary Information (Section S1) we provide a comprehensive summary of our notation.

2.1. Timeline

A time step t corresponds to one calendar day. There are N industries (one representative firm for each industry) and one representative household. The economy initially rests in a steady-state until it experiences exogenous pandemic shocks. These shocks can affect the supply side (labor compensation, productive capacity) and the demand side (preferences, aggregate spending/saving) of the economy. Every day the model executes the following steps:

1. Firms hire or fire workers depending on whether their workforce was insufficient or redundant to carry out production in the previous day.
2. The representative household decides its consumption demand and industries place orders for intermediate goods.
3. Industries produce as much as they can to satisfy demand, given that they could be limited by lack of critical inputs or lack of workers.
4. If industries do not produce enough, they distribute their production to final consumers and to other industries on a pro rata basis, that is, proportionally to demand.
5. Industries update their inventory levels and labor compensation is distributed to workers.

2.2. Model description

We first present the basic accounting structure of our economy. Let $x_{i,t}$ denote total output of industry i at time t and $Z_{ji,t}$ the intermediate consumption by industry i of good j. We adopt the standard convention that in the input-output matrix columns represent demand and rows represent supply. Following basic national accounting relationships, the output of i is equal to

$$x_{i,t} = \sum_{j=1}^{N} Z_{ij,t} + c_{i,t} + f_{i,t}, \tag{1}$$

where $c_{i,t}$ is household consumption of good i at time step t and $f_{i,t}$ is all other (exogenous) final demand, including investments, government consumption and exports.

We let $l_{i,t}$ denote labor compensation to workers in industry i. This also indicates the number of workers employed in industry i, under the assumption that all workers employed in the same industry earn the same wage. Profits of industry i can then be written as

$$\pi_{i,t} = x_{i,t} - \sum_{j=1}^{N} Z_{ji,t} - l_{i,t} - e_{i,t}, \tag{2}$$

where $e_{i,t}$ represents all other expenses (taxes, imports, etc.).

[6] https://doi.org/10.5281/zenodo.5881855.

As in related dynamic models of the COVID-19 pandemic (Guan et al., 2020; Inoue and Todo, 2020) and most conventional input-output models (Miller and Blair, 2009), we do not model physical capital explicitly, and we take prices as time-invariant. Thus, price levels are normalized to one for every industry and are constant over the short time period considered here.[7]

A core feature of our model is that in the aftermath of economic shocks, demand does not necessarily equal realized transactions, so that markets do not clear (Steenge and Bočkarjova, 2007). Demand is represented by orders placed by customers to suppliers, which is not necessarily the same as actual production.

2.2.1. Demand

Total demand. The total demand faced by industry i at time t, $d_{i,t}$, is the sum of the demand from all its customers,

$$d_{i,t} = \sum_{j=1}^{N} O_{ij,t} + c_{i,t}^d + f_{i,t}^d, \tag{3}$$

where $O_{ij,t}$ (for *orders*) denotes the intermediate demand from industry j to industry i, $c_{i,t}^d$ represents (final) demand from households and $f_{i,t}^d$ denotes all other final demand (e.g. government or non-domestic customers).

Intermediate demand. The dynamics of intermediate demand are similar to those in Henriet et al. (2012), Hallegatte (2014), and Inoue and Todo (2019). Specifically, the demand from industry i to industry j is

$$O_{ji,t} = A_{ji} d_{i,t-1} + \frac{1}{\tau}\left(n_i Z_{ji,0} - S_{ji,t-1}\right). \tag{4}$$

Intermediate demand is thus the sum of two components. First, industry i holds the naive expectation that demand on day t will be the same as on day $t-1$,[8] and demands an amount $A_{ji} d_{i,t-1}$ from j. Therefore, industries order intermediate inputs in fixed proportions of expected demand, with the proportions encoded in the technical coefficient matrix A, i.e. $A_{ji} = Z_{ji,0}/x_{i,0}$ (note that we use the zero time index to indicate the pre-pandemic steady state). Below we will allow for production mechanisms that do not strictly rely on fixed input recipes due to non-critical inputs to production. We assume, however, that the desired input usage of an industry follows the empirically observed technical coefficients before the pandemic.

The second term in Eq. (4) describes intermediate demand induced by desired reduction of inventory gaps. Due to the dynamic nature of the model, demanded inputs cannot be used immediately for production. Instead industries use an inventory of inputs in production. $S_{ji,t-1}$ denotes the stock of input j held in i's inventory at the beginning of time t. Each industry i aims to keep a target inventory $n_i Z_{ji,0}$ of every required input j to ensure production for n_i further days. The parameter τ indicates how quickly an industry adjusts its demand due to an inventory gap. Small τ corresponds to responsive industries that aim to close inventory gaps quickly. In contrast, if τ is large, intermediate demand adjusts slowly in response to inventory gaps[9].

Consumption demand. We let consumption demand for good i be

$$c_{i,t}^d = \theta_{i,t} \tilde{c}_t^d, \tag{5}$$

where $\theta_{i,t}$ is a preference coefficient giving the share of goods from industry i out of total consumption demand $\tilde{c}_t^d$. The coefficients $\theta_{i,t}$ evolve exogenously, following assumptions on how consumer preferences change due to exogenous shocks (in our case, differential risk of infection across industries, see Section 3.2 and Appendix A).

Total consumption demand evolves following an adapted and simplified version of the consumption function in Muellbauer (2020), and is consistent with standard theories of life cycle/permanent income. In particular, $\tilde{c}_t^d$ evolves according to

$$\tilde{c}_t^d = \left(1 - \tilde{\epsilon}_t^D\right) \exp\left(\rho \log \tilde{c}_{t-1}^d + \frac{1-\rho}{2} \log\left(m\tilde{l}_t\right) + \frac{1-\rho}{2} \log\left(m\tilde{l}_t^p\right)\right). \tag{6}$$

In the equation above, the factor $\left(1 - \tilde{\epsilon}_t^D\right)$ accounts for direct aggregate shocks, as is explained in detail in Appendix A. The second factor accounts for the endogenous consumption response to the state of the labor market and future income prospects. In particular, $\tilde{l}_t$ is current labor income, $\tilde{l}_t^p$ is an estimation of permanent income (see Section 3.2), and m is the share of labor income that is used to consume final domestic goods, i.e. that is neither saved nor used for consumption of

[7] An interesting dynamic input-output model of the COVID-19 pandemic which includes sluggish price adjustment mechanisms is presented in Mandel and Veetil (2020).

[8] We did not experiment with more complicated expectation formation rules because simple heuristics such as naive expectations are likely to beat more complicated rules when the world is uncertain and changing rapidly (Gigerenzer and Todd, 1999), as during the COVID-19 pandemic. In such settings, naive expectations may give better forecasting performance than other expectation formation rules (Dosi et al., 2020).

[9] It is difficult to provide microfoundations for inventory management decisions because we operate at the level of industries, rather than at the level of individual firms. However, Blinder (1981) shows that if individual firms follow (s,S) rules (this is a widely studied form of inventory management introduced by Scarf (1959)), aggregation of firm decisions leads to an aggregate functional form similar to Eq. (4).

imported goods. In the pre-pandemic steady state with no aggregate exogenous shocks, $\tilde{\epsilon}_t^D = 0$ and by definition permanent income corresponds to current income, i.e. $\tilde{l}_t^p = \tilde{l}_t$. In this case, total consumption demand corresponds to $m\tilde{l}_t$.[10]

Other components of final demand. In addition, an industry i also faces demand $f_{i,t}^d$ from sources that we do not model as endogenous variables in our framework, such as government or industries in foreign countries. We discuss the composition and calibration of $f_{i,t}^d$ in detail in Section 3.2.

2.2.2. Supply

Every industry aims to satisfy incoming demand by producing the required amount of output. Production is subject to the following two economic constraints:

Productive capacity. First, an industry has finite production capacity $x_{i,t}^{\text{cap}}$, which depends on the amount of available labor input. Initially every industry employs $l_{i,0}$ of labor and produces at full capacity $x_{i,0}^{\text{cap}} = x_{i,0}$. We assume that productive capacity depends linearly on labor inputs,

$$x_{i,t}^{\text{cap}} = \frac{l_{i,t}}{l_{i,0}} x_{i,0}^{\text{cap}}. \tag{7}$$

Input bottlenecks. Second, the production of an industry can be constrained due to an insufficient supply of critical inputs. This can be caused by production network disruptions. Intermediate input-based production capacities depend on the availability of inputs in an industry's inventory and its production technology, i.e.

$$x_{i,t}^{\text{inp}} = \mathcal{F}_i(S_{ji,t}, A_{ji}), \tag{8}$$

where $\mathcal{F}$ is one of five possible functional forms we consider for the production function.

Production function.

We introduce a new approach to formulating production functions that is designed to take into account the industry-specific dependencies of inputs when the economy is disrupted, e.g. by a disaster or a pandemic. To understand our motivation for doing this, consider the example of the steel industry. It has restaurants as an input, presumably because steel companies have a workplace canteen and sometimes entertain their clients and employees. The Leontief production function, which requires that inputs be used in fixed proportions, predicts that a drop in the output of the restaurant industry will cause a corresponding drop in steel output. This is unrealistic, particularly in the short run. In contrast, under the linear production function and under calibrations of the CES production function that are typically used, firms can substitute energy or even restaurants for iron, while still producing the same output. For situations like this, where the production process requires a fixed technological recipe, this is obviously unrealistic.

To solve this problem we introduce a new form of production function that distinguishes between critical and non-critical inputs, which we call a partially binding Leontief (PBL) production function. Here we use this at the level of the 55 industries in the World Input-Output tables. This production function allows firms to keep producing as long as they have the inputs that are absolutely necessary, which we call *critical inputs*. The steel industry cannot produce steel without the critical inputs iron and energy, but it can operate for a considerable period of time without non-critical inputs such as restaurants or management consultants. We apply the Leontief function only to the critical inputs, ignoring the others. Thus we make the assumption that during the pandemic the steel industry requires iron and energy in the usual fixed proportions, but the output of the restaurant or management consultancy industries is irrelevant. Of course restaurants and management consultants are useful to the steel industry in normal times – otherwise they probably would not use them. But during the short time-scale of the pandemic, we believe that neglecting them provides a better approximation of economic behavior than either a Leontief or a CES production function with uniform elasticity of substitution. In the Supplementary Information (Section S7), we show that our production function is close to a limiting case of an appropriately constructed nested CES, which we could have used in principle, but the two are not exactly the same, and it is less well-suited to our calibration procedure (see the Discussion section).

But which inputs are critical for which industries? To answer this question, at our request, IHS Markit analysts rated whether a given input is *critical, important* or *non-critical* for the production of a given industry, by answering the question *"Can production continue in industry X if input Y is not available for two months?"*. They specified their ratings in an excel sheet by labeling each input with "1" for critical, "0.5" for important but not critical, and "0" for non-critical[11]. We also allowed them to assign "NA" if they had no idea, though this was seldomly invoked. (See Appendix B for details.)

The results of the survey are very interesting in and of themselves. In total, for all industries 2388 inputs were rated as *not critical*, 477 were rated as *critical*, 365 as *important*, and *NA* was invoked 11 times. The behavior of the various industries was extremely heterogeneous. For example, electricity and gas were rated as critical inputs for 60% of the industries, while many other industries, such as publishing, real estate or health were only rated as critical once. There is also a great deal of diversity in the number of critical inputs that industries have, ranging from some manufacturing industries which have

[10] To see this, note that in the steady state $\tilde{c}_t^d = \tilde{c}_{t-1}^d$. Taking logs on both sides, moving the consumption terms on the left hand side and dividing by $1-\rho$ throughout yields $\log \tilde{c}_t^d = \log\left(m\tilde{l}_t\right)$.

[11] The original survey used the word "essential" rather than critical. We decided to use the word "critical" to avoid confusion with essential industries in government mandates

as many as 15 critical inputs, to the Postal industry with 3 critical inputs and Water or Wholesale, with 4 critical inputs. Industries that are often rated as "important" (but not critical) include Finance and Legal (which receive this rating 15 times) and Public Administration (16 times). The Wholesale industry has 25 inputs that are rated as important, which makes sense given that the Wholesale industry needs goods to sell but it can continue to operate even if some of them are not available. Other industries with many important inputs include Publishing and Manufacturing of Pharmaceuticals, with 17 inputs. The heterogeneity of the ratings suggests that there are devils in the details, and that a realistic rendering of the network structure is likely to be important. (Once again, see Appendix B and in particular Figs. 9 and 10 and Table B.6 to get a more detailed picture).

We formulated three possible implementations of the partially binding Leontief production function based on different interpretations of meaning of the "important" rating in the survey. For purposes of comparison we also considered Leontief and linear production functions. The five different specifications for the form of the production function are listed below in order of their restrictiveness with respect to inputs.

(1) Leontief: The most restrictive choice is the Leontief production function, in which every positive entry in the technical coefficient matrix A is a binding input to an industry. This has the functional form

$$x_{i,t}^{\text{inp}} = \min_{\{j:\, A_{ji}>0\}} \left\{ \frac{S_{ji,t}}{A_{ji}} \right\}. \tag{9}$$

Under the Leontief production function an industry halts production immediately if inventories of any input run down, even if the input represents a small and potentially negligible share of expenses.

(2) Strongly-critical: Under the most restrictive interpretation of the industry analyst survey, we treat the "important" rating as equivalent to the "critical" rating, i.e. we assume that production is equally constrained by both critical and important inputs. In contrast to the Leontief case, however, production is not constrained by the lack of non-critical inputs, which are irrelevant for production. For the strongly-critical specification, an industry's production capacity with respect to inputs is

$$x_{i,t}^{\text{inp}} = \min_{j\in\{\mathcal{V}_i \cup \mathcal{U}_i\}} \left\{ \frac{S_{ji,t}}{A_{ji}} \right\}, \tag{10}$$

where $\mathcal{V}_i$ is the set of *critical* inputs and $\mathcal{U}_i$ is the set of *important* inputs to industry i. Note that the quantity of inputs from industries j that are non critical or non important for i (i.e. $j \notin \{\mathcal{V}_i \cup \mathcal{U}_i\}$) does not affect output.

(3) Half-critical: As an intermediate case, we leave the assumptions regarding *critical* and *non-critical* inputs unchanged but interpret the *important* input to mean that its absence constrains production by a factor of 0.5 relative to a critical input. This is consistent with its label of "0.5" in the survey[12]. We implement this production scenario as

$$x_{i,t}^{\text{inp}} = \min_{\{j\in\mathcal{V}_i,\ k\in\mathcal{U}_i\}} \left\{ \frac{S_{ji,t}}{A_{ji}}, \frac{1}{2}\left(\frac{S_{ki,t}}{A_{ki}} + x_{i,0}^{\text{cap}} \right) \right\}. \tag{11}$$

This means that, assuming all inputs are available except for one *important* input, if this important input goes down by 50% compared to initial levels, production of the industry would decrease by 25%. When the stock of this input is fully depleted, production drops to 50% of initial levels.

(4) Weakly-critical: For this specification we interpret all *important* inputs as *non-critical*, such that only *critical* inputs can create input bottlenecks. This reduces the input bottleneck equation, Eq. (8), to

$$x_{i,t}^{\text{inp}} = \min_{j\in\mathcal{V}_i} \left\{ \frac{S_{ji,t}}{A_{ji}} \right\}. \tag{12}$$

(5) Linear: Finally, for comparison purposes we implement a linear production function, in which all inputs are perfect substitutes. In this case production in an industry continues even if some inputs cannot be provided, as long as there is sufficient supply of the other inputs. In this case we have

$$x_{i,t}^{\text{inp}} = \frac{\sum_j S_{ji,t}}{\sum_j A_{ji}}. \tag{13}$$

Note that while production is linear with respect to intermediate inputs, the lack of labor supply cannot be compensated by other inputs.

The strongly-critical, half-critical and weakly-critical production functions are all examples of partially binding Leontief (PBL) production functions. Input bottlenecks are most likely to arise under the Leontief assumption and least likely under the linear production function. The PBL production functions lie in-between these two extremes, ordered from strongly critical, to half-critical, to weakly-critical. For simplicity, we assume that imports never cause bottlenecks. This means that imports are treated as non-critical inputs, or equivalently that there are never shortages in foreign intermediate goods.

[12] Another motivation for reducing production by a half and not, say, to a third in the half-critical scenario is that this case is exactly in between the strongly-critical and weakly-critical cases.

Output level choice and input usage. Since an industry aims to satisfy incoming demand within its production constraints, realized production at time step t is

$$x_{i,t} = \min\{x_{i,t}^{\mathrm{cap}}, x_{i,t}^{\mathrm{inp}}, d_{i,t}\}. \tag{14}$$

This means that the output level of an industry is constrained by the smallest of three values: labor-constrained production capacity $x_{i,t}^{\mathrm{cap}}$, intermediate input-constrained production capacity $x_{i,t}^{\mathrm{inp}}$, or total demand $d_{i,t}$.

The output level $x_{i,t}$ determines the quantity of each input that is used according to the production recipe. Industry i uses an amount $A_{ji}x_{i,t}$ of input j unless j is not critical and the amount of j in i's inventory is less than $A_{ji}x_{i,t}$. In this case, the quantity of input j consumed by industry i is equal to the remaining inventory stock of j-inputs $S_{ji,t} < A_{ji}x_{i,t}$. When $S_{ji,t}$ drops to zero, industry i stops using input j.

