The Economic Case for Global Vaccinations: An Epidemiological Model with International Production Networks*

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Abstract

We develop a multi-sector open economy model that quantifies the economic costs incurred by the vaccinated countries arising from not vaccinating poor countries. As in Baqaee and Farhi (2022), the key feature of our macro-network model is the co-existence of sectoral supply and demand shocks. To calibrate our model in a multi-country setup with global linkages, we measure these shocks for 65 countries and 35 sectors using an epidemiological framework. This framework allows us to calculate the changes in sectoral employment and consumption as a function of heterogeneity in sectoral infections. The role of complementarities in the global production network is important for our results: the real GDP loss of vaccinated countries quadruples by moving from unitary to non-unitary elasticises of substitution between imported and domestic intermediate inputs. The lack of vaccinations trigger endogenous lockdowns in poor countries. The degree that the vaccinated countries can substitute away from the lockdown countries in terms of their imports and exports determines the range of their losses. Thus, our estimates based on a structural model provide both an upper and a lower bound for the negative output effects of real-life global supply chain disruptions.

Keywords: Covid-19; Sectoral Infection Dynamics; Global Trade and Production Network; International I-O Linkages.
JEL Codes: E61, F00, C51.

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No Man is an Island
"No man is an island entire of itself; every man is a piece of the continent, a part of the main; if a clod be washed away by the sea, Europe is the less, as well as if a promontory were, as well as any manner of thy friends or of thine own were; any man's death diminishes me, because I am involved in mankind. And therefore never send to know for whom the bell tolls; it tolls for thee."

– John Donne

1 Introduction

On January 28, 2021, Reuters reported that Taiwan has sought Germany's help in securing Covid-19 vaccines, after Berlin asked for the island's assistance in easing a shortage of automobile semiconductor chips. A year and a half later, such shortages spread over to broader supply chains encompassing all factors of production, including labor, leading to the highest levels of global inflation in the last four decades (di Giovanni et al., 2022; Jordà et al., 2022). Using a structural macro-network model for the global economy, our paper quantifies the real output losses due to such shortages and broader supply constraints, as a consequence of not vaccinating the entire world since the discovery of vaccines.[1]

Covid-19 is a "once in a life-time" shock for the global economy. It constitutes both a demand and a supply shock, combined with extensive uncertainty and sectoral heterogenetiy, affecting different countries at different times. While all countries are impacted by the virus, the effects are not synchronized across borders, unlike the 2008-09 global financial crisis, which was mainly a negative shock to aggregate demand in many countries.

The asynchronous effects of the crisis are due to the repeated nature of the health shock from different variants and the uneven and uncoordinated health and economic policy responses across countries. The different approaches and policies adopted by the countries regarding the decisions concerning public health, vaccination, as well as fiscal and monetary policies created demand and supply imbalances. These imbalances were propagated via the international input-output networks on a global scale.

To capture such imbalances, we focus on the period after the introduction of vaccines, from

[1] As of August, 2022, a third of the world is still not vaccinated, see, https://ourworldindata.org/covid-vaccinations.

2020q4 to 2021q4. We provide model-based estimates of real GDP losses due to supply chain disruptions in a world of uneven vaccinations resulting in heterogeneous sectoral shocks.[2]

We show that supply chain disruptions can persist as long as the pandemic prevails. The pandemic creates intermediate input and labor shortages, both due to virus related sickness, that is heterogenous across sectors and due to compositional shift in demand across sectors. At the initial stages of the pandemic, the supply side was subject to disruptions. Over time, demand improved at different times in different countries as a function of the speed of vaccinations, and economic stimuli. Our model and estimates capture the reality of this multi-speed world: as long as the supply side does not improve at the same speed as demand, recovery in demand, even in certain sectors, worsens the supply chain disruptions.

Our findings illustrate that the estimated real GDP losses of vaccinated rich countries would be in the range of 0.1 to 1 percent, relative to their 2019 real GDP, depending on the vaccine roll-out, trade and production elasticities. In a scenario that tries to mimic the real-life global vaccine roll-out in 2021, using empirically relevant short-run elasiticities with complementary inputs, vaccinated rich countries lose around 0.6 percent of their 2019 real GDP. These losses imply a rate of return of 120 percent from investing into global initiative COVAX that was setup to deliver vaccines to poor countries.[3]

Our model allows us to analyze the sectoral-pandemic shocks in an open economy setting with trade and production linkages between countries. Our estimates are based on a calibration exercise of a multi-sector multi-country network model that combines the setups in Baqaee and Farhi (2022) and Baqaee and Farhi (2019). Prices and wages are fully flexible in our set up and there are no aggregate shocks. We feed in sectoral demand and supply shocks as a function of sectoral infections. We then assume a particular vaccination scenario for each country that will amplify and/or mitigate these sectoral shocks depending on the inter-dependencies of the economies in a globalized trade and production network.

[2] At the time of our initial draft in January 2021, such disruptions were deemed to be temporary and predicted to be smoothed out before mid-2021. See, for example IMF World Economic Outlook (IMF, 2020) where it is stated that the baseline scenario assumes that the pandemic and supply chain disruptions fade in early 2021. Our initial draft as well as the current draft work with the baseline assumption that the supply chain disruptions cannot be smoothed till the end of 2021 so long as the pandemic carries on throughout that year.

[3] We arrived at this number by dividing our calculated losses to the investment asked by COVAX in early 2021 of 38 billion USD.

Our model is general as it allows for both low and high elasticity of substitution between traded final and intermediate goods used in production. In the calibrations, we use low elasticities (less than one) for the short-run, as estimated by Boehm et al. (2020) to capture the "just-in-time" nature of the global value chains. We use high elasticities (more than one) as estimated by Caliendo and Parro (2015) to capture the substitution in the medium run in response to price changes. When the countries cannot easily substitute away their imported intermediate inputs from one country to another country in the short-run, the real GDP losses increase. Domestic production elasticities imply complementarity between labor, value added and intermediate inputs, as estimated by Atalay (2017). These elasticities also play a key role under sector-specific labor supply shocks.

We model being sick and being under lockdown as negative shocks to potential labor supply in a given sector, where labor from another sector cannot substitute for. This is a reasonable assumption given lockdowns and sickness elsewhere. As shown by Fernald and Li (2022), labor re-allocation within a sector was possible but labor re-allocation between sectors did not happen at all during the pandemic. If labor demand increases or decreases via consumer demand, sectoral wages increase or decrease as well to establish equilibrium. Heterogeneity in sectoral infections will induce a compositional shift in consumers' demand (low demand for services, higher for goods). Both sectoral supply and sectoral demand shocks vary with vaccinations.

We have a two-period model which cannot perfectly match the complicated dynamics of the real world. The length of the second period in the calibration determines when the economy goes back to pre-Covid-19 equilibrium and the persistence of the supply chain bottlenecks. To capture such granularity and heterogeneity across countries, we divide the second period into 365 days and solve the model daily. We feed in daily sectoral shocks as a function of daily disease dynamics, which are estimated based on the epidemiological model with starting parameters at the onset of the vaccine discovery. The lockdown decisions are endogenous to infection dynamics. A lockdown is put into place when the number of severe cases exceeds a given country's ICU bed capacity. Hence, lack of vaccinations in poor countries make lockdowns more likely.[4] If a country is fully vaccinated by a given day, we stop feeding-in the sectoral shocks and return to the pre-pandemic equilibrium. Thus, the end of the second period is dictated by the vaccination scenarios in our calibrations.

[4]If a country Like China follows such a strategy of lockdowns, our model will deliver larger losses for rest of the world given the importance of China in global supply chains.

The challenge is the calibration of these sector-specific pandemic shocks in the absence of real-time sectoral data on changes in employment and consumption by country. Moreover, the observed labor supply shocks could be both supply driven (due to sickness/lockdowns) or demand-driven (due to a decline in demand for services). Consequently, we use sectoral infections to proxy for such changes based on an epidemiological framework that helps us to convert country level infections into sector level. For this conversion, we start with pre-pandemic sectoral employment data, which is sectoral equilibrium, and shock this sectoral equilibrium employment with infection-based demand and supply shocks. In those sectors with higher physical proximity, infections will be higher, translating into lower labor supply (e.g., dentists are affected more than farmers, factory workers are affected more than accountants). The supply shock is lower in these contact-intesive sectors where remote work is possible. We also use data on lockdowns to further fine tune the labor supply shock. Lockdowns only affect labor supply in non-essential sectors regardless of their infection intensity.

On the demand side, the sectors are affected differently due to changes in consumption patterns during the pandemic. For example, households avoided restaurants and air travel when the infection rates were high. This was mostly due to the fear of contracting and transmitting the disease (Goolsbee and Syverson, 2021). We posit that the changes in the consumption patterns are related to the infection numbers. By using sectoral consumption data from the US, we predict sectoral changes in consumption as a function of sectoral infections and project to other countries. These constitute our demand shocks.

Another challenge is the lack of real-time data on global trade and production network. To date, we do not know if and to what extent producers switch suppliers each time China or another country goes under a lockdown. It is argued by Shih (2020) and Carvalho et al. (forthcoming) that the time needed to rebuild supply networks is longer than the average business cycle. Because Covid-19 was regarded as a temporary shock, at least initially, there would be a reluctance on the firms' part to rebuild their networks. We use OECD's latest available inter-country input-output tables from 2018 to undertake our exercise for 65 countries and 35 sectors and calibrate the extent of switching by showing the results for a range of elasiticities of substitution for production and consumption.

In Figure 1, we show the global trade and production network. Out of 65 countries, 39 countries are classified as advanced economies (AEs) who have access to vaccination as early as January 2021.

The remaining countries (including a residual entity called the "Rest of the World") belong to the set of poorer countries (EMDEs) who are assumed to be unvaccinated at the onset. These international linkages are comprised of sectoral links. Industries use inputs from a variety of other industries as shown in Figure 2. It is clear from this figure that, due to indirect connections, the other industries which are not as open themselves but connected to these open industries, such as "construction and mining" will also be affected. According to OECD (2020), the total value of world trade was 18 trillion USD. Within this total, intermediate products constituted 10.6 trillion USD, corresponding to 59 percent of world trade.

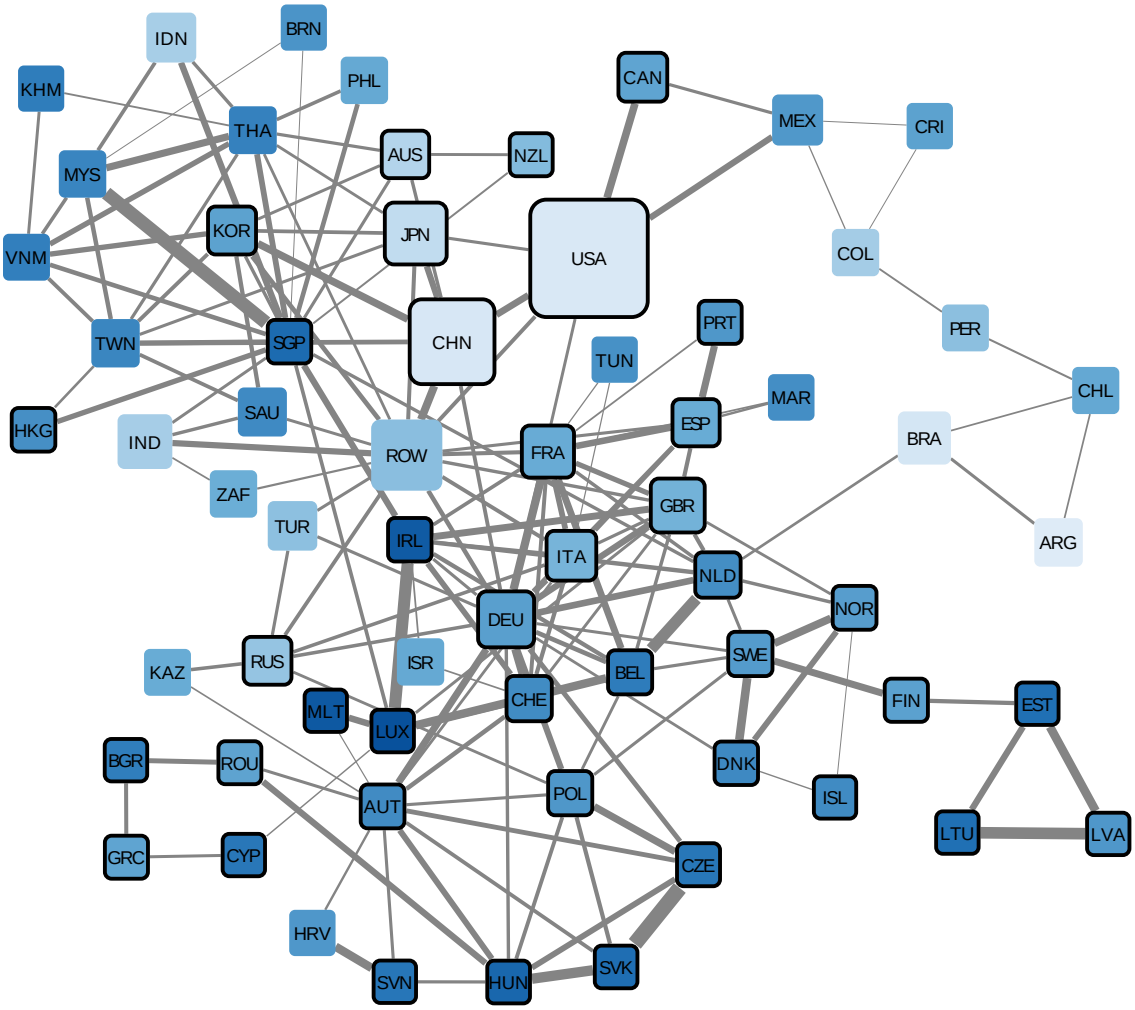
The remainder of this paper is organized as follows. In Section 2, we present the model that we develop to quantify the economic impact of the vaccine roll out on world trade. In Section 3, we describe the data and the parameters for calibration. In Section 3.3, we integrate the epidemiological framework into our economic model. In Section 4, we report our results. Section 5 concludes.