Rationing. Absent shocks, industries can always meet total demand, i.e. $x_{i,t} = d_{i,t}$. However, in the presence of production capacity and/or input bottlenecks, industries' output may be smaller than total demand (i.e., $x_{i,t} < d_{i,t}$), in which case industries ration their output across customers. We assume simple proportional rationing, although alternative rationing mechanisms could be considered (Pichler and Farmer, 2021). The final delivery from industry j to industry i is the share of orders received,

$$Z_{ji,t} = O_{ji,t}\frac{x_{j,t}}{d_{j,t}}. \tag{15}$$

Households receive a share of their demand

$$c_{i,t} = c_{i,t}^{d}\frac{x_{i,t}}{d_{i,t}}, \tag{16}$$

and the realized final consumption of agents with exogenous final demand is

$$f_{i,t} = f_{i,t}^{d}\frac{x_{i,t}}{d_{i,t}}. \tag{17}$$

Inventory updating. The inventory of i for every input j is updated according to

$$S_{ji,t+1} = \max\left\{S_{ji,t} + Z_{ji,t} - A_{ji}x_{i,t}, 0\right\}. \tag{18}$$

In a Leontief production function, where every input is critical, the maximum operator would be redundant since production could never continue once inventories are run down. It is necessary for other production functions since industries can produce even after inventories of one or more non-critical inputs j are depleted; thus the maximum operator avoids inventories becoming negative.

Hiring and separations. Firms adjust their labor force depending on which production constraints in Eq. (14) are binding. If the capacity constraint $x_{i,t}^{\mathrm{cap}}$ is binding, industry i decides to try to hire as many workers as necessary to make the capacity constraint no longer binding. Conversely, if either input constraints $x_{i,t}^{\mathrm{inp}}$ or demand constraints $d_{i,t}$ are binding, industry i lays off workers until capacity constraints become binding. More formally, at time $t > 0$ labor demand by industry i is given by $l_{i,t}^{d} = l_{i,t-1} + \Delta l_{i,t}$, with

$$\Delta l_{i,t} = \frac{l_{i,0}}{x_{i,0}}\left[\min\{x_{i,t}^{\mathrm{inp}}, d_{i,t}\} - x_{i,t}^{\mathrm{cap}}\right]. \tag{19}$$

The term $l_{i,0}/x_{i,0}$ reflects the assumption that the labor share in production is constant over the period considered.

We assume that adjustment of labor inputs is sluggish. There are two reasons for this assumption. First, at the microeconomic level, the labor economics literature has established that hiring takes firms time and resources (Pissarides, 2011) and found that firing costs (such as severance payments) diminish firms' propensity to fire (Bentolila and Bertola, 1990). The second reason is aggregation. In our model, we do not consider individual firms, but rather a representative firm for each industry that is assumed to represent the "mean firm". Thus, an alternative explanation for industry-level sluggishness is that individual firms asynchronously hire or fire groups of workers, so that sluggishness results from aggregation.

Bearing these considerations in mind, we assume that industries can increase their labor force only by a fraction γ_{H} in the direction of their target (i.e. of their labor demand). Similarly, industries can decrease their labor force only by a fraction γ_{F} in the direction of their target. This sluggish adjustment towards a target labor demand has been used in other out of equilibrium labor market models (del Rio-Chanona et al., 2021). Following from the sluggishness assumption, the industry-specific employment evolves according to

$$l_{i,t} = \begin{cases} l_{i,t-1} + \gamma_{\mathrm{H}}\Delta l_{i,t} & \text{if } \Delta l_{i,t} \geq 0, \\ l_{i,t-1} + \gamma_{\mathrm{F}}\Delta l_{i,t} & \text{if } \Delta l_{i,t} < 0. \end{cases} \tag{20}$$

The parameters γ_{H} and γ_{F} can be interpreted as policy variables. For example, the implementation of a furloughing scheme makes re-hiring of employees easier, corresponding to an increase in γ_{H}.

Table 1
Overview of model setup, shocks and parameters. WIOD 2014 means that the variables are taken from the World Input-Output Database (year 2014). Direct pandemic shocks are discussed in Section 3.2 and presented in full detail in Appendix A. We show extensive results on model sensitivity with respect to parameters and shocks in the Supplementary Information (Section S5).

Basic model setup	Symbol	Value
Number of industries	N	55
Input-output variables	Z_{ij}, A_{ij}, f_i, x_i, l_i, c_i, θ_i	WIOD 2014
Inventory targets	n_i	Suppl. Section S3
Production function	$\mathcal{F}$	half-critical
Pandemic shocks	Symbol	Value
Labor supply	$\epsilon^S_{i,t}$	Appendix A.1
Household consumption	$\epsilon^D_{i,t}$, $\xi_{i,t}$	Appendix A.2
Investment		15%
Export		15%
Government consumption		0%
Parameters	Symbol	Value
Propensity to consume	m	0.82
Government benefits	b	0.80
Inventory adjustment	τ	10
Upward labor adjustment	γ_H	1/30
Downward labor adjustment	γ_F	1/15
Consumption adjustment	ρ	0.99
Change in savings rate	Δs	0.50

3. Model calibration and initialization

The standard procedure for model calibration is to estimate free parameters based on a best fit between model outputs and real data.[13] When fitting the original model in Pichler et al. (2020) we were not able to do this because we had no past pandemics to use for comparison. Although it is possible in principle to do this now, when we updated our model we have refrained from doing so because we have only one realization of the pandemic, and estimating free parameters this way would almost certainly result in over-fitting. The only exception, discussed in Section 3.1, is the specification of the form of the production function.

We used the following approach to select key assumptions, parameters and initial conditions.

- When a variable or parameter can be observed in data, we simply select the observed value—in fact, we designed our model so that many key quantities could be observed, minimizing latent variables and unobserved parameters.
- When a parameter has little effect on results, we pick a reasonable value, and perform a sensitivity analysis to explore the effect of other choices.
- For the specification of the production function we chose between the five hypothesized functional forms based on a comparison of aggregate and sectoral errors between model predictions and empirical data, as described below.

We describe all our calibration choices in detail in the next subsections. Table 1 gives an overview of the basic model set-up, pandemic shocks and parameter choices.

3.1. Model set-up

The box at the top of Table 1 contains the industry-level macroeconomic quantities that specify the model setup. We use the World Input-Output Database (WIOD) (Timmer et al., 2015), which divides the economy into $N = 55$ sectors. The industry level input-output macroeconomic variables are the entries of the $N \times N$ matrix specifying intermediate consumption Z, and the components of the $N-$dimensional vectors for consumption c, other final demand f, production x and labor compensation l. From these variables we compute the technical coefficients A (which are held fixed throughout the simulation) and the consumption shares θ. These variables are all initialized using the latest year available in the WIOD, which is 2014 (see Section S2 of the Supplementary Information for a visualisation of the UK input-output network). Although this is six years before we make our forecasts, the structure of the UK economy as captured by the matrix A only changed slowly, so that this was good enough for our purposes here. (For example, McNerney et al., 2022 show that the technical coefficients change slowly. Moreover, since we mostly care about relative outcomes with respect to the pre-pandemic situation, the absolute value of initial conditions matters little: if all variables grew by a fixed amount, it would make no difference to our results.)

[13] See Platt (2020) for a review of recent progress on estimating the parameters of agent-based models.

We set the inventory target parameters n_i using data from the Office for National Statistics on the usual stock of inventories (for details on inventories see the Supplementary Information, Section S3). These target inventories are highly heterogeneous across industries. Typically, manufacturing and trade have much higher inventory targets than services.

As discussed in Section 2.2.2, we considered five possible specifications of the production function. While we had a strong prior that neither the Leontief nor linear forms would work well, for the PBL production functions the best way to interpret industries that were classified as "important" in the survey was not obvious to us. To choose between the three possibilities, in the original model we compared the predictions of the model to preliminary data for the effect of the pandemic on employment statistics for Washington state in April 2020. This seemed to indicate that the weakly-critical specification was best. However, subsequent analysis based on UK data favors the half-critical specification, which is also a better match with our prior, so we used the half-critical specification for the updated model. As already mentioned, when combined with the other changes made, the performance of the updated model is similar to that of the original model.

3.2. Pandemic shocks

Simulations of the model described in Section 2 start in the pre-pandemic steady state. While there is evidence that consumption started to decline prior to lockdown (Surico et al., 2020), for simplicity we apply the pandemic shock all at once at the date of the start of the lockdown (March 23rd in the UK).

We initialize the model with pandemic supply and demand shocks derived by del Rio-Chanona et al. (2020). Their estimates of the shocks were derived a priori, based on empirically motivated assumptions on labor supply constraints and changes in preferences. During the lockdown, workers who cannot work on-site and are unable to work from home become unproductive, resulting in lowered productive capacities of industries. At the same time demand-side shocks hit as consumers adjust their consumption preferences to avoid getting infected and reduce overall consumption out of precautionary motives due to the depressed state of the economy. Here, we give an overview of the direct shock assumptions, referring the reader to Appendix A for a detailed exposition on supply and demand shocks.

Supply shocks. At every time step during the lockdown an industry i experiences an exogenous labor supply shock $\epsilon^S_{i,t} \in [0,1]$ that reduces the amount of labor available. Shocks act immediately, so that since the beginning and until the end of the lockdown the labor supply is constrained by

$$l_{i,t} \leq (1-\epsilon^S_{i,t})l_{i,0}, \tag{21}$$

where $l_{i,0}$ is the initial labor supply i.e., the labor available before the lockdown. If $\epsilon^S_{i,t} > 0$, the productive capacity of industry i is smaller than in the initial state of the economy. We assume that the reduction of total output is proportional to the labor loss. In that case the productive capacity of industry i at time t is

$$x^{\text{cap}}_{i,t} = \frac{l_{i,t}}{l_{i,0}} x^{\text{cap}}_{i,0} \leq (1-\epsilon^S_{i,t})x_{i,0}. \tag{22}$$

Following Eq. (20) firms sluggishly recruit and lay off employees to adjust their productive capacity to demand and supply constraints. Thus, labor inputs $l_{i,t}$ are determined endogenously by the model, but are bounded by the above Eq. (21).

To set the values of the supply shocks $\epsilon^S_{i,t}$, we use the estimates of del Rio-Chanona et al. (2020) which we mapped to the UK using the World Input-Output industry classification. These estimates are based on the *Remote Labor Index* RLI_i, a proxy for the fraction of workers that can work from home in industry i without compromising productivity and the essential scores of industries ESS_i. The essential industry scores are based on the official government mandate of Italy on essential industries. (We used the Italian mandate because at the time we were unable to obtain the British mandate).

To calculate the supply shocks, del Rio-Chanona et al. (2020) interpreted the Remote Labor Index and an industry's essential score as independent probabilities. Following this approach, we estimate that the expected value of the fraction of workers of industry i that cannot work is

$$\epsilon^S_{i,t} = \begin{cases} (1-\text{RLI}_i)(1-\text{ESS}_i) & \text{if} \quad t \in [t_{\text{start\_lockdown}}, t_{\text{end\_lockdown}}), \\ 0 & \text{otherwise}. \end{cases} \tag{23}$$

The supply shocks are constant through lockdown and zero before and after lockdown. In Supplementary Sections S4 and S5 we investigate different temporal profiles and magnitudes of supply shocks. We find that our model is quite sensitive to supply shock inputs. Moreover, we find that the specification of direct supply shocks is key for making good empirical predictions, and that the specification considered here (which is the same as the one chosen in the initial version of this paper) is the one that gives best aggregate and sectoral forecasts. In Appendix A we provide full details on assumptions and derivations of the supply shocks we use in the main text.

Demand shocks.

The COVID-19 pandemic caused strong shocks to all components of demand, including private and government consumption, investment, and exports. We model shocks to private consumption demand in detail, distinguishing shocks due to fear of infection vs. those due to fear of unemployment. We model shocks to the other components of final demand, namely investment, government consumption and exports, in less detail.

Shocks due to fear of infection affect the consumption shares $\theta_{i,t}$ in Eq. (5) and aggregate consumption demand $\tilde{c}^d_t$ in Eq. (6). During a pandemic, people reduce their demand for customer-contact services, such as restaurants, shopping, cinemas, etc. due to fear of infection (Chang et al., 2021). Consumption decisions also depend on the state of the pandemic. When the number of infections and deaths is high, people reduce their demand for customer-contact services more strongly than at times when the pandemic is subsiding. At the same time, people can save the money that they are no longer spending on customer-contact services, or increase their consumption of other goods and services, such as durable goods (Chetty et al., 2020).

Our modeling of consumption demand shocks captures all these features. We use estimates by the Congressional Budget Office (2006) to assess which industries face strongest direct shocks due to fear of infection[14] and we let people redirect a fraction $1-\Delta s$ of the money that they are not spending on these industries towards consumption of goods and services from other industries.[15]

In addition to shocks caused by fear of infection, we also consider more traditional shocks due to fear of unemployment. On the one hand, we consider the typical Keynesian consumption function, where consumption is proportional to labor income, $m\tilde{l}_t$ (see Eq. (6)). (Recall that m is the propensity to consume and $\tilde{l}_t$ is total labor income). We model the government support program that was in place in the UK at the time, in which the government pays out social benefits to workers to compensate income losses. The total income $\tilde{l}_t$ that enters Eq. (6) is replaced by an effective income $\tilde{l}_t^{\star} = b\tilde{l}_0 + (1-b)\tilde{l}_t$, where b is the fraction of pre-pandemic labor income that workers who are fired or furloughed are able to retain. On the other hand, we also consider expectations of permanent income $\tilde{l}_t^p$, which may differ between parts of the population.

Finally, we consider demand shocks to other components of final demand. We assume no shocks to government consumption, and a 15% shock to investments and exports (see Appendix A.2 for a justification). Model sensitivities with respect to these assumptions are investigated in detail in the Supplementary Information (Section S5). We find that overall results are fairly robust across alternative specifications of these assumptions.

3.3. Parameters

We calibrate the parameters m and b directly from the data. The propensity to consume m (Eq. (6)) is the share of labor income that is used to buy final domestic goods from the input-output tables, resulting in $m = \left(\sum_i c_{i,0}\right)/\left(\sum_i l_{i,0}\right) = 0.82$. The income compensation "benefit" parameter b is based on the Coronavirus Job Retention Scheme, promoted by the UK government in March 2020. This policy required employers to furlough rather than fire their employees when they were not needed due to lockdown measures, and in exchange the government would pay 80% of their wage, so $b = 0.8$ (meaning that furloughed workers only lose 20% of their wage).

The remaining parameters are difficult to directly calibrate from data, so we are forced to simply pick reasonable values (we keep the same calibration as in the initial version of this paper). Fortunately, as we show in the Supplementary Information (Section S5), these have relatively little effect on our results. The values we chose for the remaining parameters are:

- The parameter τ captures responsiveness to inventory gaps. We fix $\tau = 10$ days, which indicates that firms aim at filling most of their inventory gaps within two weeks. This lies within the range of values used by related studies (e.g. $\tau = 6$ in Inoue and Todo, 2019 and $\tau = 30$ in Hallegatte, 2014).
- The parameters γ_{H} and γ_{F} control the rate of hiring and firing. We choose $\gamma_{\mathrm{H}} = 1/30$ and $\gamma_{\mathrm{F}} = 2\gamma_{\mathrm{H}}$. Given our daily time scale, this is a rather rapid adjustment of the labor force, with firms adjusting to their demanded labor in about a month when hiring and 15 days when firing. Our calibration choices imply that firing happens faster than hiring, in line with empirical evidence from the COVID-19 pandemic (Chetty et al., 2020).
- The parameter ρ indicates sluggish adjustment to new consumption levels. We select the value assumed by Muellbauer (2020), adjusted for our daily timescale[16], which results in $\rho = 0.99$.
- The savings parameter Δs specifies the fraction of pandemic-averted consumption that is saved. We take $\Delta s = 0.5$, meaning that households save half the money they are not spending in goods and services due to fear of infection, and direct the other half of that money to spending on other goods and services. Empirical evidence shows that consumers increased their consumption of durable goods relative to pre-pandemic levels, but at the same time the aggregate saving rate went up, so a value of Δs that is between 0 and 1 is a reasonable choice.

[14] We use the Congressional Budget Office "severe scenario" which represents a better fit to the COVID-19 pandemic than their "mild scenario". We show the model sensitivity with respect to this assumption in the Supplementary Information (Section S5).

[15] We do not model savings re-entering the economy at a later stage, although that could in principle be an interesting phenomenon. In this paper we are concerned with the short-run dynamics of the lockdown rather than with medium- and long-run time scales when savings could play a more important role. Tracking savings is mostly useful to track wealth, and given how unevenly distributed net worth is, we think that modeling wealth effects with a representative household is of limited use.

[16] Assuming that a time step corresponds to a quarter, Muellbauer (2020) takes $\rho = 0.6$, implying that more than 70% of adjustment to new consumption levels occurs within two and a half quarters. We modify ρ to account for our daily timescale: By letting $\bar{\rho} = 0.6$, we take $\rho = 1 - (1-\bar{\rho})/90$ to obtain the same time adjustment as in Muellbauer (2020). Indeed, in an autoregressive process like the one in Eq. (6), about 70% of adjustment to new levels occurs in a time ι related inversely to the persistency parameter ρ. Letting Q denote the quarterly timescale considered by Muellbauer (2020), time to adjustment ι^Q is given by $\iota^Q = 1/(1-\bar{\rho})$. Since we want to keep approximately the same time to adjustment considering a daily time scale, we fix $\iota^D = 90\iota^Q$. We then obtain the parameter ρ in the daily timescale such that it yields ι^D as time to adjustment, namely $1/(1-\rho) = \iota^D = 90\iota^Q = 90/(1-\bar{\rho})$. Rearranging gives the formula that relates ρ and $\bar{\rho}$.

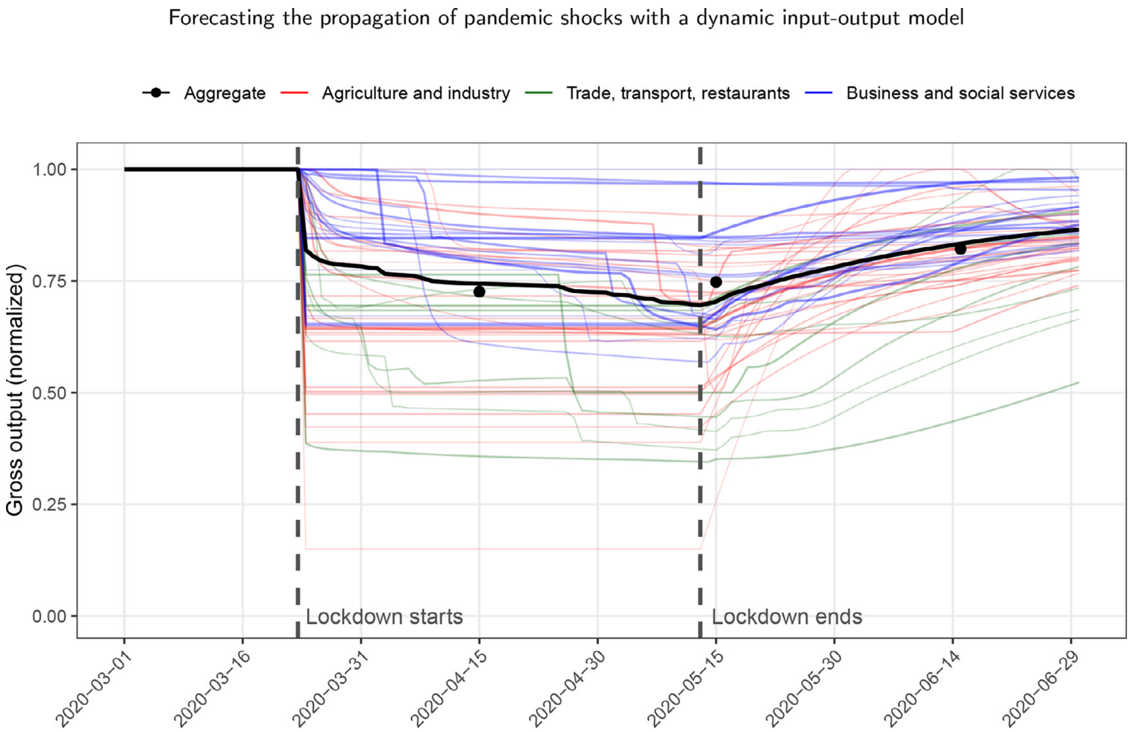

Fig. 1. Economic production predicted by the model as a function of time. We plot production (gross output) as a function of time for each of the 55 industries. Aggregate production is a thick black line and each sector is colored. Agricultural and industrial sectors are colored red; trade, transport, and restaurants are colored green; service sectors are colored blue. Sectoral production is normalized to pre-lockdown levels and line size is proportional to the steady-state gross output of the corresponding sector. For comparison, the black dots indicate empirical gross output, normalized with respect to March 2020.

4. Empirical results

In this section we analyze the economic impact of the COVID-19 pandemic on the UK economy in the second quarter of 2020. In Section 4.1 we discuss the forecasting performance of the model, for several macroeconomic variables and across industries. Next, in Section 4.2, we distinguish between the direct and indirect impact of demand and supply shocks

4.1. Model predictions

Qualitative dynamics. We start by giving a qualitative idea of the overall dynamics produced by the model and discuss more detailed aggregate and industry results later. Fig. 1 shows model results for the calibrated model for production (gross output); results for other important variables, such as profits, consumption and labor compensation (net of government benefits) are similar. When the lockdown starts, there is a sudden drop in economic activity, shown by a sharp decrease in production. Some industries further decrease production over time as they run out of critical inputs. Service sectors tend to perform better than manufacturing, trade, transport and accommodation sectors. The main reason for that is that most service sectors face both lower supply and demand shocks, as a high share of workers can effectively work from home and business and professional services depend less on consumption demand.

In the UK, there was not a clear-cut lifting of the lockdown that was simultaneous for all industries, but we make the approximation that all lockdown measures are lifted for all industries on May 13th, so that the supply shock disappears then. By the end of June, the economy is still far from recovering. In part this is due to the fact that the aggregate level of consumption does not return to pre-lockdown levels. This is due to a reduction in expectations of permanent income (Appendix A.2.2) and due to the fact that we do not remove shocks to investment and exports (see Section 3.2) when the lockdown is lifted. This choice, which was already done in the original version of the model, captures the effect of lingering uncertainty about the end of the pandemic, which disrupted firm decisions and international trade.

Aggregate macroeconomic variables. We now evaluate how well our model describes the economic effects of COVID-19 on the UK economy. Aggregate value added in the second quarter of 2020 is very close to the data. The prediction of the revised model is the same as that of the predictions of the original model, which were released in the first version of this work in May 2020. As mentioned in the introduction, we predicted a 21.5% contraction of GDP in the UK economy in the second quarter of 2020 with respect to the last quarter of 2019, whereas a contraction of 22.1% was actually observed. This

Table 2
Comparison between data and predictions for the main aggregate variables. All percentage changes refer to the last quarter of 2019, which we take to represent the pre-pandemic economic situation.

Variable (compared to Q4-2019)	Data	Model
Value added Q2	-21.5%	-22.1%
Gross output April	-27.4%	-25.3%
Gross output May	-25.2%	-26.9%
Gross output June	-17.8%	-16.8%
Private consumption Q2	-25.3%	-21.3%
Investment Q2	-26.3%	-29.7%
Government consumption Q2	-17.5%	-14.2%
Inventories Q2	-1.8%	-0.5%
Exports Q2	-23.3%	-27.8%
Imports Q2	-30.6%	-23.9%
Wages and Salaries Q2	-1.1%	-4.3%
Profits Q2	-26.7%	-22.3%

is closer to data than most other forecasts released in the same period (see footnote[4]). Looking at the monthly predictions in Table 2, the model slightly underestimates the recession in April and slightly overestimates it in May, while it correctly estimates a strong recovery in June.

In Table 2 we compare the predictions of our model to the data for variables other than gross output and value added. To do this we collect data from national accounts on private and government consumption, investment, change in inventories[17], exports and imports (expenditure approach to GDP); wages and salaries and profits (income approach to GDP). Looking at the expenditure approach to GDP, some variables have a worse reduction in the model, such as investment and exports, while other variables have a worse reduction in the data, such as private and government consumption, inventories and imports.[18] However, the model predicts relative reductions fairly well, as we find a stronger collapse in private consumption and investment than in government consumption or inventories, as in the data. Finally, considering the income approach to GDP, we overestimate the reduction in wages and salaries and underestimate the reduction in profits.[19] Nonetheless, we correctly predict that the absolute reduction in wages and salaries is much smaller than in profits. (This is due to government subsidies).

Industry-level predictions. Turning to the performance of our model at the disaggregate level of industries, Fig. 2 shows gross output as predicted by the model and in the data. Gross output is averaged over the values it takes in April, May and June 2020, both in the model and in the data, and compared to the value it had in Q4 2019. The majority of sectors decreased production up to 60% of initial levels, both in the model and in the data, but a few sectors were forced to decrease production much more. To interpret this figure, note that for points on the left of the identity line, model predictions are higher than in the data, i.e. the model is optimistic. Conversely, for points on the right of the identity line, model predictions are lower than in the data, i.e. the model is pessimistic. The Pearson correlation coefficient weighted by industry size is 0.75, indicating that model predictions and empirical data are strongly (but not perfectly) correlated.

While model predictions in general tend to be in agreement with the empirical data, there are some exceptions. We conjecture that these are due to information that we did not have access to, or idiosyncratic features of certain industries that we could not take into account without overly complicating our model. For example, the predictions of our model are very poor for Sector C29 - Manufacturing of vehicles. Although not officially mandated, almost all car manufacturing plants were completely closed in the UK in April and May, and so production was essentially zero (7% of the pre-pandemic level in April and 14% in May). While they reopened in June, production in Q2 is slightly above 20% of the pre-pandemic level. In contrast, our model predicts about 63% of the pre-pandemic production level.

There are two reasons for this discrepancy. First, car manufacturing is highly integrated internationally, and in a period where most developed countries were implementing lockdown measures, international supply chains were highly disrupted. For simplicity, however, in our model we did not model input bottlenecks due to lack of imported goods. Second, as already mentioned, many firms producing non-essential goods such as automobiles voluntarily decided to stop production to protect the health of their workers, even though they were not forced to do so.

Another example for which the predictions of our model are poor is Sector H51 - Air transport. Production in the data is 3% of pre-lockdown levels. In the UK and around the world, the almost complete shutdown of the air transport industry

[17] The number shown in Table 2 is an estimate of the reduction of the *level* of inventories in Q2 2020 with respect to the pre-pandemic level. To compute this number, we have taken the change in inventories for Q2 2020 provided by the ONS and divided that number by the total stock of inventories as estimated using the same ONS data that we used to calibrate inventory target parameters. We then compute the same quantity in simulated data.

[18] The model predicts a current account deficit, while in reality there was a current account surplus. However, we do not model international trade explicitly, but treat exports as exogenous and imports as another (non-critical) input.

[19] Note that these categories are not jointly exhaustive, in the sense that wages and salaries and profits are not all components of value added according to the income approach. Indeed, the ONS also considers mixed income and taxes less subsidies, which are difficult to compare to variables in our model.

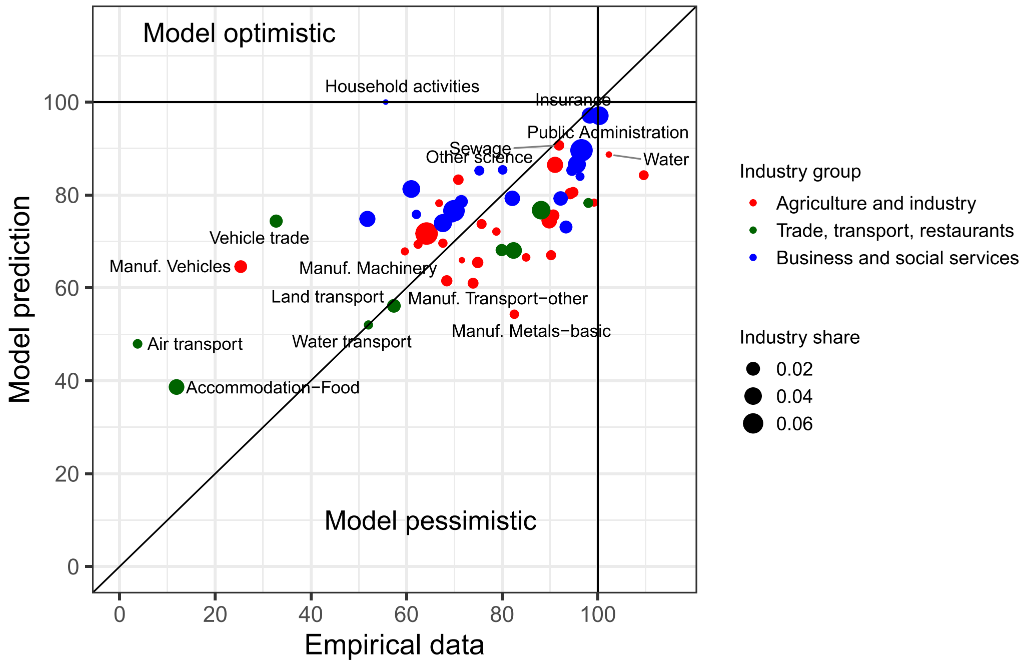

Fig. 2. Comparison between model predictions and empirical data. Predicted production (gross output) for each of 53 industries, against the actual values from the ONS data, averaged across April, May and June. Values are relative to pre-lockdown levels and dot size is proportional to the steady-state gross output of the corresponding sector. Agricultural and industrial sectors are colored red; trade, transport, and restaurants are colored green; service sectors are colored blue. Dots above the identity line means that the predicted recession is less severe than in the data, while the reverse is true for dots below the identity line.

was caused by the mobility restrictions that removed almost all intermediate and consumption demand, not by supply shocks, because large parts of the transports sector were considered essential. Our model captures the fact that supply shocks were not a key determinant of the performance of the air transport industry, as we only apply a small supply shock (10%). What our model does not capture is mobility restrictions. On the one hand, we assume a 67% consumption demand shock, while in reality is was closer to 100%. On the other hand, we do not assume any direct impact of restrictions on intermediate consumption—which can be interpreted as business travel. So, in our model there is considerable activity of the Air transport industry during lockdown due to business travel, which is a non-critical input to many industries and was not exogenously suspended.

For many other sectors, however, our model gave accurate predictions, even when the answer was far from obvious. Compare, for instance, industries M74_M75 (Other Science) and O84 (Public Administration). Both received a very weak supply shock: 3% for Other Science and 1.1% for Public Administration (Table 5 in Appendix A), and no private consumption demand shocks. Yet Public Administration had almost no reduction in production, while Other Science reduced its production to about 75% of its pre-pandemic level. The ONS report in May (see footnote [4]) quotes reduced intermediate demand as the reason why Other Science reduced its activity. Conversely, Public Administration's output is almost exclusively sold to the government, which did not reduce its consumption. Because of its ability to take into account supply chain effects and the resulting reductions in intermediate demand, our model is able to endogenously predict the dramatic difference between these two sectors, even though their shocks are small in both cases.

Fig. 3 shows the ability of the model to predict sectoral dynamics. It is similar to Fig. 2 but shows output in both April and June. The dots that represent the same industry in April and June are connected by a black line. We focus on a few industries, making all other points light grey (Fig. 11 in Appendix C.2 shows labels for all industries). To interpret changes from April to June, note that a line close to vertical implies that a given industry had a much stronger recovery in the data than in the model, while a horizontal line implies the opposite. A line parallel to the identity line indicates that the recovery was as strong in the data as in the model. Almost all sectors experience a substantial recovery from April to June, both in the model and in the data.

An example in which our model correctly predicts dynamic supply chain effects is the recovery experienced by C23 (Manufacture of other non-metallic mineral products) as a consequence of the recovery by F (Construction). According to ONS reports, increased activity in construction in June is explained by the lifting of the lockdown and by adaptation to social distancing guidelines by construction firms. At the same time, industry C23 recovers due to the production of cement, lime, plaster, etc. to satisfy intermediate demand by construction (construction is by far the main customer of C23, buying almost 50% of its output). This pattern is accurately predicted by the endogenous dynamics in our model.

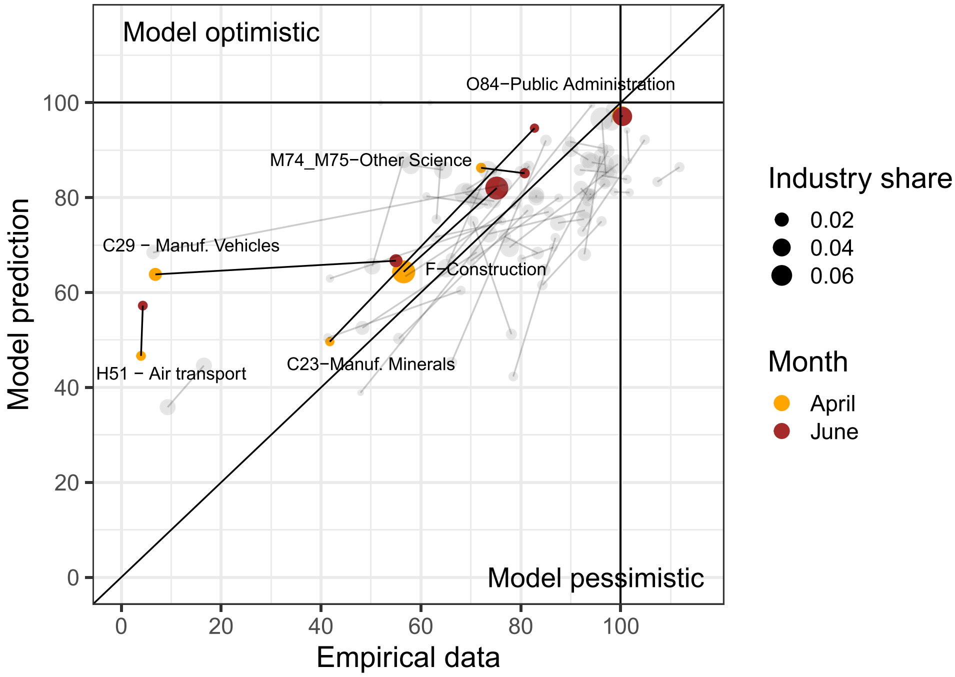

Fig. 3. Comparison between model predictions and empirical data. We plot predicted production (gross output) vs. observed values from ONS data. Production is relative to pre-lockdown levels and dot size is proportional to the steady-state gross output of the corresponding sector. Yellow is April and red is June. Black lines connect the same industry from April to June. Only a few industries are highlighted (see main text).

4.2. Direct shocks and higher-order impacts

On the aggregate level our model predicted a reduction in gross output of almost 27% (Table 2) which is substantially larger than the 17% direct shock (Table 5). We observe similar amplification effects for final consumption and other final demand categories. Since model results closely correspond to empirical observations, this makes clear that the endogenous dynamics of the model have been important to make accurate forecasts. In this section we zoom into the relative contribution of direct shocks and higher-order effects for different industries, to better understand what drives the model forecasts.