2 The Model

Our model combines Baqaee and Farhi (2019) trade network model with Baqaee and Farhi (2022) closed economy framework involving sectoral supply and demand shocks. In our global network model, each country produces and consumes goods and services, final and intermediate, made by other countries with factors present in those countries. We denote the set of countries with $\mathcal{C}$ and we index countries with c, v or m. $\mathcal{N}$ denotes the set of industries, indexed by i, j or k. Set of factors is represented by $\mathcal{F}$ and indexed by f or g. Because we work with more than 2 countries, more than 2 sectors, and more than 2 factors, this notation is essential. We denote the set of factors present and owned by country c with $\mathcal{F}_c$.

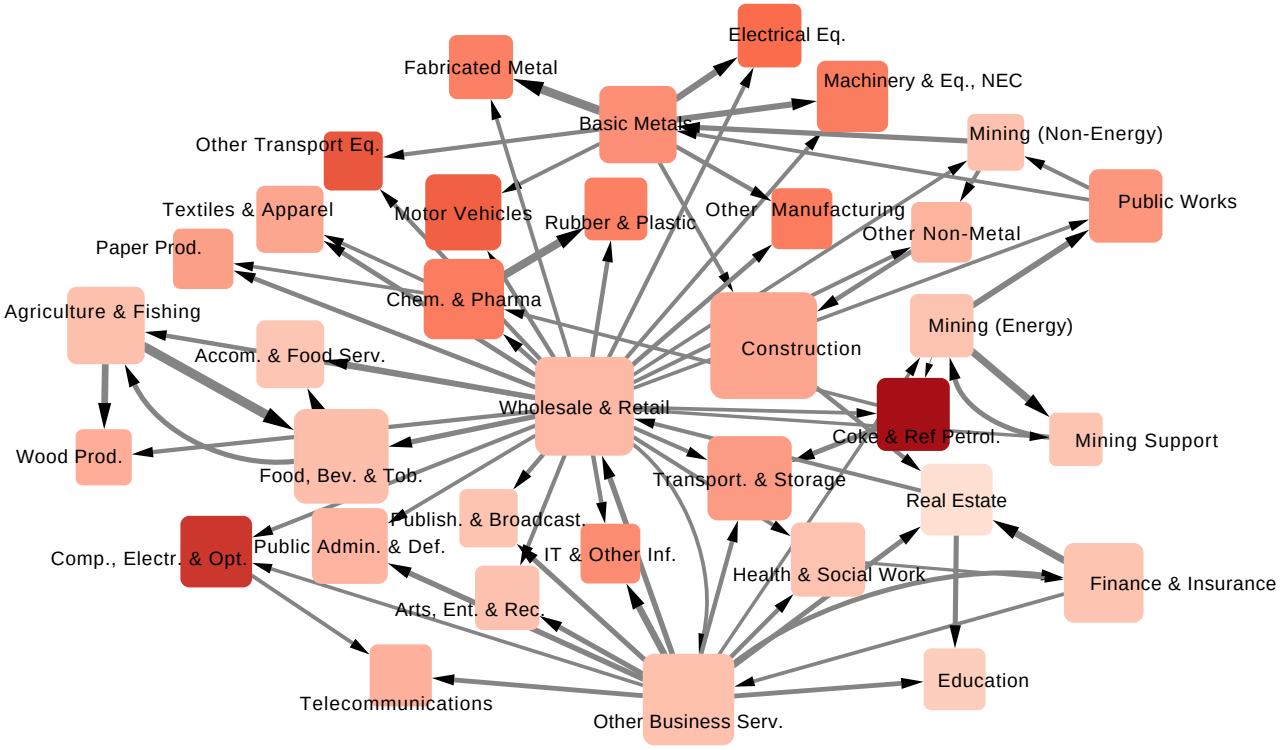
The model has both an intratemporal and intertemporal set-up. Within a given period, the trade-network and, hence, the intratemporal side will matter and across the two periods, the consumption will adjust to demand and supply shocks. We assume that there are no additional trade distortions and no aggregate demand shock. Because there is no aggregate demand shock the intertemporal side becomes irrelevant. We want to keep this assumption in the baseline as we want to analyze the impact of sectoral-pandemic shocks in the absence of expansionary fiscal or monetary policy

Figure 1: International Trade Linkages



NOTES: In this network, we show a summary of international linkages. Each node corresponds to a country, with the node sizes proportional to the GDP of the country. The node color represents the openness of the country where openness is defined as the ratio of imports and exports to GDP. Darker shades represent more openness to trade. The vaccinated countries are denoted by black borders. We show the trade linkages as lines between nodes. The line gets thicker as the ratio of trade to GDP increases. In total, there are 65 nodes and 168 lines shown on the network. The trade values, openness calculations, and the GDP values are all based on OECD (2020) Tables.

Figure 2: Inter-industry Trade Linkages



NOTES: In this network, we show aggregated inter-industry linkages. Each node corresponds to an industry. The node size represents the total intermediate usage of the industry. The smallest node corresponds to 184 billion USD for Mining Support industry and the largest node corresponds to 5.9 trillion USD in Construction industry. The node color represents the share of imported inputs in the industry. The lightest shade represents 5.9% in Real Estate industry and the darkest shade represents 37% in the Coke & Refined Petroleum industry. We show the trade linkages from the supply industry to the target industry with directed lines. The thickness of the lines show the strength of the relation based on: (i) the intermediate input from the supply industry constitutes at least 10 percent of the inputs of target industry; or (ii) the supply industry is among the top two suppliers of the target industry. In total, there are 35 nodes and 72 lines shown on the network. Inter industry linkages are based on OECD (2020) Tables.

response to contracting aggregate demand. Hence, our baseline model also does not feature any nominal rigidity. We focus on changes in *sectoral* real domestic production (real GDP) and prices as a result of sectoral supply and demand shocks arising from the pandemic.

2.1 Production

We assume that production of goods and services in each industry is achieved by combining sector-specific labor and intermediate inputs. The assumption of sector-specific labor implies that labor is not mobile between sectors but can fluctuate within a sector over time. The empirical evidence during the pandemic for within sector reallocation but lack there-of between sector reallocation supports this assumption Fernald and Li (2022).