We begin by defining the direct changes to output and consumption. We define the *direct* output change as

$$\mathrm{OC}_i^{\mathrm{direct}} \equiv -\epsilon_{i,0}^S. \tag{24}$$

This is justified because exogenous supply shocks lead to an immediate reduction in gross output. To get a similar measure for direct shocks to final demand we define the shocked household consumption as

$$c_{i,0}^{\mathrm{shocked}} = \frac{1-\epsilon_{i,0}^D}{1-\tilde{\epsilon}_0^D} c_{i,0}, \tag{25}$$

where $\epsilon_{i,0}^D$ is the direct household demand shock to industry i and $\tilde{\epsilon}_0^D$ is the overall household demand shock taking changes in savings into account. Note that Eq. (25) only considers exogenous shocks to consumer demand directly relevant at the first day of lockdown, and ignores changes in consumer preferences over time due to fear of infection and fear of unemployment, as explained in detail in Appendix A.2.

Recall that $f_{i,0}$ denotes non-household final consumption (investment + exports + government consumption) and we further define f_i^{shocked} as the non-household final consumption after shocks have been applied. The *direct* final consumption change is then given as

$$\mathrm{CC}_i^{\mathrm{direct}} \equiv \frac{(c_i^{\mathrm{shocked}} + f_i^{\mathrm{shocked}}) - (c_{i,0} + f_{i,0})}{c_{i,0} + f_{i,0}}. \tag{26}$$

The upper panel of Fig. 4 visualizes our estimates of direct changes in gross output $\mathrm{OC}_i^{\mathrm{direct}}$ and final consumption $\mathrm{CC}_i^{\mathrm{direct}}$ for each sector of the UK economy. As discussed in del Rio-Chanona et al. (2020), some industries face large immediate reductions in output (e.g. several manufacturers), some industries face strong shocks to demand (e.g. transport (H49-51)) and some industries experience both strong supply shocks and strong demand shocks (e.g. Accommodation and Food (I)). Due to the reordering of consumer preferences, some industries even experience small positive demand shocks (e.g. Utilities (D35-E36), Real Estate (L68)), despite an overall decline in consumer demand.

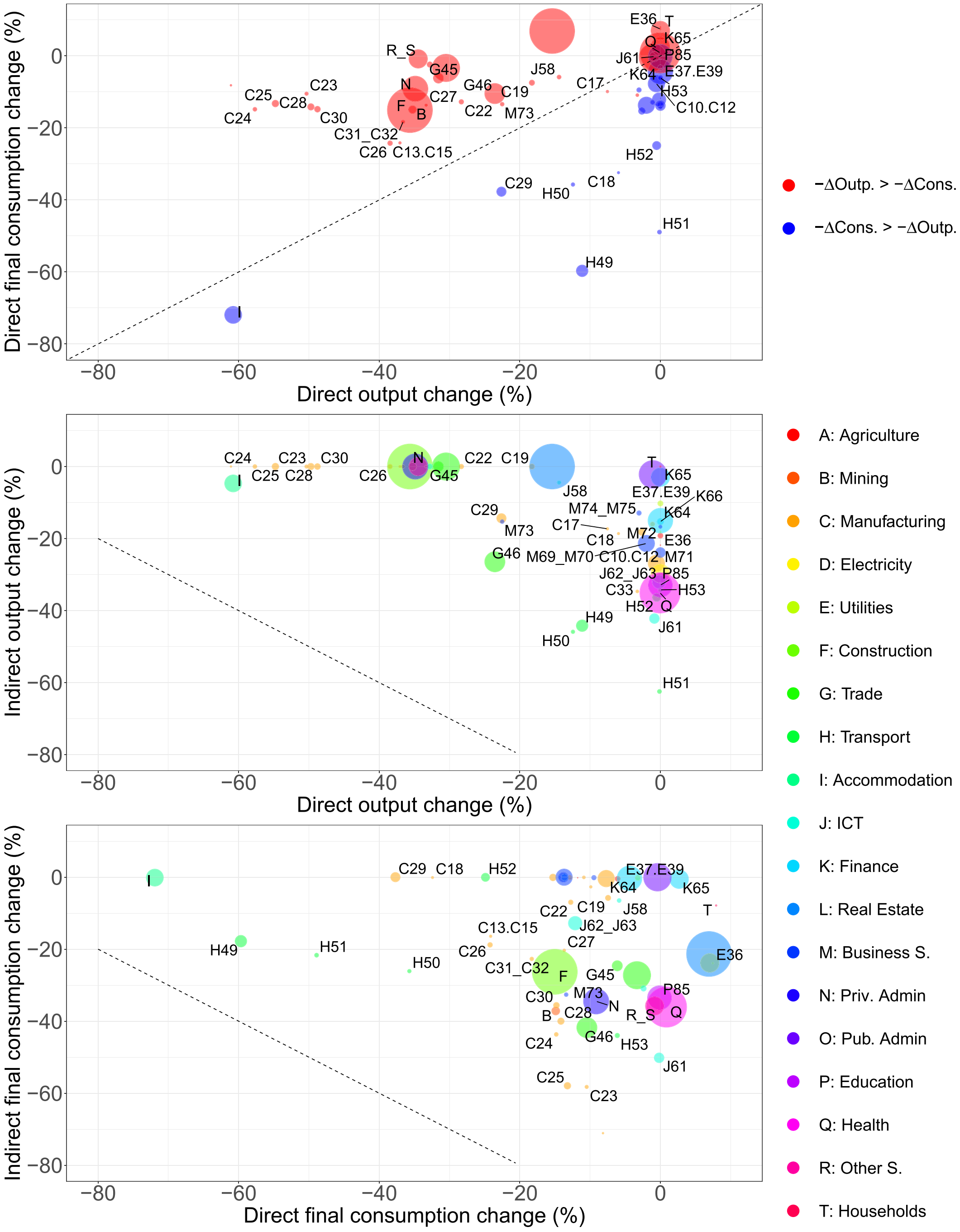

Fig. 4. Comparison of direct and indirect impacts. *Upper panel:Sectoral first-order shocks to supply and demand in the UK economy*. The percentage change in final consumption is plotted against the percentage change in gross output one month after the lockdown begins. A blue disk indicates that the monetary shock in absolute terms is larger on the demand side than on the supply side (blue disks can thus lie below the identity line and vice versa). Disk size corresponds to initial gross output of industries. *Center panel:* Comparison of direct and indirect output changes. Direct changes in sectoral output on the horizontal axis are plotted against indirect impacts on sectoral production on the vertical axis. The dashed line indicates the impact possibility frontier $(x, 100 - x)$. Disk size corresponds to initial gross output of industries. *Bottom panel:* Comparison of direct and indirect final consumption changes. Direct final demand changes on the horizontal axis are plotted against indirect impacts on final demand on the vertical axis. The dashed line indicates the impact possibility frontier $(x, 100 - x)$. Disk size corresponds to the initial level of final demand satisfied per industry. The descriptions of the industry labels can be found in Appendix B, Table B.6

We next quantify higher-order impacts, i.e. indirect impacts that are created endogenously by the economy as a result of the direct shocks. Because the overall economic performance changes in time, the indirect effects are time-dependent, as seen in the simulations in Section 4.1. Higher-order impacts in gross output are not necessarily caused by supply-side shocks – they can also result from a lack of demand. Conversely, final consumption reductions can by forced by lowered production levels, which mean there is less available to consume. We let the *total* change in output at any time be

$$\mathrm{OC}_{i,t}^{\mathrm{total}} = x_{i,t}/x_{i,0} - 1.$$

The indirect output change is then computed as the residual of the total output change $\mathrm{OC}_{i,t}^{\mathrm{total}}$ and direct output change $\mathrm{OC}_{i}^{\mathrm{direct}}$. This means the *indirect* output change is

$$\mathrm{OC}_{i,t}^{\mathrm{indirect}} = \mathrm{OC}_{i,t}^{\mathrm{total}} - \mathrm{OC}_{i}^{\mathrm{direct}}. \tag{27}$$

Similarly, the change in *indirect* final consumption is defined as

$$\mathrm{CC}_{i,t}^{\mathrm{indirect}} = \mathrm{CC}_{i,t}^{\mathrm{total}} - \mathrm{CC}_{i}^{\mathrm{direct}}, \tag{28}$$

where $\mathrm{CC}_{i,t}^{\mathrm{total}} = (c_{i,t} + f_{i,t})/(c_{i,0} + f_{i,0}) - 1$ is the *total* change in final consumption.

The center panel of Fig. 4 compares the direct output change $\mathrm{OC}_{i}^{\mathrm{direct}}$ to the indirect output change $\mathrm{OC}_{i,t}^{\mathrm{indirect}}$ on the last day of lockdown. The industries located in the extreme upper right corner of the center panel are only mildly affected by the pandemic, and experience only very small shocks. The industries in this group include Finance and Insurance (K64-66), Water and Sewage (E36-39) and R&D (M72).

There is a strip of industries scattered along the horizontal axis that experience substantial direct shocks but only minor indirect effects. This group includes some manufacturing industries, such as Minerals (C23), Metals (C24-25) and Transport (C30). In Section S6 of the Supplementary Information we plot for each industry their temporal evolution of output, as well as their production constraints (capacity, input, demand). These figures make clear that the productive capacity of these manufacturing industries has been limited by direct supply shocks throughout the lockdown, outweighing any adverse indirect effects on demand or input supply.

There is also a substantial strip of industries scattered along the vertical axis that experience minor direct shocks but nonetheless have their production drop substantially by the end of the lockdown. Among those industries are the transport sectors (H51-H53). As shown in the Supplementary Information, these sectors experience fairly complex dynamics according to our model. In the early phase of the lockdown the transport sectors have been mostly demand-constrained, but also suffered from input bottlenecks in the later phase of the lockdown. Their recovery after the lockdown was relaxed, in turn, has been slowed down by the lack of employees.

The bottom panel of Fig. 4 compares direct and indirect effects on final consumption. Most industries experience both direct and indirect effects, with substantial heterogeneity in the size of the effects. An extreme case with a strong direct effect on consumption (about 70%) but almost no indirect effect is Accommodation-Food (I). In contrast, industry C23 (Manufacturing Minerals) has a direct consumption shock of only 10% but has an indirect effect of about 54%. Among the few exceptions that are relatively unaffected are Insurance (K65), Public Administration (O84) and Agriculture (A01).

So are our results driven by the direct shocks or model-derived indirect impacts? The answer is that it highly depends on the industry. Some industries were strongly affected by direct supply side constraints and others by the lack of final demand. While some of these effects were directly induced by social distancing measures, others only materialized endogenously over time through economic interactions between firms and consumers (Supplementary Information, Section S6).

5. Theoretical results

In this section we study a number of counterfactuals and explore theoretical properties of the model. The common ground between these exercises is to understand which aspects of the model were important for the empirical performance described in the previous section. In Section 5.1 we explore the role of production functions and inventory levels for shock propagation dynamics; in Section 5.2 we investigate how simpler input-output metrics such as upstreamness or output multipliers compare with the model predictions; and in Section 5.3 we study the effect of reopening certain industries under different production function specifications.

5.1. Production functions and input criticality

A key innovation of our model is that it uses a production function that distinguishes between critical and non-critical inputs based on industry analyst ratings (as discussed at length in Section 2.2.2). The nonlinearity of production functions is bracketed by the Leontief production function, which is the most restrictive, and the linear production function, which is the least restrictive. Under the Leontief production function all inputs are critical and every input, regardless of its share in the input mix, creates an input bottleneck if it is missing. Since the input-output network at the level of 55 industries is extremely dense ($\approx 98\%$ of possible links are present), this means that under the Leontief production function, almost any industry can cause substantial downstream disruptions. The linear production function, in contrast, assumes no critical inputs at all. Downstream shock propagation only occurs when the total input level (measured in dollar terms) is insufficient.

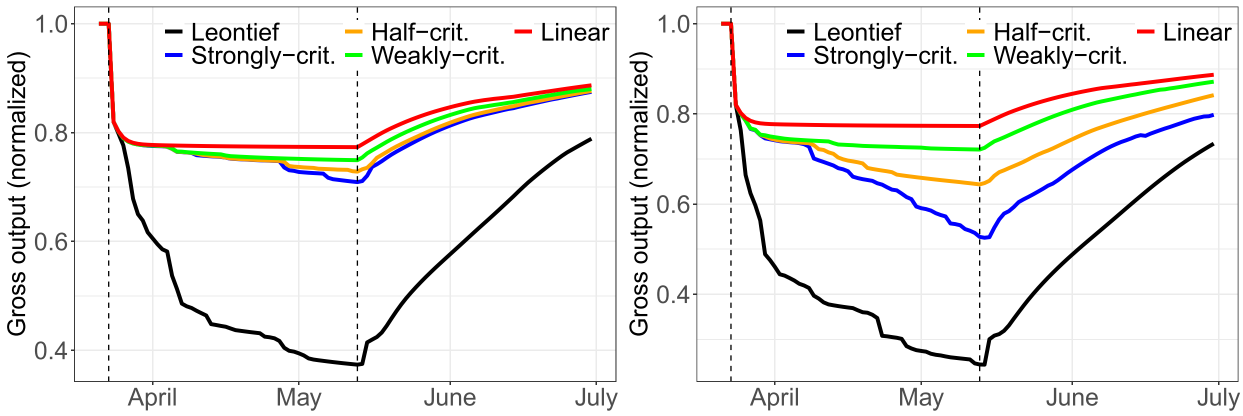

Fig. 5. Comparison of economic output under different production functions. The left panel shows results when the model is parametrized as outlined in Section 4 and only the production function is varied. The right panel is the same, except that we downscale inventories to a half of actual levels. The dashed vertical lines indicate that the shocks are applied on March 23rd 2020 and partly relaxed from May 13th 2020 onward as discussed in Section 4. Output values are normalized to the initial no-lockdown steady state.

Our survey-based production functions consider only a subset of inputs as critical for short-term production, and so lie in-between the Leontief and linear cases.

To test the sensitivity of our assumptions to the results of the survey, we explored different interpretations of the survey data. As described in Section 2.2.2, in the *strongly critical* specification we counted inputs that were rated as either critical or important as being critical. This is closest to the Leontief case, and results in about 25% of all possible ($\approx N^2$) supplier-customer links being rated as critical. In contrast, in the *weakly critical* specification, inputs that were rated as important were assumed to be non-critical. This is closest to the linear case, and results in about 15% of all possible links being critical. In the *half-critical* specification, we rate important inputs as counting half as much as critical inputs. This in-between case results in 15% of the possible inputs being critical and 10% being half-critical.

In the left panel of Fig. 5 we show simulation results for aggregate gross output under alternative production function assumptions. All other parameters are set as outlined in Section 4. As expected, we find the largest drop in production for the Leontief production function, where every input can potentially become binding (black line). For the Leontief economy our model predicts a drop in gross output of up to 60% compared to initial levels, which is much higher than was observed empirically. Again in line with intuition, we obtain the mildest economic impacts for the linear production function (red). There is a substantial drop at the beginning of the lockdown, but virtually no further adjustments. The dynamics are essentially flat in the linear case because it is just a reflection of the first order shocks, with no amplification due to network effects.

As expected, the production function specifications based on the industry analyst survey lie between the two extreme cases, but they are closer to the linear production function. In contrast to the linear production function, however, there are higher-order effects that build over time after the initial shock hits the economy. In the Supplementary Information (Section S4) we discuss how the choice of the production function affects the model performance and demonstrate that it is best for the intermediate survey-based functional forms.

Another key feature of our analysis is that we use data from the Office of National Statistics to calibrate sector-specific inventory levels. Inventories play a role in the spread of economic shocks, as they act as short-term buffers in case critical suppliers are not able to deliver production inputs. We demonstrate the effect of inventory levels in the right panel of Fig. 5 where we hypothetically reduce the initial inventory levels to half their actual size and rerun the simulation.[20] The linear and Leontief cases are almost unaffected. However, the survey-based production function cases are all strongly affected. The difference from the linear case is much larger and the differences among the three critical production function specifications are more pronounced. The drop in output builds through time and becomes substantial as the higher-order effects become more important, until they are comparable in size to the direct shocks. This demonstrates that with more realistic production functions there are strong dependencies on inventory levels, which play an essential role for understanding higher-order dynamics.

In a circumstance such as the COVID-19 pandemic where strong shocks are imposed quickly, these results show that it is very important to model the production function and inventory effects realistically. Both inventory levels and production functions are highly industry specific. Our model suggests that, even for aggregate production, it is important to capture

[20] We achieve this by substituting n_i^{reduced} for n_i in Eq. (4) where $n_i^{\text{reduced}} = \max(1, \frac{1}{2}n_i)$. The maximum operator is needed to ensure that the model starts in steady state, as $n_i^{\text{reduced}} < 1$ would immediately lead to a decline in economic output.

network effects at a fine-grained level and with a high degree of verisimilitude. If we had considered a linear production function which only reflects first-order shocks, we would have underestimated the UK recession by several percentage points.

5.2. Static production network measures

Our model demonstrates that supply shocks have very different shock propagation dynamics than demand shocks and the amplification of supply and demand shocks depends on which industries are involved in spreading the shocks. The elasticity of aggregate output to a shock to a given sector depends on the type of shock and on the position of the sector in the input-output network. Are there properties of an industry that could be computed ex-ante to know how systemic it is? Is this different for supply and demand shocks? Is a model needed to understand this, or can it be understood more simply using static network statistics?

To answer these questions, we ran the model with a single shock to a single industry, which can be either a supply shock or a demand shock. The other industries experience no shock, have their initial productive capacities and their initial levels of final demand. We then let the economy evolve under this scenario for one month.[21] We repeat this procedure for every industry, every production function specification and different shock magnitudes. We then investigate whether the decline in total output can be explained by simple measures such as shock magnitude, output multipliers or upstreamness levels, which we formally define below. We first explain the supply and demand shock scenarios in more detail.