Suppose the output of industry i in country c is denoted with y_{ic} and its price with p_{ic}. This industry uses inputs from other industries as well as labor. We show the inputs used from country m and industry j by industry ic with x_{jm}^{ic} and the price of this input in this country with p_{jm}^{c}. The input share of industry $jm \in \mathcal{N}$ in industry ic is defined by:

$$\Omega_{jm}^{ic} = \frac{p_{jm}^{c} x_{jm}^{ic}}{p_{ic} y_{ic}}. \tag{1}$$

Since we model the changes in the log prices and quantities to implement hat algebra used in the trade literature (Costinot and Rodríguez-Clare, 2014; Caliendo and Parro, 2015), we assume that the trade costs are not changing during the period, and for illustrative purposes we assume that $p_{jm}^{c} = p_{jm}$.[5]

We assume that the factors are sector specific. For any factor f in country c, we denote the corresponding labor with L_{fc} and its wage with w_{fc}.[6] We denote the specific factor used in industry ic with f_{ic}. We define the share of the value-added (or factor share) in sector ic as:

$$\alpha_{ic} \equiv \Omega_{f_{ic}}^{ic} = \frac{w_{f_{ic}} L_{f_{ic}}}{p_{ic} y_{ic}} = 1 - \sum_{jm \in \mathcal{N}} \Omega_{jm}^{ic}. \tag{2}$$

[5]The increase in shipping costs enter into the model because transportation industry is represented as a separate entry in the Input-Output matrix.

[6]We can extend our notation that we used for industries above to factors with $x_{f_c}^{ic} \equiv L_{fc}$ and $p_{fc} \equiv w_{fc}$. Since each factor is sector specific and there is a single factor (labor) used in each industry, we also use L_{ic} to denote the labor used in sector ic.

This notation boils down to the following structure. The Equation 1 represents shares of plastic, glass, etc. used in car industry in a given country, where these inputs can be sourced domestically and internationally and can be used by other industries in all countries. The Equation 2 represents share of labor used in car industry, where that labor cannot be used in other industries in a given country.

The final good is produced by combining the sector-specific labor and the intermediate bundle. The intermediate bundle consists of all the goods used as inputs by industry ic and we denote the price of this bundle with p_M^{ic} and its quantity with M^{ic}. We assume that in the final good production, the production technology is constant elasticity of substitution (CES) with elasticity ϕ. The normalized production function can be written as:

$$y_{ic} = \frac{A_{ic}}{\bar{A}_{ic}} \left[\alpha_{ic} \left(\frac{L_{ic}}{\bar{L}_{ic}} \right)^{\frac{1-\phi}{\phi}} + (1 - \alpha_{ic}) \left(\frac{M_{ic}}{\bar{M}_{ic}} \right)^{\frac{1-\phi}{\phi}} \right]^{\frac{\phi}{1-\phi}}. \tag{3}$$

and the corresponding price index is:

$$p_{ic} = \left[\alpha_{ic} \left(w_{f_{ic}} \right)^{1-\phi} + (1 - \alpha_{ic}) \left(p_M^{ic} \right)^{1-\phi} \right]^{\frac{1}{1-\phi}}. \tag{4}$$

We assume $0 \leq \phi < 1$, i.e., labor and inputs are complements. As we show in our calibration section, this assumption is supported by the estimates we use from the empirical literature.

The intermediate bundle, M_{ic}, is an aggregate of all types of inputs used by an industry. Going back to our car industry example, assume ic denotes the German car industry, then these inputs are plastic, steel, energy, etc. that are used to produce this car. These inputs are aggregates of varieties produced by different countries. For instance, the steel bundle is an aggregate of steel purchased by German car industry from different countries such as Turkey, India, China and Russia. Hence, intermediate bundles are composed of sector bundles, which are, in turn, aggregates of country-industry varieties.

The price of intermediate bundle, p_M^{ic}, can be written as a function of price of sector bundle of j to be used in industry ic, which we denote by p_j^{ic}. Assuming a CES aggregator with elasticity of

substitution of ε, we can write the price for the intermediate bundle as:

$$p_M^{ic} = \left[\sum_{j \in \mathcal{N}} \frac{\Omega s_j^{ic}}{1 - \alpha_{ic}} \left(p_j^{ic} \right)^{1-\varepsilon} \right]^{\frac{1}{1-\varepsilon}}, \tag{5}$$

with

$$\Omega s_j^{ic} \equiv \sum_{m \in \mathcal{C}} \Omega_{jm}^{ic}.$$

Ωs_j^{ic} captures the share of sector j in production of ic and is calculated by summing over the country varieties. We assume that $0 \leq \varepsilon < 1$, i.e., all sectoral inputs for the intermediate bundle are complements. This assumption says that the plastic and steel cannot be easily substituted in the auto production, of which is backed by the estimates from the empirical literature as we show in our calibration section.

Sector bundles are aggregates of varieties coming from different countries, with price:

$$p_j^{ic} = \left[\sum_{m \in \mathcal{C}} \frac{\Omega_{jm}^{ic}}{\Omega s_j^{ic}} \left(p_{jm}^{c} \right)^{1-\xi_j} \right]^{\frac{1}{1-\xi_j}} \tag{6}$$

using a CES aggregator with a sector-specific elasticity of substitution ξ_j. These sector specific elasticities are calculated to create substitutions between varieties coming from different countries in the long term (Costinot and Rodríguez-Clare, 2014; Caliendo and Parro, 2015) such that $\xi_j \geq 1$. But in the short term, we assume that it is hard to immediately substitute varieties from different countries. This assumption is done not only to make the model and the empirical section consistent—as we assume global trade and production network does not change in the short run and the price impact will be limited—but also to capture the real-life supply chain bottlenecks associated with the pandemic and higher prices: when China lockdowns, US construction industry could not substitute away from the lumber and steel bought from China immediately leading to price rises in many inputs later in the pandemic. Our empirical exercise presents results for both cases of low and high substitution, showing results for the range of both $\xi_j \leq 1$ & $\xi_j \geq 1$. The case with $\xi_j \leq 1$, where all different inputs are assumed to be substitutes, have been used by Bonadio et al. (2021).

2.2 Consumption

As the multi-layer nested production structure, we also assume a nested structure in the consumption of consumers. Suppose that $i = 0$ denotes the consumption of households in all countries. We assume $y_{0c} = C_c$ is the total consumption in country c and the price index of the consumption is denoted by p_{0c}. Let's denote the total nominal expenditure of country c with $E_c = p_{0c}y_{0c} = p_{0c}C_c$. The total world expenditure is $E \equiv \sum_c E_c$. We denote the expenditure share of industry jm in final good consumption with:

$$\Omega_{jm}^{0c} = \frac{p_{jm}x_{jm}^{0c}}{E_c},$$

where x_{jm}^{0c} denotes the amount of industry jm's output consumed by the households in country c.