Supply shock scenarios. When considering only supply shocks, we completely switch off any adverse demand effects, i.e. $\epsilon^D_{i,t} = 0$ (which implies $\theta_{i,t} = \theta_{i,0}$ and $\tilde{\epsilon}^D_t = 0$), $\xi_t = 1$ and $f^d_{i,t} = f^d_{i,0}$ for all i and t. We also set the supply shocks to all other industries equal to zero $\epsilon^S_{i,t} = 0$, except for the industry j that experiences a supply shock from the set $\epsilon^S_{j,t} \in \{0.1, 0.2, \ldots, 1\}$. We then do this for every possible j, average the results, and repeat this procedure for each of the five production functions.

Demand shock scenarios. In our demand shock scenarios there are no supply shocks ($\epsilon^S_{i,t} = 0 \; \forall \; i, t$) and similarly there are no demand shocks for all but one industry j ($\epsilon^D_{i,t} = 0$, $f^d_{i,t} = f^d_{i,0} \; \forall i \neq j, \forall t$). For the single industry j we again let shocks vary between 10 and 100%, i.e. $\epsilon^D_{j,t} \in \{0.1, 0.2, ..., 1\}$. For simplicity we assume uniform shocks across all final demand categories of the given industry, resulting in $f^d_{j,t} = (1 - \epsilon^D_{j,t}) f^d_{j,0}$. To keep things as simple as possible, we assume that there is no fear of unemployment $\xi_t = 1$ and that final consumers do not switch to alternative products at all ($\Delta s = 1$). Under these assumptions the values for $\theta_{i,t}$ and $\tilde{\epsilon}^D_t$ are then computed as outlined in Section A.2.

Fig. 6 shows how the drop in aggregate gross output depends on the shock magnitude and the restrictiveness of the production function. The coloring and the value of a tile represent the average aggregate output as a fraction of initial output, where the average is taken over all N runs. Results obtained from the demand shock scenarios, Fig. 6(b), do not differ across alternative production function specifications and thus we only show one representative case. The reason for this is that, following our assumption in Eq. (4), demand shocks to an industry are passed on proportionally to all of its suppliers, so that the output of each supplier industry drops by the same amount regardless of its production function. This is in stark contrast to the supply shock scenarios, Fig. 6(a), where economic impacts depend strongly on the choice of production function. While the economic impact of supply constraints is limited in the linear production model and depends fairly smoothly on the shock magnitude, this is not the case in the Leontief model. Here the economy can experience a major disruption even if only a single industry is shut down. The results for the partially binding Leontief production functions lie in-between these two extremes.

The numbers reported in Fig. 6 are averages. This hides the fact that, except for the linear production function, there is a wide distribution of economic impacts. In addition to the shock size, it also matters *which* industry is affected by the shocks. For example, applying an 80% supply shock to the Repair-Installation industry (C33) using the half-critical production function assumption collapses the economy to 50% of its normal output, even though this industry accounts for less than half a percent of the overall economy. On the other hand, applying the same shock to the comparatively large Other Services (R_S) industry, which is 3% of the economy, leads to a mere 6% reduction of aggregate output.

For a policymaker, knowing what properties of an industry drive the amplification of shocks can help inform the design of lockdown measures and reopening policies. To explore this more systematically, we regress output levels against potential explanatory factors such as upstreamness, output multipliers and industry sizes. An industry's upstreamness in a production network is its average distance to the final consumer (Antràs et al., 2012), a property that is also known as Total Forward Linkages (Miller and Temurshoev, 2017). High upstreamness implies that the output of an industry requires several subsequent production steps before it is purchased by final consumers. Thus, relaxing shocks on industries with high upstreamness could potentially stimulate further economic activity. Since upstreamness boils down to the row sums of the Gosh inverse (Miller and Temurshoev, 2017), we obtain the N-dimensional upstreamness vector as $u = (\mathbb{I} - B)^{-1}\mathbf{1}$, where a matrix element $B_{ij} = Z_{ij,0}/x_{i,0}$ represents "allocation coefficients". Upstreamness ranges from 1.004 (Household activities) to 2.742 (Warehousing) in our sample of UK industries.

Output multipliers, or alternatively Total Backward Linkages, are an important metric in many economic studies. In input-output analysis, output multipliers quantify the impact of a change in final demand in a given sector on the entire economy.

[21] We also did the analysis with model simulations up to two months after the initial shock is applied. Since results are similar for the two cases, we only report results for the one month simulations.

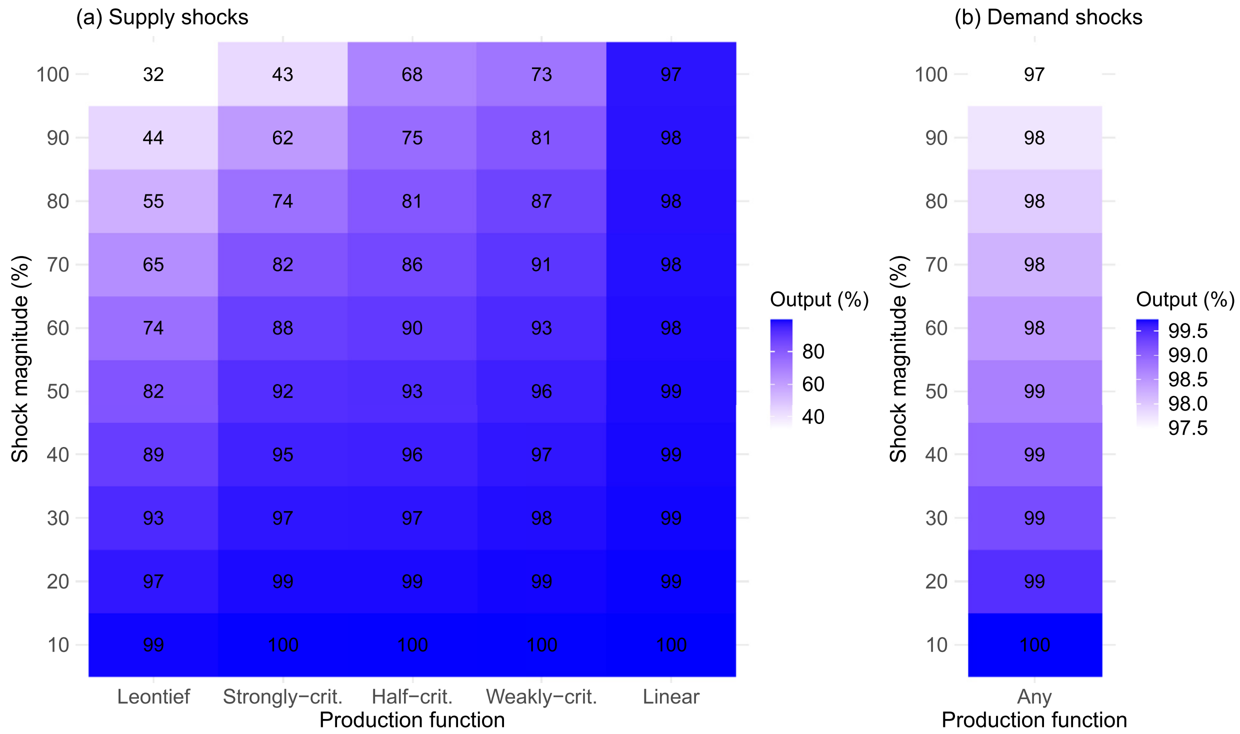

Fig. 6. Aggregate gross output as percentage of pre-shock levels after shocking single industries. A column depicts different production functions and rows distinguish the supply (a) and demand (b) shock magnitude which an industry is exposed to. Results in (b) are only shown for one production function, since they are identical across alternative specifications. The values in the tiles and their coloring denote aggregate output levels as percentage of pre-shock levels one month after the shock hits a given industry. These values are computed as averages from N runs, always shocking only a single industry.

Output multipliers are related to network centrality measures and have been shown to be strongly predictive of long-term growth (McNerney et al., 2022). Since shocking an industry with a high multiplier should lead to larger decreases in intermediate demand, it is plausible that high-multiplier industries tend to amplify shocks more. The output multiplier is computed as the column sum of the Leontief inverse, i.e. $m = (\mathbb{I} - A^\top)^{-1}\mathbf{1}$. In our sample output multipliers range from 1 (Household activities) to 2.379 (Forestry). Upstreamness and output multipliers are different, but they are correlated, with a Pearson correlation of 0.45.

We regress the logarithm of simulated aggregate output one month after the initial shock hits the economy against the shocked industry's log upstreamness and log output multiplier levels. We would naturally expect a larger decline from a shock that hits a large industry. To take this into account we control for total industry size measured in log gross output, $\log(x_{i,0})$, and industry-specific total demand, $\log(c^d_{i,0} + f^d_{i,0})$, in our regressions.[22] We then run the regression for every given shock magnitude and production function separately.

Table 3 summarizes the regression results for the supply shock scenarios. For supply shocks we find that upstreamness is a very good predictor of adverse economic impact under the Leontief production function. In contrast, for the linear production function, the size of the industry explains reductions in aggregate output, and the upstreamness has no explanatory value. For the intermediate assumption of the half-critical production function, both upstreamness and industry size significantly affect aggregate impacts, although the overall model fit (as measured by R^2) drops substantially.

Note that supply shocks are to a large extent a policy variable as they are directly coupled to non-pharmaceutical interventions such as industry-specific shutdowns. Our results indicate that upstreamness levels of industries are an important aspect for designing lockdown scenarios. For highly restrictive production functions, such as the Leontief or strongly critical specifications, upstreamness may be a better indicator of the impact of industry closures than the size of the industry.

Regression results for the demand shock experiments are shown in Table 4. The first four columns show the results from univariate regressions where we include only one of the potential covariates: upstreamness, output multipliers, final consumption and gross output. Somewhat surprisingly, output multipliers, which are a key metric for quantifying aggregate impacts from demand side shocks in simpler input-output models, have no predictive power here. In contrast, upstreamness is positively associated with aggregate output values, indicating that demand shocks to upstream industries have less ad-

[22] We do not include gross output and final demand values together as regressors to avoid multicolinearity. Industry gross output and final consumption are highly correlated; $\mathrm{cor}\{\log(x_{i,0}), \log(c_{i,0} + f_{i,0})\} = 0.89$ (p-value $< 10^{-16}$).

Table 3
Regression results for supply shock experiments. For details on variable definitions see caption of Table 4.

	Dependent variable: Aggregate output after 30 days					
Shock size:	40%	40%	40%	80%	80%	80%
Production:	Leontief	Half-crit.	Linear	Leontief	Half-crit.	Linear
Upstreamness	−0.233***	−0.114***	0.008	−0.440***	−0.383***	0.016
	(0.018)	(0.019)	(0.003)	(0.023)	(0.071)	(0.007)
Multiplier	0.067	0.065	−0.013	0.037	0.306	−0.025
	(0.038)	(0.041)	(0.007)	(0.049)	(0.150)	(0.014)
Output	−0.006	−0.019***	−0.008***	−0.011	−0.079***	−0.016***
	(0.004)	(0.004)	(0.001)	(0.005)	(0.016)	(0.001)
Constant	15.512***	15.673***	15.560***	15.224***	16.175***	15.641***
	(0.050)	(0.053)	(0.009)	(0.065)	(0.197)	(0.018)
Observations	55	55	55	55	55	55
Adjusted R^2	0.776	0.456	0.722	0.890	0.448	0.719

Note: *p<0.01; **p<0.001; ***p<0.0001.

Table 4
Regression results for demand shock experiments. All variables (dependent and independent) are in logged form. More formally, *Upstreamness* denotes $\log(u_{i,0})$, *Multiplier*, $\log(m_{i,0})$, *Final demand*, $\log(c_{i,0} + f_{i,0})$ and *Output*, $\log(x_{i,0})$. The independent variable is $\log(\sum_i x_{i,30})$. In this table we show only a scenario that assumes 60% shocks to final consumption, since results are similar for alternative shock sizes. Economic impacts are identical across alternative production functions.

	Dependent variable: Aggregate output after 30 days					
	(1)	(2)	(3)	(4)	(5)	(6)
Upstreamness	0.040**				0.012	0.036***
	(0.010)				(0.010)	(0.008)
Multiplier		0.021			−0.024	−0.030
		(0.024)			(0.019)	(0.018)
Final demand			−0.012***		−0.011***	
			(0.002)		(0.002)	
Output				−0.014***		−0.013***
				(0.002)		(0.002)
Constant	15.443***	15.453***	15.588***	15.618***	15.586***	15.599***
	(0.006)	(0.013)	(0.016)	(0.023)	(0.025)	(0.023)
Observations	55	55	55	55	55	55
Adjusted R^2	0.217	−0.004	0.522	0.452	0.522	0.580

Note: *p<0.01; **p<0.001; ***p<0.0001.

verse impact on the economy than downstream industries. Better model fits are obtained when regressing aggregate output against indicators of industry size, such as gross output or final consumption.

Upstreamness and output size explain complementary components of aggregate impacts (column six), resulting in a better model fit than any regression using final consumption values. However, combining final consumption values with upstreamness and output multipliers in a multivariate regression (column five) does not improve explanatory power at all. Thus, industries' upstreamness and output sizes are important determinants for the propagation and amplifications of both supply and demand shocks.

The results above indicate that upstream industries play an important role in the amplification of exogenous shocks. Nonetheless, while static measures are indicative of the amplification of supply and demand shocks, they only explain them partially. This is true even in the simplified case where shocks are applied to only one industry at time. In general, supply and demand shocks operate simultaneously and multiple industries are affected. This complicates the dynamics of shock propagation, and makes a model like ours necessary to accurately predict economic impacts.

5.3. Re-opening a network economy

One of the key questions during the first pandemic wave was how to effectively unwind social distancing measures without letting the pandemic get out of control. We study this question here. As before, we initialize the model with first-order shocks to represent the economy at the beginning of the lockdown. We then consider two scenarios. First, we study the re-opening scenario where lockdown is lifted after six weeks for a given set of industries. For these industries we set $\epsilon^S_{i,t} = 0$ and let demand adjust as discussed in Section 3.2. Second, we study the scenario where the lockdown continues and no shocks are removed, which we call the "lockdown scenario". We then compare the two scenarios to make predictions about how much economic activity is boosted as a result of re-opening a given set of industries.

Fig. 7 summarises our findings. Each panel shows total production normalized by pre-shock output on the vertical axis for both scenarios (re-opened economy in red, continued lockdown in black). The horizontal axis shows the number of calendar

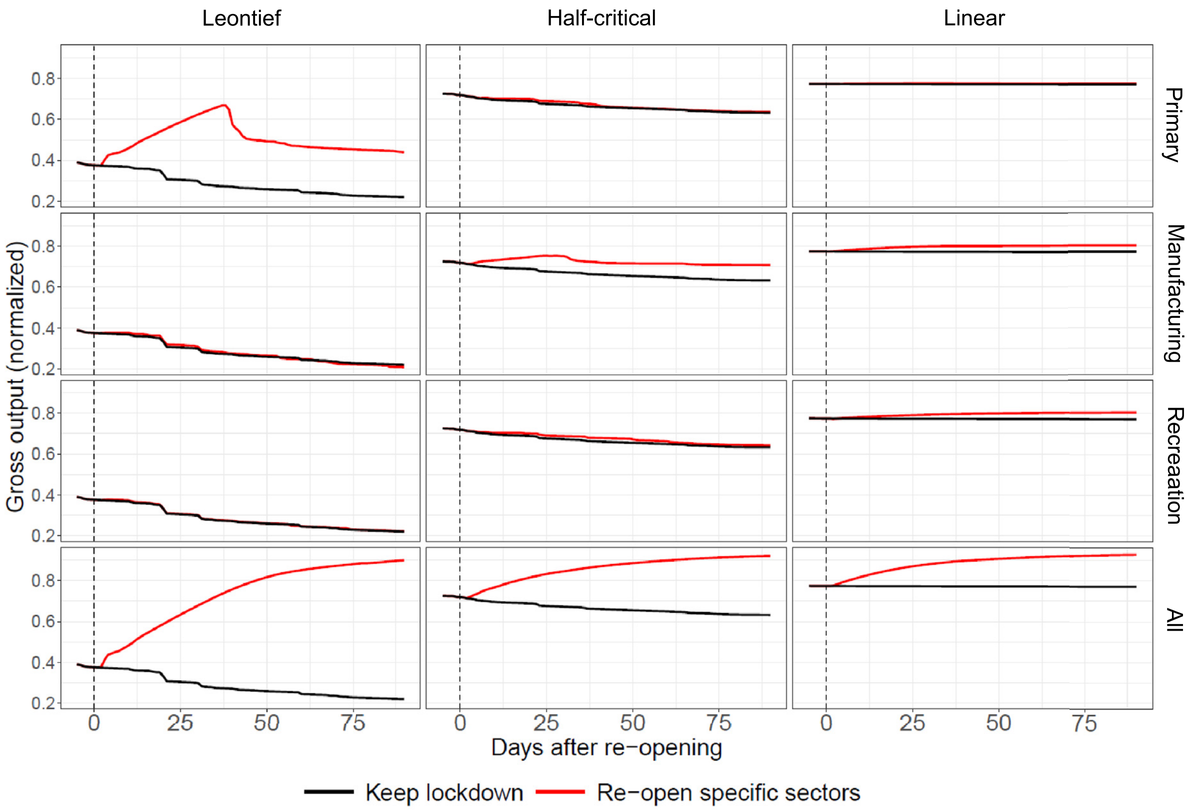

Fig. 7. Aggregate (total economy) output for indefinite lockdown vs. re-opening some sectors, for different production functions. Black lines indicate aggregate output if the lockdown continues and red lines if a given set of sectors is re-opened at $t = 0$. Columns represent different production functions, rows denote the sectors which are re-opened. The left column shows the effect of re-opening for different sectors in a Leontief economy. The center and right columns show the same for the half-critical and linear production functions. Row 1 shows economic effects of re-opening only primary sectors (ISIC A and B). Row 2 shows the same for opening Manufacturing (ISIC C), row 3 for "Recreation" (ISIC I, R, S) and row 4 for opening all sectors simultaneously.

days after the lockdown is lifted in the re-opening scenario. In both cases the economy was already six weeks in lockdown before day zero, which is not shown since production is identical for both scenarios during that period. Panel columns represent simulation results for different production function specifications. Panel rows indicate the industries which are re-opened if the lockdown is relaxed.