We assume that the consumers in country c enjoy goods and services at the sectoral consumption bundle levels. Hence, the consumption price index can be written as:

$$p_{0c} = \left[\sum_{j\in\mathcal{N}} \Omega s_j^{0c} \left(p_j^{0c}\right)^{1-\sigma}\right]^{\frac{1}{1-\sigma}}, \tag{7}$$

where p_j^{0c} denotes the price of consumption bundle j in country c and

$$\Omega s_j^{0c} \equiv \sum_{m\in\mathcal{C}} \Omega_{jm}^{0c}$$

denotes the share of industry j in final consumption of consumers in country c. We assume σ to be close to 1. $\sigma = 1$ correspond to the Cobb-Douglas case, with constant expenditure shares, where the price index, in the limit, becomes:

$$\log p_{0c} = \sum_{j\in\mathcal{N}} \Omega s_j^{0c} \log p_j^{0c}.$$

Like the production side, consumption bundles are made of varieties from different countries. The price equation for consumption bundle i of country c is:

$$p_j^{0c} = \left[\sum_{m\in\mathcal{C}} \frac{\Omega_{jm}^{0c}}{\Omega_j^{0c}} \left(p_{jm}^{c}\right)^{1-\xi_j'}\right]^{\frac{1}{1-\xi_j'}}. \tag{8}$$

As in the production side, ξ_i is the trade elasticity (consumption side), usually taken from Caliendo and Parro (2015) as greater than or equal to 1. In our baseline analysis, we use the same ξ_i elasticity as sector bundles in the production side but we also model the cases where the elasticities are markedly different from each other.

2.3 Equilibrium and Perturbation

Given the parameters, a general equilibrium consists of good prices, factor prices, outputs, intermediate inputs, factor inputs and consumption levels such that producers minimize their costs, households maximize their utilities, and good and factor markets clear. The equilibrium is stable in the absence of any shocks. We perturb this equilibrium with sectoral demand and supply shocks.

The pandemic changes the "potential" labor supply because it is a health shock, similar to a war destroying capital stock. Given the vertical potential labor supply, L_f, wages adjust to equilibriate labor supply and demand. During the pandemic, labor demand curve shifts (up or down) due to the changes in the demand patterns as a function of infections, vaccinations and/or economic stimulus. Figure 3 reflect alternative labor demand curves in red. Initially, at the pre-pandemic equilibrium in 2019, both labor and wages are normalized to be one. The wage level could be lower or higher than the initial equilibrium depending on labor demand shifts. The important point is that vertical labor supply will not go back to initial equilibrium as long as pandemic related sector specific shocks are not eliminated. The way to eliminate these fully is by global vaccinations in our model. This structure can capture both unemployment and wage inflation/deflation, as equilibrium outcomes.

Figure 3: Labor and wage during pandemic

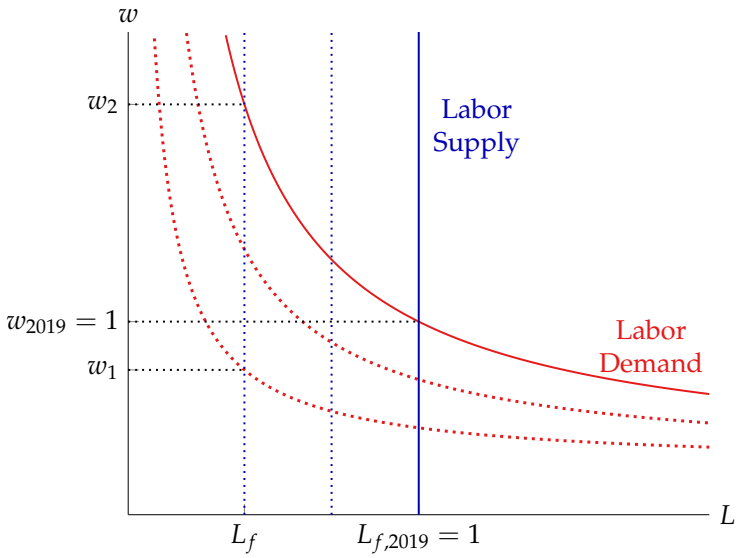


Figure 4 illustrates importance of changes in labor supply in detail in determining equilibrium level of labor, L_f. As the pandemic progresses, equilibrium labor initially declines, both due to low demand and sickness shown with L_f with blue line. During lockdowns only teleworkable can work so labor supply is capped with the dotted blue line. During the recovery phase, depending on demand, vaccinations and teleworkable shares of labor, equilibrium labor can go up and down but never will reach the pre-pandemic full employment level of one as the initial shock to labor supply never eases. Hence, our model can capture real-life labor shortages which got worse in the face of higher demand during the pandemic. Figure 5 shows evidence for pandemic related labor supply shocks for US from the Current Population Survey.[7]

[7]U.S. Bureau of Labor Statistics provides time series data for employed people with a job not at work by selected reasons. See Figure A.2 in Appendix A.2 for the list of those reasons.

Figure 4: Equilibrium Labor due to changes in Labor Supply and Labor Demand

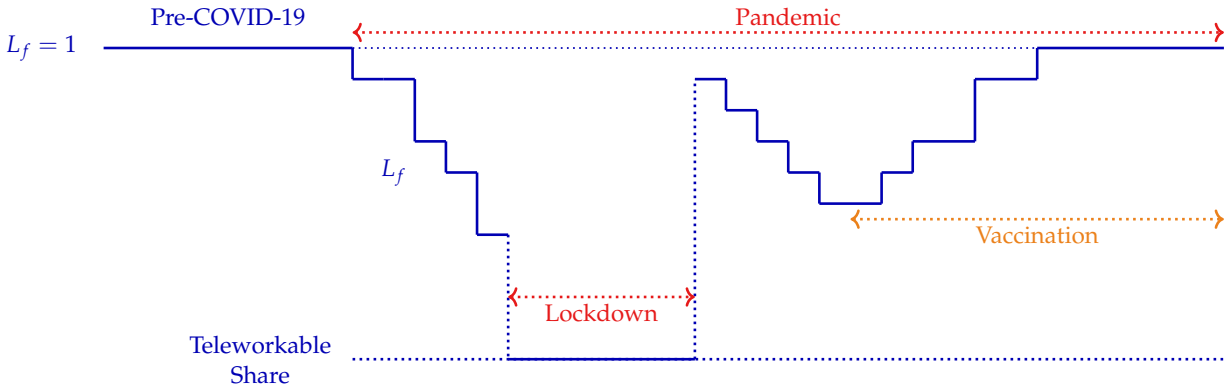
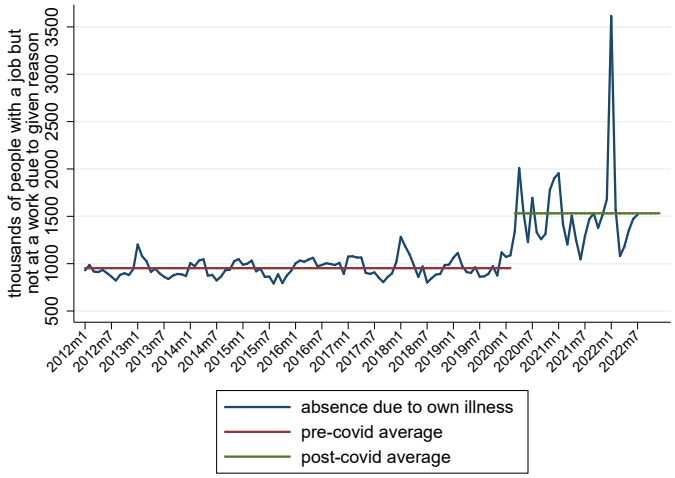


Figure 5: The Effects of Covid-19 on US Labor Supply



(a) not working due to own illness

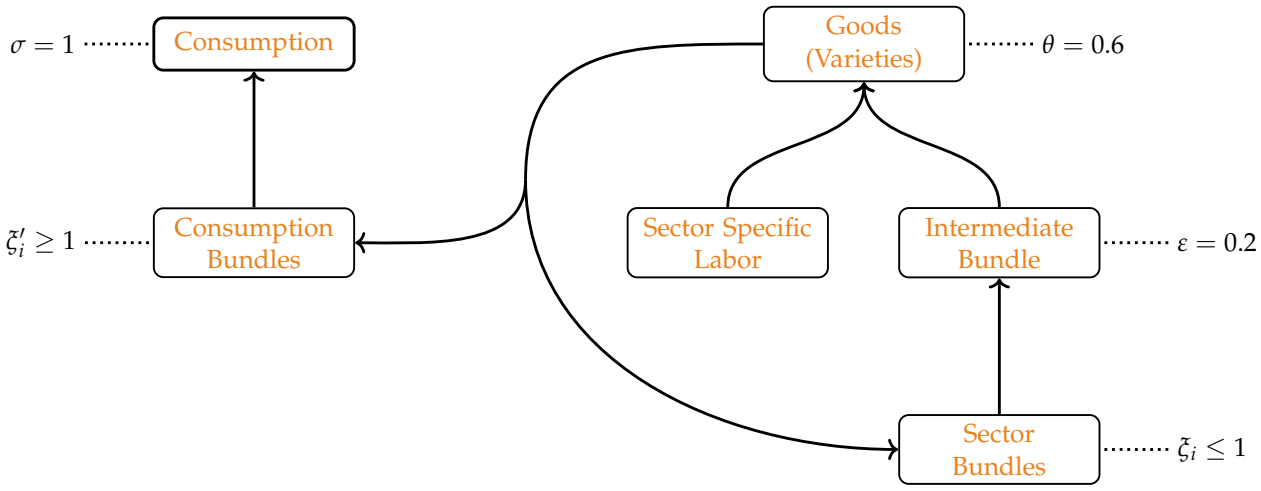
NOTES: Figure 5 plots the number of employed people in US labor market who are absent in a given month. The sample period is from January 2012 to July 2022. The U.S. Bureau of Labor Statistics conducts Current Population Survey which provides a monthly measure that tracks the number of employed people who are absent from work due to own illness, injury or medical problems.

2.4 Model Solution with Sectoral Pandemic Shocks

Figure 6 shows the nested CES structure of our model both on the production side and the consumption side. We solve our model in a similar way to Baqaee and Farhi (2019), where the second order

terms are incorporated in the system via cross-factor and industry elasticities. By applying small perturbations to the system, and following the trajectory of the prices and wages, we can arrive at a new equilibrium where the system re-optimizes around the old one. This methodology is akin to the Euler integration method to calculate the solutions of differential equations. Hence, we can calculate differential exact hat-algebra to characterize the changes in the system by iterative means.

Figure 6: Model Schematic with Nested Constant Elasticity of Substitution (CES)

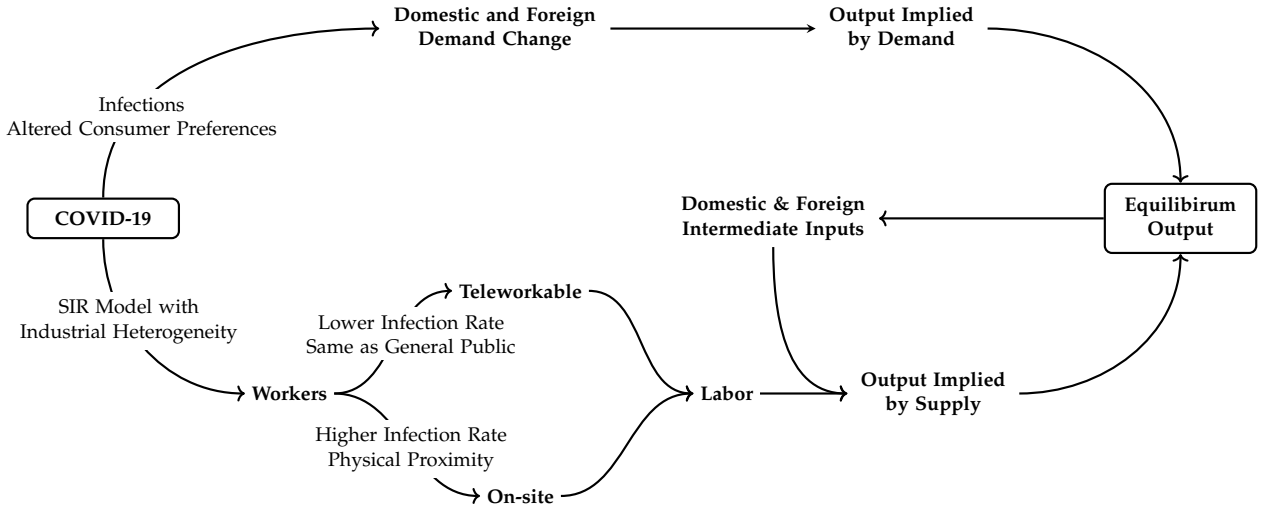


NOTES: This figure presents a schematic of the underlying economic model. The two boxes on the left hand side reflect the demand side and the three boxes on the right hand side show the supply side.

To perform the exact-hat-algebra, we need to trace through the changes in prices and shares after we introduce sectoral shocks related to the pandemic. Most infection dynamics models, including Acemoğlu et al. (2021), Alvarez et al. (2021), Farboodi et al. (2021), and Eichenbaum et al. (2021), do not use the sectoral heterogeneity in disease dynamics.

Figure 7 summarizes how we combine our model with the epidemiological framework. We ponder the figure for a given industry in a country that is exposed to Covid-19 shock. The bottom half of the figure describes the supply side and the upper half depicts the demand side. On the supply side, the transmission dynamics of the virus would differ depending on whether the workers are on-site or at a remote location like home. Among the professions that need to be carried out on the work site, we assume that the viral transmission depends on the physical proximity between the workers or between the workers and the customers. An on-site worker could be exposed to infection either at work or outside work. Intermediate inputs, including the imported ones, directly affect

Figure 7: Modelling the effects of the Covid-19 shock in a multi-country multi-sector open economy



NOTES: The top half of the figure represents the demand channel and the bottom half represents the supply channel. The demand shock stems from altered consumer preferences during the pandemic. Supply shocks can be separated into two parts: labor and intermediate inputs. The labor shock of an industry depends on its teleworkable share and its physical proximity requirements for the workers. The intermediate inputs vary during the pandemic as the output of these industries decline. When endogenous lockdowns are implemented, only the essential industries remain open (see Table B.3 for the list of essential industries) and the workers in the non-essential sectors stay at home.

supply. These imports are function of the pandemic in the other countries. The viral transmission dynamics are also affected from the implementation of different lockdown policies and vaccinations. Similarly, demand changes depending on the infection levels in the population.