The economic boost from re-opening industries depends strongly on both the sector that is reopened and the choice of production function. In the top row panels we show the results of re-opening only the primary sectors Agriculture and Mining, which are fairly upstream, while keeping the lockdown otherwise unchanged. As shown in the left column, under the Leontief production function this leads to a dramatic increase in economic output, despite the fact that primary sectors only account for 2% of the UK's total economic output. Opening primary sectors has a much smaller effect under the half-critical production function (center column) or the linear production function (right column).

As shown in the second row, re-opening the much larger manufacturing sector, which is 15% of total output, has a completely different impact on economic output. Strikingly, under a Leontief production function there is almost no increase economic output. This is because Manufacturing is a large sector relying on many inputs from non-manufacturing industries, which are critical inputs for other sectors too. Production constraints in other non-manufacturing industries still in lockdown can render it impossible to provide larger amounts of these inputs. If manufacturing sectors are re-opened, competition for these scarce inputs increases, resulting in less intermediate consumption for non-manufacturing industries that might face input bottlenecks as a consequence. For the less restrictive production functions, in contrast, there is an economic recovery of several percentage points.

Once again, we find very different results from reopening Other Services and Food and Accommodation, here for brevity called Recreation (third row). These sectors comprise 6% of total output and are heavily affected by the lockdown since they include theaters, hotels, restaurants and other social activities. Remarkably, under the Leontief production function reopening these industries has no impact on overall economic production. This is because these are downstream industries and their economic output has little significance for the intermediate consumption of other industries. Thus, opening recreational sectors has mostly demand-side effects, and due to the capacity constraints of upstream sectors that are still locked down, this extra demand cannot be satisfied, so there is no change in overall production. There is essentially no boost to economic output from opening the recreational sector under the half-critical production function, but there is a small positive boost under the linear production function.

The bottom row of panels compares the restart of the economy when the lockdown is lifted for all industries simultaneously. There is a strong recovery under all three production functions, though this recovery takes some time. In all three cases the economy is substantially below capacity a month after reopening, and around 90% of capacity three months after reopening. The Leontief economy re-starts at very low levels after lockdown, and so the recovery is the most dramatic, but the absolute levels of economic output are always lower than in the other two cases.

These findings indicate that our model predicts very different recovery paths depending on which industries are re-opened and depending on the production function. We released our real-time forecast around mid-May 2020, a few days before the UK government announced the plan for lifting the lockdown, and, lacking better information, simply assumed that all supply shocks would be removed. This was not fully accurate: many customer-facing industries such as entertainment and restaurants remained closed until the end of June. The analysis above suggests that this was not a major issue, as these industries do not cause substantial bottlenecks, and so do not strongly affect the aggregate dynamics of the recovery.

6. Discussion

In this paper we have investigated how locking down and re-opening the UK economy as a policy response to the COVID-19 pandemic affects economic performance. We introduced a novel economic model specifically designed to address the unique features of the pandemic that gives a key role to production network and inventory dynamics. We used survey results by industry experts that allowed us to capture the heterogeneity of the production functions of different industries in their response to the pandemic.

In simulation experiments where we studied simpler shock scenarios and a simplified model setup, we found that an industry's upstreamness is predictive of shock amplification. However, the relationship is noisy and strongly depends on the underlying production mechanism in case of downstream propagation of supply shocks. These results underline the necessity of using a model like the one we have built here to quantify the economic impact of lockdowns.

Real time GDP predictions for the UK economy made in an early version of this paper turned out to be accurate (Pichler et al., 2020). But was this because we did things right, or because we just got lucky? Our analysis here shows that it was a mixture of the two. By investigating both alternative shock scenarios, alternative production functions and studying the sensitivity to parameters and initial conditions, we are able to see how the quality of the predictions depends on these factors. We find that the production function is the most important determinant, but supply shocks are also very important, and some of the other parameters can affect the results as well.

To make a real time forecast we had to act quickly. There were no data available about which industry classifications were considered essential in the UK and little data available on UK jobs that could be performed from home. In the interest of time, we estimated the UK supply shocks using the US supply shocks predicted by del Rio-Chanona et al. (2020). These supply shocks were based on a list of essential industries that was considerably less permissive (i.e. fewer industries were considered essential) than the UK guidelines. This turned out to be lucky: respecting social distancing guidelines caused many industries in the UK to close even though they were not formally and explicitly required to do so. If we had had a list of essential British industries our supply shocks would have been too weak, or we would have had to model social distancing constraints by industry, which is difficult. Even if they missed some of the details, the supply shocks estimated by del Rio-Chanona et al. (2020) provided a reasonable approximation to the truth.

The choice of production function matters a great deal. Our results suggest that the Leontief production function, which is widely used for understanding the response to disasters, is a poor choice. This is for an intuitive reason: Some inputs are not critical, and an industry can operate reasonably well without them, at least for a few months. At the other extreme, our results also suggest that the linear production function is a poor choice. In contrast, the partially binding Leontief (PBL) production function that we introduced here performs well in predicting the response to the pandemic.

A more conventional approach would have been to calibrate a nested CES production function to specify possible substitutions for the inputs of each industry. In Section S7 of the Supplementary Information, we show that the two approaches are not the same, but there are situations where they can closely approximate each other. Under the appropriate limiting case in the nested CES framework, the non-critical inputs bundle is an input to a Leontief production function, so the non-critical inputs can become binding. By contrast, the non-critical inputs are entirely ignored in the Partially Binding Leontief (PBL) production function. For example, under the PBL production function, if management consultants are non-critical, steel factories can operate without them for three months with no effect on production in the short term. The production function that we introduce here implicitly assumes that the factors that influence short-term production during crises may be different from those affecting production during normal times. The difference between the two is not relevant here: Simulating the model but replacing the PBL production function by the closest corresponding CES-derived production functions yields exactly the same results, indicating that the bundle representing non-critical inputs was never a binding constraint.

Our results indicate that dynamic models of the type that we developed here can do a good job of forecasting disruptions in the economy. However, there are several lines of research that could potentially make it better. One of the most obvious is to make the model more granular. While 55 industries is much better than one, this level of granularity still lumps together many productive activities that are quite different. This is an issue in estimating the original supply shocks, where in many cases different sub-industries require very different types of labor; furthermore, a better breakdown of labor by age and gender would have allowed us to better understand how lack of daycare or schools affected production. More granularity would be useful in estimating the demand shocks, where some products within an industry may remain in high demand while others do not. Better granularity would be particularly useful in tracking the shock dynamics: Our work here shows the essential importance of network effects, which cannot be understood at an aggregate level. If the data were available, it would have been much better to do this analysis at the level of hundreds of industries, or even better, at the level of individual firms and products.

There are many other possible improvements. While we have used a state of the art aggregate consumption function, diverse demographic groups have different patterns of consumption that likely made a big difference in their response to the pandemic. We assumed that imports do not affect economic production, and included exports, investments and government consumption only as exogenous variables in our model. Though it would have required an effort on a larger scale, it is reasonably straightforward to apply our approach here to all of the major economies in the world and couple them together, which would have allowed us to close the model and treat imports and exports endogenously. We assumed constant prices and no inflation, which were good assumptions in the short term but become poor assumptions in the long term. The temporal accuracy of our model could also be improved by taking transportation times for the movement of goods into account (Bierkandt et al., 2014; Colon et al., 2021; Verschuur et al., 2021) and by incorporating heterogeneity in the time it takes to make different goods.[23] Our model assumes synchronous decision making across firms. Future developments could also consider heterogeneous decision making regarding how firms hire and fire employees, order inputs or ration outputs (Pichler and Farmer, 2021).

We want to emphasize the need for better data that is made available in a timely manner. A clear example is the choice of inventory levels. In our original model we had no data for inventory levels of UK industries, so we used data for the US. Replacing this by UK data made a substantial improvement in our sectoral results. Similarly, the economic data we had available was from 2019, and the input-output data was from 2014 – better real time measurements about the response of industries to the pandemic would likely have improved our predictions. A more extensive study of the importance of different inputs to production could have reduced ambiguity about the choice of production function.

At the highest level, our results here illustrates the value of the key features of our model. These are modeling at the sectoral level, allowing both supply and demand shocks to operate simultaneously, using a realistic production function that properly captures nonlinearities without exaggerating them, and using a dynamic model that incorporates inventory effects. Although we designed this model to cope with the COVID-19 pandemic, the supply and demand shocks are the only aspect of the model that is specific to the pandemic. The shock propagation mechanisms that we model here are likely generic to many types of disasters. Our results demonstrate that dynamic input-output models capable of coping with disequilibrium conditions can yield insights about the amplification of shocks and can be used to make real-time forecasts for the economics of disasters.

Acknowledgements

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Appendix A. Supply and demand shocks

Due to the COVID-19 pandemic, industries experience supply-side restrictions due to the closure of non-essential industries, workers not being able to perform their activities at home. Many industries also face substantial reductions in demand. The supply and demand shocks used in this paper are based on del Rio-Chanona et al. (2020) who provide quantitative predictions of these direct shocks for the US economy. In this appendix we explain the origin of these supply and demand shocks and how we mapped them into the UK economy.

[23] An example of non-constant production schedules is Avelino and Dall'erba (2019) who apply the sequential interindustry model (Romanoff and Levine, 1977) to study the 2007 Chehalis River Flood and distinguish between three types of production modes (just-in-time, anticipatory and responsive). Another interesting example of diverse time scales in firm decisions is Basurto et al. (2020).

A1. Supply shocks

To estimate industry supply shocks, del Rio-Chanona et al. (2020) constructed an industry-specific Remote Labor Index and essential score. The Remote Labor Index of industry i (RLI_i) was constructed by classifying the work activities of the occupations of workers employed in each industry into “can be performed at home successfully” or “cannot be performed at home successfully”. The essential score was built to capture whether an industry can operate during a lockdown, according to government mandates, even if working from home is not possible. This index was built by mapping a list of essential industries from the Italian government into the 6-digit NAICS industry classification and then aggregating into the 4-digit NAICS industry classification to create the essential score (ESS_i) for each industry i. The resulting 4-digit NAICS list of essential industries was then revised for implausible cases, leading to the manual (re-)classification of 11 industries.

RLI_i can be interpreted as the probability that a worker from industry i can work from home. Similarly, ESS_i can be interpreted as the probability that a worker from industry i has a job that is considered essential and can work on-site if needed. Using these interpretations and assuming independence between these two probabilities, del Rio-Chanona et al. (2020) calculated that the expected value of the number of workers who could not work during the lockdown was given by

$$(1-\mathrm{RLI}_i)(1-\mathrm{ESS}_i). \tag{29}$$

These shocks were calculated for US industries by using the NAICS classification system. To translate these shocks into the UK economy we mapped the shocks from the NAICS to the WIOD classification as explained below.

NAICS to WIOD mapping. To map the industry supply shocks from NAICS to WIOD, we build a crosswalk from the NAICS 4-digit industry classification to the classification system used in WIOD, which is a mix of ISIC 2-digit and 1-digit codes. We make this crosswalk using the NAICS to ISIC 2-digit crosswalk from the European Commission and then aggregating the 2-digit codes presented as 1-digit in the WIOD classification system[24]. We then do an employment-weighted aggregation of the index or score in consideration from the 277 industries at the NAICS 4-digit classification level to the 55 industries in the WIOD classification. Some of the 4-digit NAICS industries map into more than one WIOD industry classification. When this happens, we assume employment is split uniformly among the WIOD industries the NAICS industry maps into.

After mapping the supply shocks to the WIOD classification system, we do one modification to the real-estate sector shock. The real-estate sector includes imputed rents, which account for 69% of the monetary value of the sector[25]. Because we think applying a supply shock to imputed rent does not make sense, for all scenarios we compute that the supply shock derived from the RLI and essential score only affects 31% of the sector. With this modification the final supply shock to the Real Estate Sector is 15%.[26]

We note that the product in Eq. (29) was calculated using the Remote Labor Index and essential score at the NAICS level. Afterwards the supply shock was mapped into the WIOD system. The resulting shocks would be slightly different if the remote labor index and the essential score were first mapped into the WIOD system and afterwards the product was calculated.

A2. Demand shocks

We distinguish between demand shocks to private consumption due to fear of infection and to fear of unemployment, and demand shocks to other components of final demand. Table 5 shows the demand shock for each sector and Fig. 8 illustrates the demand shock scenarios over time.

A2.1. Demand shocks due to fear of infection

During a pandemic, consumption/saving decisions and consumer preferences over the consumption basket are changing, leading to pandemic-driven demand shocks (Congressional Budget Office, 2006; del Rio-Chanona et al., 2020). For example, consumers are likely to demand less services from the hospitality industry, even when the hospitality industry is open. Transport is very likely to face substantial demand reductions, despite being classified as an essential industry in many countries. A key question is whether reductions in demand for “risky” goods and services is compensated by an increase in demand for other goods and services, or if lower demand for risky goods translates into higher savings.

We consider a demand shock vector ϵ_t^D, whose components $\epsilon_{i,t}^D$ are the relative changes in demand for goods of industry i at time t. Recall from Eq. (5), $c_{i,t}^d = \theta_{i,t}\tilde{c}_t^d$, that consumption demand is the product of the total consumption scalar $\tilde{c}_t^d$ and the preference vector θ_t, whose components $\theta_{i,t}$ represent the share of total demand for good i. We initialize the preference vector by considering the initial consumption shares, that is $\theta_{i,0} = c_{i,0}/\sum_j c_{j,0}$. By definition, the initial preference vector θ_0 sums to one, and we keep this normalization at all following time steps. To do so, we consider an auxiliary preference

[24] The WIOD industry sector 'T' ("Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use") only maps into one NAICS code for which we do not have a supply shock. Since this sector is likely to be essential, we assume a zero supply shock.

[25] https://www.ons.gov.uk/economy/grossvalueaddedgva/datasets/nominalandrealregionalgrossvalueaddedbalancedbyindustry, Table 1B.

[26] Due to an error, the original version of this work used a value of 4.7% for the real estate shock. If we had used the correct real estate shock we would have predicted a 22.1% reduction, exactly like in the data. In the main text, we still describe our prediction as having been a 21.5% contraction, as explicitly stated in our original paper.

Table 5
Industry-specific supply and demand shocks. Column x denotes relative shares of gross output and column ϵ^S supply shocks. Column c denotes relative shares of household consumption (which here aggregates column *C1* and *C2* in the WIOD) and ϵ^D represents household consumption shocks. Columns f and f *shock* are relative shares of other final demand and the shocks applied to other final demand, respectively. All values are in %.