2.4.1 The Epidemiological SIR Model

We use the main workhorse framework in many epidemiological studies, namely the Susceptible-Infected-Recovered (SIR) model.[8] Let's take a population of size N. At any given time, we can split the population into three classes of people: Susceptible (S_t), Infected (I_t) and Recovered (R_t) as of time t. Here we provide the model for a single country suppressing the country index for the ease of the demonstration. The susceptible group does not yet have immunity to disease, and the individuals in this group have the possibility of getting infected. The recovered group, on the other hand, consists of individuals who are immune to the disease. Immunity can be developed either because the individual goes through the infection or because she gets vaccinated. The SIR model

[8] See for example Allen (2017) among others.

builds on the simple principle that a fraction of the infected individuals in the population, $\frac{I_{t-1}}{N}$, can transmit the disease to susceptible ones S_{t-1} with an (structural) infection rate of β. Therefore, the number of newly infected individuals in the current period is $\beta S_{t-1}\frac{I_{t-1}}{N}$. The newly infected individuals should be deducted from the pool of susceptible individuals in the current period. Meanwhile, in each period, a fraction γ of the infected people recovers from the disease, which in turn reduces the number of actively infected individuals.[9] To track any changes in the number of individuals in the above-mentioned three groups, the following set of difference equations is used:

$$\Delta S_t = -\beta S_{t-1}\frac{I_{t-1}}{N} \tag{9}$$

$$\Delta R_t = \gamma I_{t-1} \tag{10}$$

$$\Delta I_t = \beta S_{t-1}\frac{I_{t-1}}{N} - \gamma I_{t-1} \tag{11}$$

The law of motion for the number of infected individuals shows the trajectory of the pandemic at the aggregate level. Note that, $\Delta S_t + \Delta R_t + \Delta I_t = 0$ holds at any given time, assuming that the size of the population remains constant.

We modify the canonical SIR model to allow for sectoral heterogeneity in terms of the size and working conditions that can lead to distinct infection trajectories in each sector. The transmission of the virus accelerates with close physical proximity. Hence, employees working in the industries with higher physical proximity are infected with a higher probability. Below, we write everything in terms of a single country and, therefore, drop the country subscripts. We assume that the economy is composed of K sectors. We denote the industries by subscript $i = 1, \ldots, K$. Each industry has L_i workers (since factors are industry specific, we can index them with industry index) and there is also the non-working population which we denote by N_{NW}. Each industry has two types of workers: (i) employees who can perform their jobs remotely (i.e., teleworkable) and (ii) employees who need to be on-site to fulfill their tasks. In each industry, we denote the number of employees in the first group with TW_i and the second group with N_i. Hence:

$$L_i = TW_i + N_i. \tag{12}$$

[9] See also Atkeson (2020), Bendavid and Bhattacharya (2020), Dewatripont et al. (2020), Fauci et al. (2020), Li et al. (2020), Linton et al. (2020), and Vogel (2020) on different mortality estimates.

For the disease propagation, we lump the non-working population and the employees in the teleworkable jobs together, and call them the "at-home" group. We denote the at-home group with index $i = 0$. The total number of individuals in this group is, therefore,:

$$N_0 = N_{NW} + \sum_{i=1}^{K} TW_i. \tag{13}$$

Suppose that the infection rate in the at-home group is β_0. In order to account for heterogeneous physical proximities across industries, we compute the rate of infection for each industry i, denoted by β_i, as:

$$\beta_i = \beta_0 \text{Prox}_i \qquad \text{for} \quad i = 1, \ldots, K \tag{14}$$

where Prox_i is the proximity index for industry i that captures the contact intensive nature of the industry.

Here, $S_{i,t}$, $I_{i,t}$ and $R_{i,t}$ denote the number of susceptible, infected and recovered individuals, respectively, and $N_i = S_{i,t} + I_{i,t} + R_{i,t}$ denotes the total number of on-site individuals in industry i and the at-home group ($i = 0$). Susceptible individuals in the at-home group can get infected from the infected individuals in the entire society:

$$\Delta S_{0,t} = -\beta_0 S_{0,t-1} \frac{I_{t-1}}{N} \tag{15}$$

where $I_t = \sum_{i=1}^{K} I_{i,t} + I_{0,t}$ captures the total number of infected individuals. An on-site worker in sector i, however, could be exposed to infection either at work, at the rate of $\beta_i S_{i,t-1} \frac{I_{i,t-1}}{N_i}$, or outside work, that involves all the remaining activities –including family life, shopping and commuting– at the rate $\beta_0 S_{i,t-1} \frac{I_{t-1}}{N}$. Hence, the number of susceptible individuals among the on-site workers in industry i changes as:

$$\Delta S_{i,t} = -\beta_i S_{i,t-1} \frac{I_{i,t-1}}{N_i} - \beta_0 S_{i,t-1} \frac{I_{t-1}}{N} \tag{16}$$

The recovery rate is the same for all types of infected individuals:

$$\Delta R_{i,t} = \gamma I_{i,t-1} \tag{17}$$

The number of infected individuals changes as the susceptible individuals get infected and some infected individuals recover from the disease:

$$\Delta I_{i,t} = -\left(\Delta R_{i,t} + \Delta S_{i,t}\right) \tag{18}$$

With industrial heterogeneity, we match the employment size weighted average β_i's of the infected individuals to observed overall β in a country. For an on-site worker in industry i, the implied β parameter can be approximated by $(\beta_0 + \beta_i)$. For a non-working individual, this parameter is only β_0. Using equation (14), we impose:

$$\beta_0 \frac{N_0}{N} + \sum_{i=1}^{K} (\beta_0 + \beta_i) \frac{N_i}{N} = \beta_0 + \beta_0 \sum_{i=1}^{K} \text{Prox}_i \frac{N_i}{N} = \beta \tag{19}$$

Hence, we solve for β_0 in terms of β, industry size, and the proximity levels as:

$$\beta_0 = \beta \left(1 + \sum_{i=1}^{K} \frac{\text{Prox}_i N_i}{N}\right)^{-1}. \tag{20}$$