ISIC	Sector	x	ϵ^S	c	ϵ^D	f	f shock
A01	Agriculture	0.8	0.0	0.9	10	0.3	13.8
A02	Forestry	0.0	85.0	0.0	10	0.0	11.9
A03	Fishing	0.1	0.0	0.0	10	0.1	14.8
B	Mining	1.3	35.3	0.1	10	1.5	15.3
C10.C12	Manuf. Food-Beverages	2.8	0.6	2.4	10	1.4	15.0
C13.C15	Manuf. Textiles	0.4	37.1	0.1	80	0.5	13.4
C16	Manuf. Wood	0.2	61.1	0.1	10	0.1	11.2
C17	Manuf. Paper	0.4	7.5	0.1	10	0.2	14.1
C18	Media print	0.3	6.0	0.1	66	0.1	9.4
C19	Manuf. Coke-Petroleum	0.9	18.3	1.4	10	0.7	14.8
C20	Manuf. Chemical	1.1	2.6	0.3	25	1.7	14.7
C21	Manuf. Pharmaceutical	0.7	1.1	0.3	10	1.2	14.9
C22	Manuf. Rubber-Plastics	0.7	28.3	0.1	10	0.6	14.0
C23	Manuf. Minerals	0.5	50.3	0.1	10	0.2	13.0
C24	Manuf. Metals-basic	0.6	57.7	0.0	10	1.7	15.0
C25	Manuf. Metals-fabricated	1.1	54.8	0.1	10	0.8	14.4
C26	Manuf. Electronic	0.8	38.5	0.2	100	1.5	14.9
C27	Manuf. Electric	0.4	33.3	0.1	10	0.8	14.9
C28	Manuf. Machinery	1.1	49.7	0.2	10	2.2	15.0
C29	Manuf. Vehicles	1.6	22.6	1.2	100	2.8	14.8
C30	Manuf. Transport-other	1.0	48.8	0.1	10	2.6	15.1
C31_C32	Manuf. Furniture	0.6	36.6	0.2	40	0.8	14.7
C33	Repair-Installation	0.4	3.3	0.0	10	0.0	11.8
D35	Electricity-Gas	3.2	0.0	3.4	0	0.1	14.8
E36	Water	0.2	0.0	0.5	0	0.0	14.8
E37.E39	Sewage	0.8	0.0	0.5	0	1.1	7.6
F	Construction	7.9	35.6	0.3	10	12.1	15.2
G45	Vehicle trade	1.7	31.6	1.9	10	0.6	15.0
G46	Wholesale	3.5	23.6	3.1	10	4.5	15.0
G47	Retail	4.7	30.5	15.5	10	0.6	14.1
H49	Land transport	2.0	11.1	2.5	67	0.2	14.9
H50	Water transport	0.6	12.4	0.6	67	0.7	15.0
H51	Air transport	0.6	0.1	1.2	67	0.5	15.0
H52	Warehousing	1.4	0.5	0.1	67	0.4	15.0
H53	Postal	0.7	0.0	0.1	0	0.1	14.8
I	Accommodation-Food	2.9	60.8	7.9	80	0.8	15.0
J58	Publishing	0.6	14.4	0.5	0	0.6	14.7
J59_J60	Video-Sound-Broadcasting	0.9	32.8	1.0	0	1.2	9.9
J61	Telecommunications	1.6	0.9	1.8	0	0.8	15.0
J62_J63	IT	2.3	0.2	0.2	0	2.7	13.6
K64	Finance	4.3	0.0	3.0	0	3.1	14.9
K65	Insurance	3.2	0.0	6.0	0	1.6	14.9
K66	Auxil. Finance-Insurance	1.1	0.0	0.1	0	2.1	15.0
L68	Real estate	7.8	15.4	23.8	0	1.0	15.0
M69_M70	Legal	2.8	2.0	0.1	0	1.4	14.4
M71	Architecture-Engineering	1.7	0.0	0.1	0	1.4	15.1
M72	R&D	0.5	0.0	0.0	0	1.1	14.9
M73	Advertising	0.6	22.5	0.0	0	0.3	14.0
M74_M75	Other Science	0.7	3.0	0.4	0	1.0	14.6
N	Private Administration	4.4	34.9	1.0	0	2.8	14.1
O84	Public Administration	4.8	1.1	0.5	0	12.5	0.7
P85	Education	4.2	0.0	4.7	0	6.4	1.8
Q	Health	7.0	0.1	3.7	0	14.8	0.2
R_S	Other Service	3.2	34.5	6.7	5	1.3	8.5
T	Household activities	0.2	0.0	0.7	0	0.0	14.8
	Average	1.8	19.0	1.8	18	1.8	13.3
	Weighted average		16.6		14.0		9.8

vector $\bar{\theta}_t$, whose components $\bar{\theta}_{i,t}$ are obtained by applying the shock vector $\epsilon^D_{i,t}$. That is, we define $\bar{\theta}_{i,t} = \theta_{i,0}(1 - \epsilon^D_{i,t})$ and define $\theta_{i,t}$ as

$$\theta_{i,t} = \frac{\bar{\theta}_{i,t}}{\sum_j \bar{\theta}_{j,t}} = \frac{(1 - \epsilon^D_{i,t})\theta_{i,0}}{\sum_j (1 - \epsilon^D_{j,t})\theta_{j,0}}. \tag{30}$$

Table 6
Summary table of critical input ratings by IHS Markit analysts. Columns below *Input-based rankings* show how often an industry has been rated as critical (score=1), half-critical (score=0.5) or non-critical (score=0) input for other industries, or how often the input was rates as NA. Columns under *Industry-based rankings* give how often an input has been rated as with 1, 0.5, 0 or NA for any given industry. Column *n* indicates the number of analysts who have rated the inputs of any given industry. Industry *T* uses no inputs and is therefore not rated.

		Input-based rankings				Industry-based rankings				
ISIC	Sector (abbreviated)	1	0.5	0	NA	1	0.5	0	NA	n
A01	Agriculture	4	2	49	0	9	9	37	0	1
A02	Forestry	2	3	50	0	7	9	39	0	1
A03	Fishing	2	1	52	0	8	5	42	0	1
B	Mining	7	1	47	0	9	2	44	0	3
C10-C12	Manuf. Food-Beverages	5	6	44	0	14	5	36	0	1
C13-C15	Manuf. Textiles	2	5	48	0	6	2	47	0	1
C16	Manuf. Wood	3	3	49	0	8	3	44	0	1
C17	Manuf. Paper	5	10	40	0	14	11	30	0	1
C18	Media print	3	6	46	0	6	3	46	0	1
C19	Manuf. Coke-Petroleum	18	4	33	0	15	6	33	2	1
C20	Manuf. Chemical	21	10	24	0	15	6	34	0	1
C21	Manuf. Pharmaceutical	2	2	51	0	9	17	25	7	1
C22	Manuf. Rubber-Plastics	11	7	37	0	14	5	36	0	1
C23	Manuf. Minerals	8	2	44	2	7	1	47	0	1
C24	Manuf. Metals-basic	8	2	45	0	12	7	36	0	3
C25	Manuf. Metals-fabricated	12	4	39	0	5	3	47	0	1
C26	Manuf. Electronic	10	7	38	0	14	10	31	0	1
C27	Manuf. Electric	7	6	42	0	13	9	33	0	1
C28	Manuf. Machinery	10	12	32	2	5	1	49	0	1
C29	Manuf. Vehicles	4	5	46	0	14	10	31	0	1
C30	Manuf. Transport-other	2	6	47	0	12	10	33	0	1
C31_C32	Manuf. Furniture	1	1	53	0	8	4	43	0	1
C33	Repair-Installation	17	9	29	0	8	2	45	0	1
D35	Electricity-Gas	31	3	21	0	10	5	40	0	1
E36	Water	19	3	33	0	4	5	46	0	1
E37-E39	Sewage	18	3	34	0	6	8	41	0	1
F	Construction	5	3	47	0	14	9	32	0	1
G45	Vehicle trade	2	5	48	0	9	7	39	0	1
G46	Wholesale	19	3	33	0	4	25	26	0	1
G47	Retail	2	3	50	0	6	10	39	0	1
H49	Land transport	28	3	24	0	11	2	42	0	1
H50	Water transport	9	8	38	0	8	5	42	0	1
H51	Air transport	5	7	43	0	10	6	39	0	1
H52	Warehousing	12	9	34	0	9	7	39	0	1
H53	Postal	6	7	41	2	3	5	47	0	1
I	Accommodation-Food	5	3	47	0	7	6	42	0	1
J58	Publishing	1	2	52	0	10	14	31	0	1
J59_J60	Video-Sound-Broadcasting	2	2	51	0	9	5	37	7	1
J61	Telecommunications	26	11	18	0	7	5	42	2	1
J62_J63	IT	16	13	26	0	7	6	42	0	1
K64	Finance	10	19	26	0	6	3	46	0	1
K65	Insurance	6	12	36	2	6	3	46	0	1
K66	Auxil. Finance-Insurance	5	7	41	4	6	4	45	0	1
L68	Real estate	1	3	51	0	7	5	43	0	1
M69_M70	Legal	12	15	28	0	5	3	46	2	1
M71	Architecture-Engineering	6	10	39	0	4	2	49	0	1
M72	R&D	1	2	52	0	4	3	48	0	1
M73	Advertising	1	7	47	0	5	2	48	0	1
M74_M75	Other Science	1	8	46	0	4	1	50	0	1
N	Private Administration	16	16	23	0	3	2	50	0	1
O84	Public Administration	6	3	45	2	5	2	48	0	1
P85	Education	1	4	50	0	6	8	41	0	1
Q	Health	1	6	48	0	7	7	41	0	1
R_S	Other Service	1	1	50	5	4	0	51	0	1
T	Household activities	0	0	54	2	0	0	55	0	0

The difference $1 - \sum_i \bar{\theta}_{i,t}$ is the aggregate reduction in consumption demand due to the demand shock, which would lead to an equivalent increase in the saving rate. However, households may not want to save all the money that they are not spending. For example, they most likely want to spend on food the money that they are saving on restaurants. Therefore,

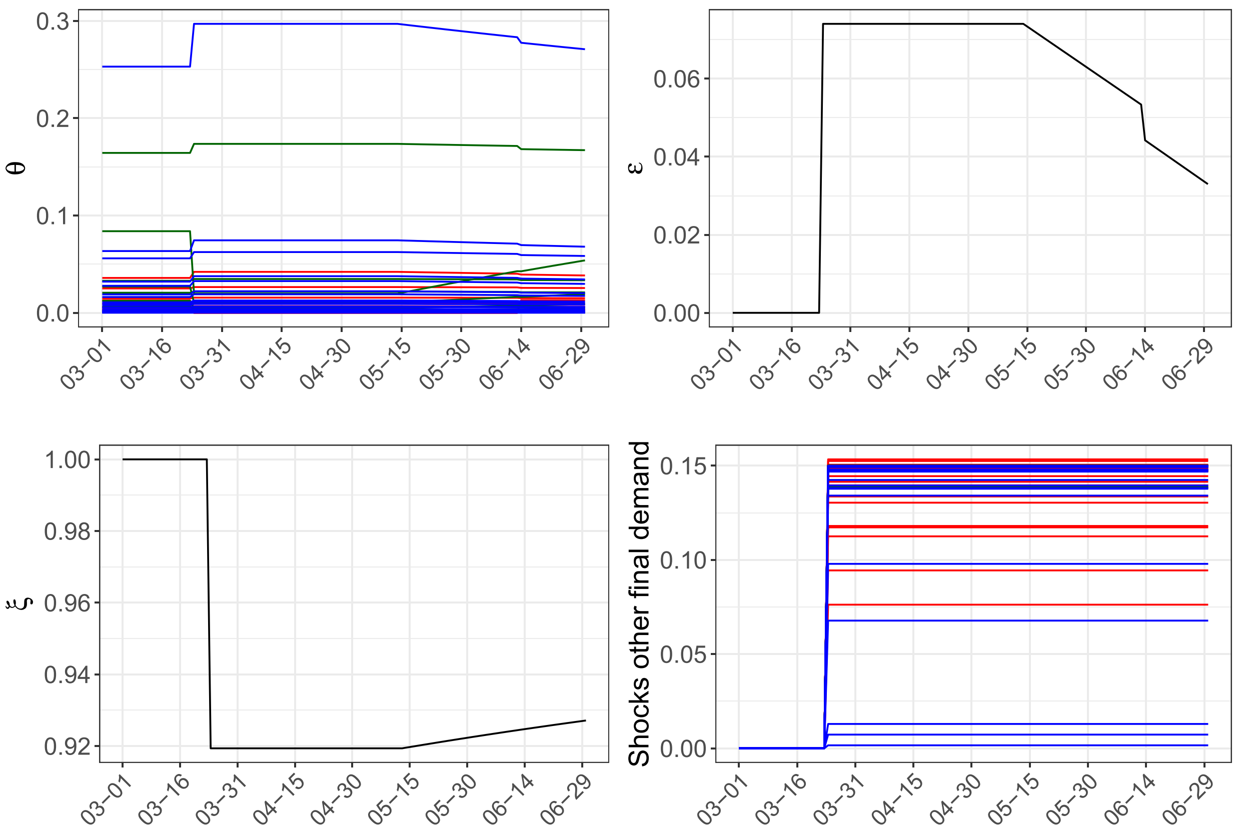

Fig. 8. Industry-specific demand shocks over time. The upper left panel shows the change in preferences $\theta_{i,t}$. The upper right panel is the aggregate demand shock $\tilde{\epsilon}_t$ taking the savings rate of 50% into account. The bottom left right panel shows demand shocks due to fear of unemployment ξ_t. The bottom right panel shows shock magnitudes to investment and export. The coloring of the lines for industry-specific results follows the same code as in Fig. 1.

we define the aggregate demand shock $\tilde{\epsilon}_t^D$ in Eq. (6) as

$$\tilde{\epsilon}_t^D = \Delta s\left(1 - \sum_{i=1}^{N} \bar{\theta}_{i,t}\right), \tag{31}$$

where Δs is the change in the savings rate. When $\Delta s = 1$, households save all the money that they are not planning to spend on industries affected by demand shocks; when $\Delta s = 0$, they spend all that money on goods and services from industries that are affected less[27]

To parameterize $\epsilon_{i,t}^D$, we adapt consumption shock estimates by the Congressional Budget Office (2006) and del Rio-Chanona et al. (2020). Roughly speaking, these shocks are massive for restaurants and transport, mild for manufacturing and null for utilities. We make two modifications to these estimates. First, we remove the positive shock to the health care sector, as in the UK the cancellation of non-urgent treatment for other diseases than COVID-19 far exceeded the additional demand for health due to COVID-19.[28] Second, we apportion to manufacturing sectors the reduced demand due to the closure of non-essential retail. For example, retail shops selling garments and shoes were mandated to shut down, and so we apply a consumption demand shock to the manufacturing sector producing these goods.[29]

[27] Because we look at the very short-run, we do not model how savings may re-enter the economy at a later stage, for instance inducing catching-up consumption.

[28] https://www.ons.gov.uk/economy/grossdomesticproductgdp/bulletins/gdpfirstquarterlyestimateuk/apriltojune2020

[29] To be fully consistent with the definition of demand shock, we should model non-essential retail closures as supply shocks, and propagate the shocks to manufacturing through reduced intermediate good demand. However, there are two practical problems that prevent us to do so: (i) the sectoral aggregation in the WIOD is too coarse, comprising only one aggregate retail sector; (ii) input-output tables only report margins of trade, i.e. they do not model explicitly the flow of goods from manufacturing to retail trade and then from retail trade to final consumption. Given these limitations, we conventionally interpret non-essential retail closures as demand shocks.

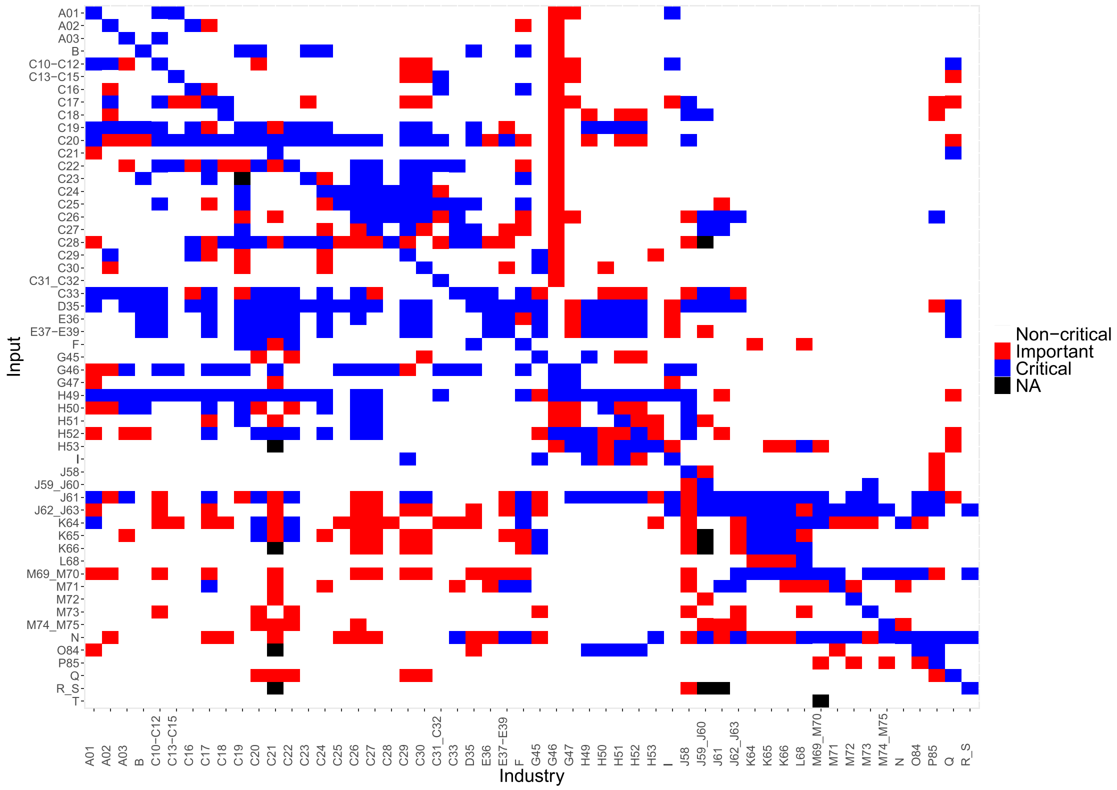

Fig. 9. Criticality scores from IHS Markit analysts. Rows are inputs (supply) and columns industries using these inputs (demand). The blue color indicates critical (score=1), red important (score=0.5) and white non-critical (score=0) inputs. Black denotes inputs which have been rated with NA. The diagonal elements are considered to be critical by definition. For industries with multiple input-ratings we took the average of all ratings and assigned a score=1 if the averaged score was at least 2/3 and a score=0 if the average was smaller or equal to 1/3.

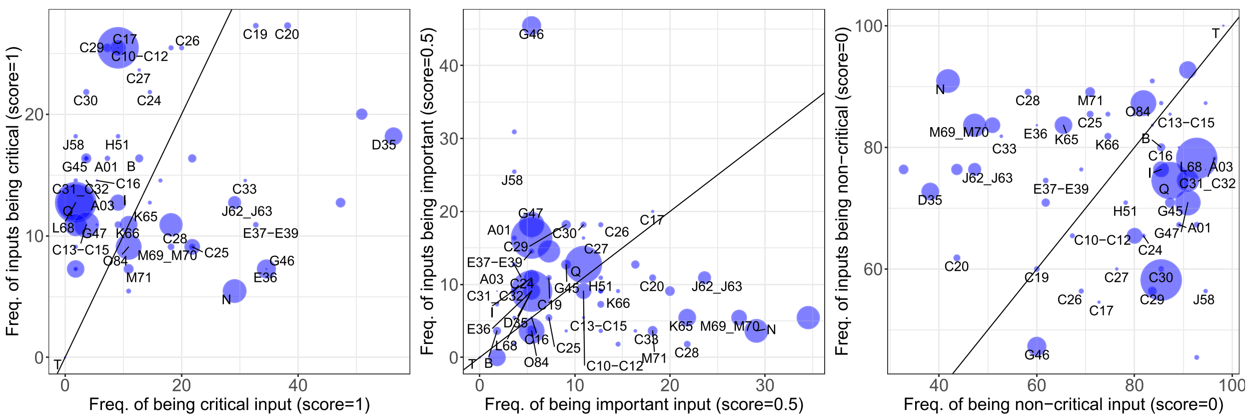

Fig. 10. (Left panel) The figure shows how often an industry is rated as a critical input to other industries (x-axis) against the share of critical inputs this industry is using. The center and right panel are the same as the left panel, except for using half-critical and non-critical scores, respectively. In each plot the identity line is shown. Point sizes are proportional to gross output.

We keep the intensity of demand shocks constant during lockdown. We then reduce demand shocks when lockdown is lifted according to the situation of the COVID-19 pandemic in the UK. In particular, we assume that consumers look at the daily number of COVID-19 deaths to assess whether the pandemic is coming to an end, and that they identify the end of the pandemic as the day in which the death rate drops below 1% of the death rate at the peak. Given official data[30], this happens on August 11$^{\text{th}}$. Thus, we reduce $\epsilon^D_{i,t}$ from the time lockdown is lifted (May 13$^{\text{th}}$) by linearly interpolating between

[30] https://coronavirus.data.gov.uk/

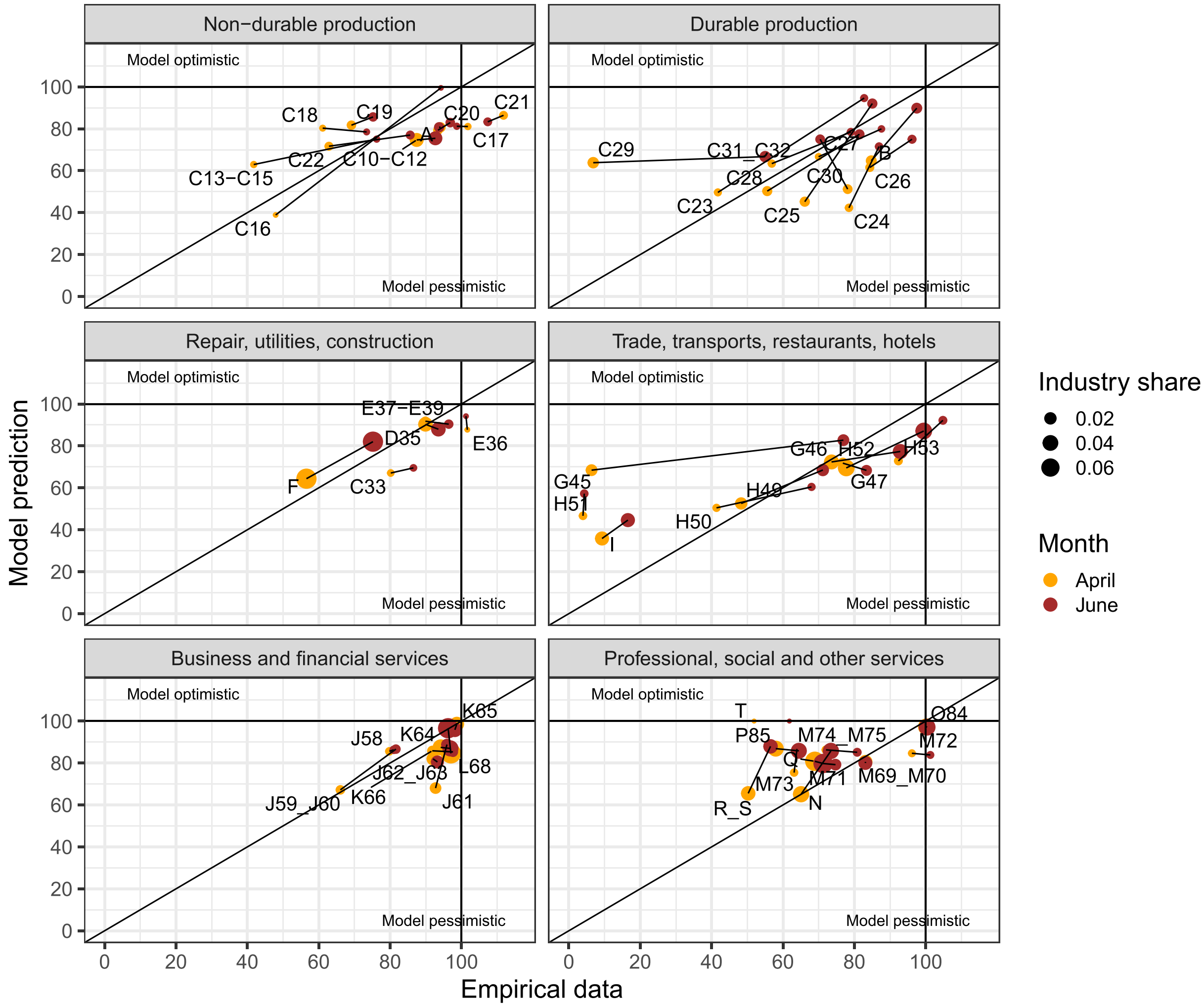

Fig. 11. Comparison between model predictions and empirical data. We plot production (gross output) for each of 53 industries, both as predicted by our model and as obtained from the ONS' indexes. Each panel refers to a different group of industries. Different colors refer to production in April and June 2020. Black lines connect the same industry across these three months. All sectoral productions are normalized to their pre-lockdown levels, and each point size is proportional to the steady-state gross output of the corresponding sector.

the value of $\epsilon_{i,t}^{D}$ during lockdown and $\epsilon_{i,t}^{D}=0$ on August 11th. The choice of modeling behavioral change in response to a pandemic by the death rate has a long history in epidemiology (Funk et al., 2010).

A2.2. Demand shocks due to fear of unemployment

A second shock to consumption demand occurs through reductions in current income and expectations for permanent income.

Reductions in current income are due to firing/furloughing, due to both direct shocks and subsequent upstream or downstream propagation, resulting in lower labor compensation, i.e. $\tilde{l}_t < \tilde{l}_0$, for $t \geq t_{\text{start\_lockdown}}$. To support the economy, the government pays out social benefits to workers to compensate income losses. In this case, the total income $\tilde{l}_t$ that enters Eq. (6) is replaced by an effective income $\tilde{l}_t^{\star} = b\tilde{l}_0 + (1-b)\tilde{l}_t$, where b is the fraction of pre-pandemic labor income that workers who are fired or furloughed are able to retain.

A second channel for shocks to consumption demand due to labor market effects occurs through expectations for permanent income. These expectations depend on whether households expect a V-shaped vs. L-shaped recovery, that is, whether they expect that the economy will quickly bounce back to normal or there will be a prolonged recession. Let expectations for permanent income $\tilde{l}_t^{p}$ be specified by

$$\tilde{l}_t^{p} = \xi_t \tilde{l}_0 \tag{32}$$

In this equation, the parameter ξ_t captures the fraction of pre-pandemic labor income $\tilde{l}_0$ that households expect to retain in the long run. We first give a formula for ξ_t and then explain the various cases.

$$\xi_t = \begin{cases} 1, & t < t_{start\_lockdown}, \\ \xi^L = 1 - \frac{1}{2}\frac{\tilde{l}_0 - \tilde{l}_{t_{start\_lockdown}}}{\tilde{l}_0}, & t \in [t_{start\_lockdown}, t_{end\_lockdown}], \\ 1 - \rho + \rho\xi_{t-1} + \nu_{t-1}, & t > t_{end\_lockdown}. \end{cases} \tag{33}$$

Before lockdown, we let $\xi_t \equiv 1$, i.e. permanent income expectations are equal to current income. During lockdown, following Muellbauer (2020) we assume that ξ_t is equal to one minus half the relative reduction in labor income that households experience due to the direct labor supply shock, and denote that value by ξ^L. (For example, given a relative reduction in labor income of 16%, $\xi^L = 0.92$.)[31] After lockdown, we assume that 50% of households believe in a V-shaped recovery (McKibbin and Fernando, 2021), while 50% believe in an L-shaped recovery (Fornaro and Wolf, 2020).[32] We model these expectations by letting ξ_t evolve according to an autoregressive process of order one, where the shock term $\nu_t = \nu$ is a permanent shock that reflects beliefs in an L-shaped recovery. With 50% of households believing in such a recovery pattern, it is $\nu \equiv -(1-\rho)(1-\xi^L)/2$.[33] We show in the sensitivity analyses of the Supplementary Information that our model is highly robust with respect to changing recovery expectations of households.

A2.3. Other final demand shocks

Note that WIOD distinguishes five types of final demand: (I) *Final consumption expenditure by households*, (II) *Final consumption expenditure by non-profit organisations serving households*, (III) *Final consumption expenditure by government* (IV) *Gross fixed capital formation* and (V) *Changes in inventories and valuables*. Additionally, all final demand variables are available for every country, meaning that it is possible to calculate imports and exports for all categories of final demand. The endogenous consumption variable $c_{i,t}$ corresponds to (I), but only for domestic consumption. All other final demand categories, including all types of exports, are absorbed into the variable $f_{i,t}$.

We apply different shocks to $f_{i,t}$. We do not apply any exogenous shocks to categories (III) *Final consumption expenditure by government* (we assume a balance between reduction in spending in some government activities and increases in spending and healthcare and other essential services) and (V) *Changes in inventories and valuables* (inventories are modeled endogenously), while we apply the same demand shocks to category (II) as we do for category (I). To determine shocks to investment (IV) and exports we start by noticing that, before the COVID-19 pandemic, the volatility of these variables has generally been three times the volatility of consumption.[34] The overall consumption demand shock is around 5% so, as a baseline, we assume shocks to investment and exports to be 15%. In the Supplementary Information we show that the model results are fairly robust with respect to alternative choices.

Appendix B. Critical vs. non-critical inputs

A survey was designed to address the question of when production can continue during a lockdown. For each industry, IHS Markit analysts were asked to rate every input of a given industry. The exact formulation of the question was as follows: "For each industry in WIOD, please rate whether each of its inputs are essential. We will present you with an industry X and ask you to rate each input Y. The key question is: Can production continue in industry X if input Y is not available for two months?" Analysts could rate each input according to the following allowed answers:

- **0** – This input is *not* essential
- **1** – This input is essential
- **0.5** – This input is important but not essential
- **NA** – I have no idea

To avoid confusion with the unrelated definition of essential industries which we used to calibrate first-order supply shocks, we refer to inputs as *critical* and *non-critical* instead of *essential* and *non-essential.*

[31] During lockdown, labor income may be further reduced due to firing. For simplicity, we choose not to model the effect of these further firings on permanent income.

[32] While the assumption of a 50% share for each belief is rather arbitrary, it reflects profound disagreements in society about the end of the pandemic. Moreover, we show in our sensitivity analysis in the Supplementary Information that results are not much different if we assume that everyone believes in a V-shaped recovery, or if everyone believes in a L-shaped recovery.

[33] The specification in Eq. (33) reflects the following assumptions: (i) time to adjustment ρ is the same as for consumption demand, Eq. (6); (ii) absent permanent shocks, $\nu_t = 0$ after some t, ξ_t returns to one, i.e. permanent income matches current income; (iii) when $\nu_t = \nu = -(1-\rho)(1-\xi^L) * \pi^L$, ξ_t reaches a steady state given by $1 - (1-\xi^L) * \pi^L$, where π^L is the share believing in an L-shaped recovery. With 50% households believing in an L-shaped recovery (and so $\pi^L = 0.5$), and with $\xi^L = 0.92$ as in the example above, ξ_t reaches a steady state at 0.96, so that permanent income remains stuck four percentage points below pre-lockdown income.

[34] This is computed by calculating the standard deviation of consumption, investment and export growth over all quarters from 1970Q1 to 2019Q4. These are 1.03%, 2.87% and 3.24% respectively. Source: https://www.ons.gov.uk/file?uri=%2feconomy%2fgrossdomesticproductgdp%2fdatasets%2frealtimedatabaseforukgdpcomponentsfortheexpenditureapproachtothemeasureofgdp%2fquarter2aprtojune2020firstestimate/gdpexpenditurecomponentsrealtimedatabase.xls

Analysts were provided with the share of each input in the expenses of the industry. It was also made explicit that the ratings assume no inventories such that a rating captures the effect on production if the input is not available.

Every industry was rated by one analyst, except for industries Mining and Quarrying (B) and Manufacture of Basic Metals (C24) which were rated by three analysts. In case there are several ratings we took the average of the ratings and rounded it to 1 if the average was at least 2/3 and 0 if the average was at most 1/3. Average input ratings lying between these boundaries are assigned the value 0.5.

The ratings for each industry and input are depicted in Fig. 9. A column denotes an industry and the corresponding rows its inputs. Blue colors indicate *critical*, red *important, but not critical* and white *non-critical* inputs. Note that under the assumption of a Leontief production function every element would be considered to be critical, yielding a completely blue-colored matrix. The results shown here indicate that the majority of elements are non-critical inputs (2,338 ratings with score = 0), whereas only 477 industry-inputs are rates as critical. 365 inputs are rated as important, although not critical (score = 0.5) and *NA* was assigned eleven times.

The left panel of Fig. 10 shows for each industry how often it was rated as a critical input to other industries (x-axis) and how many critical inputs this industry relies on in its own production (y-axis). Electricity and Gas (D35) are rated most frequently as critical inputs in the production of other industries (score=1 for almost 60% of industries). Also frequently rated as critical are Land Transport (H49) and Telecommunications (J61). On the other hand, many manufacturing industries (ISIC codes starting with C) stand out as relying on a large number of critical inputs. For example, around 27% of inputs to Manufacture of Coke and Refined Petroleum Products (C19) as well as to Manufacture of Chemicals (C20) are rated as critical.

The center panel of Fig. 10 shows the equivalent plot for 0.5 ratings (important, but not critical inputs). Financial Services (K64) are most frequently rated as important inputs which do not necessarily stop the production of an industry if not available. Conversely, the industry relying on many important, but not binding inputs is Wholesale and Retail Trade (G46) of which almost half of its inputs got rated with a score = 0.5. This makes sense given that this industry heavily relies on all these inputs, but lacking one of these does not halt economic production. This case also illustrates that a Leontief production function could vastly overestimate input bottlenecks as Wholesale and Retail Trade would most likely still be able to realize output even if a several inputs were not available.

In the right panel of Fig. 10 we show the same scatter plot but for non-critical inputs. 25 industries are rated to be non-critical inputs to other industries in 80% of all cases, with Household Activities (T) and Manufacture of Furniture (C31-32) being rated as non-critical in at least 96%. Industries like Other Services (R-S), Other Professional, Scientific and Technical Activities (M74-75) and Administrative Activities (N) rely on mostly non-critical inputs (>90%).

A detailed breakdown of the input- and industry-specific ratings are given in Table B.6.

Appendix C. Details on validation

In this appendix we provide further details about validation (Section 4 in the main paper). In Appendix C.1 we describe the data sources that we used for validation, and we explain how we made empirical data comparable to simulated data. In Appendix C.2 we give more details about the dynamics from April to June in the model and in the data (Fig. 3 in the main paper).

C1. Validation data

- Index of agriculture (release: 12/08/2020): https://www.ons.gov.uk/generator?format=xls&uri=/economy/grossdomesticproductgdp/timeseries/ecy3/mgdp/previous/v26
- Index of production (release: 12/08/2020): https://www.ons.gov.uk/file?uri=/economy/economicoutputandproductivity/output/datasets/indexofproduction/current/previous/v59/diop.xlsx
- Index of construction (release: 12/08/2020): https://www.ons.gov.uk/file?uri=/businessindustryandtrade/constructionindustry/datasets/outputintheconstructionindustry/current/previous/v67/bulletindataset2.xlsx
- Index of services (release: 12/08/2020): https://www.ons.gov.uk/file?uri=/economy/economicoutputandproductivity/output/datasets/indexofservices/current/previous/v61/ios1.xlsx

All Office of National Statistics (ONS) indexes are monthly seasonally-adjusted chained volume measures, based such that the index averaged over all months in 2016 is 100. Although these indexes are used to proxy value added in UK national accounts, they are actually gross output measures, as determining input use is too burdensome for monthly indexes.

There is not a perfect correspondence between industry aggregates as considered by ONS and in the World Input-Output Database (WIOD). For example, the ONS only releases data for the agricultural sector as a whole, without distinguishing between crop and animal production (A01), fishing and aquaculture (A02) and forestry (A03). In this case, when comparing simulated and empirical data we aggregate data from the simulations, using initial output shares as weights. More commonly, there is a finer disaggregation in ONS data than in WIOD. For example, ONS provides separate information on food manufacturing (C10) and on beverage and tobacco manufacturing (C11, C12), while these three sectors are aggregated into just one sector (C10_C12) in WIOD. In this case, we aggregate empirical data using the weights provided in the indexes of production and services. These weights correspond to output shares in 2016, the base year for all time series.

Finally, after performing aggregation we rebase all time series so that output in February 2020 takes value 100.

C2. Dynamics of all industries

Fig. 11 shows the dynamics from April to June of all industries, both in the model and in the data. Interpretation is the same as in Fig. 3 in the main text. For readability, industries are grouped into six broad categories.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.jedc.2022.104527

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