Once the parameters are computed the evolution of infections in the extended multi-sector SIR model can be written as:

$$\Delta \mathcal{I}_t \quad = \quad F \mathcal{I}_{t-1} - \gamma \, \mathbb{I}_{\mathbb{K}} \, \mathcal{I}_{t-1} \tag{21}$$

where $\mathcal{I}_t = (I_{0,t}, I_{1,t}, \ldots, I_{i,t}, \ldots, I_{K,t})'$ and $\mathbb{I}_{\mathbb{K}}$ is the K dimensional identity matrix. F matrix is defined as:

$$F = \begin{bmatrix} \beta_0 \frac{S_{0,t-1}}{N} & \beta_0 \frac{S_{0,t-1}}{N} & \cdots & \cdots & \beta_0 \frac{S_{0,t-1}}{N} & \beta_0 \frac{S_{0,t-1}}{N} \\ \beta_0 \frac{S_{1,t-1}}{N} & \beta_0 \frac{S_{1,t-1}}{N} + \beta_1 \frac{S_{1,t-1}}{N_1} & \beta_0 \frac{S_{1,t-1}}{N} & \cdots & \cdots & \beta_0 \frac{S_{1,t-1}}{N} \\ \beta_0 \frac{S_{2,t-1}}{N} & \beta_0 \frac{S_{2,t-1}}{N} & \beta_0 \frac{S_{1,t-1}}{N} + \beta_1 \frac{S_{1,t-1}}{N_2} & \beta_0 \frac{S_{2,t-1}}{N} & \cdots & \beta_0 \frac{S_{2,t-1}}{N} \\ \vdots & \vdots & & \ddots & & \vdots \\ \vdots & \vdots & & & \ddots & \vdots \\ \beta_0 \frac{S_{K,t-1}}{N} & \beta_0 \frac{S_{K,t-1}}{N} & \cdots & \cdots & & \beta_0 \frac{S_{K,t-1}}{N} + \beta_K \frac{S_{K,t-1}}{N_K} \end{bmatrix}$$

Using these system matrices, R_0 can be computed using the largest eigenvalue of the matrix

$F^{-1}\nu$. Given the initial size of the groups based on employment numbers, the eigenvalue would approximately correspond to the normalization present in equation (20).

2.4.2 Sectoral Infections and Production

Sectoral heterogeneity in terms of the share of teleworkable workers as well as physical proximity requirements results in differential labor supply shocks across sectors during the pandemic. The total number of available workers for a given country-sector ic changes to L'_{ic} as a function of the infections as:

$$L'_{ic} = (N_{ic} - I_{ic}) + TW_{ic}\left(1 - \frac{I_{0c}}{N_{0c}}\right) \tag{22}$$

where N_{ic} is the number of on-site workers in industry i in country c, I_{ic} is the number of infected workers among on-site workers, and TW_{ic} is the number of at-home workers (i.e., those who can work remotely) in industry i. The ratio I_{0c}/N_{0c} captures the fraction of individuals who are infected in the at-home group, which includes the non-working population as well as all at-home workers (i.e., teleworkers) in the economy.

If there are no shocks to intermediate inputs, changes in the local labor supply will be the only factors that lower aggregate supply during to the pandemic. This could be the case if the industries have sufficient inventories for their intermediate inputs. Once we incorporate intermediate products, however, labor supply shocks in an industry affect all domestic and international sectors that use this industry's output as their inputs.

Sector specific shock to sector specific labor (factory workers vs accountants):

$$y_{ic} = \frac{A_{ic}}{\bar{A}_{ic}}\left[\alpha_{ic}\left(\frac{\Delta_{ic}(I_{c,t})L_{ic}}{\bar{L}_{ic}}\right)^{\frac{1-\phi}{\phi}} + (1-\alpha_{ic})\left(\frac{M_{ic}}{\bar{M}_{ic}}\right)^{\frac{1-\phi}{\phi}}\right]^{\frac{\phi}{1-\phi}}. \tag{23}$$

The shocks propagate through input-output linkages. The initial shock that an industry experiences is the labor supply shock. Later on, this labor shock translates into an intermediate input shock for a downstream industry.

2.4.3 Sectoral Infections and Consumption

Papers such as Farboodi et al. (2021), Eichenbaum et al. (2021), Krueger et al. (2020), and Eichenbaum et al. (2021) model the endogenous response of consumption to the pandemic. The empirical evidence shows the importance of both supply and demand shocks at the sectoral level, where the size of the demand shock is more pronounced. Using granular data for the US, Chetty et al. (2020) document a decline of 39% in consumer spending in the top-quartile of income distribution and 13% in the bottom quartile during the first month of the pandemic. The decline is heterogeneous across sectors with more significant drops in industries that require in-person contacts. The authors emphasize that the fear of contacting the disease is the main source of the decline in spending at the initial stages of the pandemic. Similarly, using cell phone data to track movements of individuals, Goolsbee and Syverson (2021) show that even though the consumer traffic fell by 60%, only 7% could be explained by the shutdown restrictions. The authors suggest that the changes in consumer behavior are most likely driven by the fear of infection.

In our setting, we modify the pricing of the sectoral consumption bundle described in (7) to allow for a sectır specific demand shifter, denoted as δ_j^{0c}. The demand shifter evolves over time depending on the trajectory of the pandemic as a function of the country specific active infected cases, that is, $\delta_j^{0c} = \delta_j^{0c}(I_{c,t})$. The resulting sector specific equation takes the following form

$$p_{0c} = \left[\sum_{j \in \mathcal{N}} \left(\delta_j^{0c}(I_{c,t}) \right)^{\sigma} \Omega s_j^{0c} \left(p_j^{0c} \right)^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \tag{24}$$

2.4.4 Solution

Given the sectoral pandemic shocks to the supply term ($\Delta_{fc}(I_{c,t})$ in Equation (23)) and demand term ($\delta_j^{0c}(I_{c,t})$ in Equation (24)) we can write the changes in wages for any factor using the following proposition:

Proposition 1 *Given the supply shock* $d \log L_f$*, which is a small step towards the overall supply shock* $\Delta_f(I_{c_f,t})$*, where* c_f *denotes the country that factor* f *belongs to, and the demand shock* ω_j^{0c}*, which is also a small step toward the overall demand shock* $\delta_j^{0c}(I_{c,t})$*, the changes in the wages can be calculated as:*

$$
\begin{aligned}
d\log w_f = & \sum_{jm\in\mathcal{N}}\sum_{c\in\mathcal{C}} \chi_c \Omega^{0c}_{jm}\sigma d\log \omega_j^{0c}\Psi_f^{jm}/\lambda_f \\
\textit{Line 2:} \quad & + \sum_{jm\in\mathcal{N}}\sum_{c\in\mathcal{C}}\sum_{g\in\mathcal{F}_c} \lambda_g[d\log w_g + d\log L_g]\Omega^{0c}_{jm}\Psi_f^{jm}/\lambda_f \\
\textit{Line 3:} \quad & + \sum_{jm\in\mathcal{N}}\sum_{g\in\mathcal{F}}\sum_{c\in\mathcal{C}} \chi_c \Omega^{0c}_{jm}(1-\xi'_j)\Psi_g^{jm} d\log w_g \Psi_f^{jm}/\lambda_f \\
\textit{Line 4:} \quad & + \sum_{jm\in\mathcal{N}}\sum_{c\in\mathcal{C}}\sum_{v\in\mathcal{C}}\sum_{g\in\mathcal{F}} \chi_c b^c_{jm}\left(\frac{\xi'_j-\sigma}{\Omega s_j^{0c}}\right)\Omega^{0c}_{jv}\Psi_g^{jv} d\log w_g \Psi_f^{jm}/\lambda_f \\
\textit{Line 5:} \quad & + \sum_{jm\in\mathcal{N}}\sum_{c\in\mathcal{C}}\sum_{iv\in\mathcal{N}}\sum_{g\in\mathcal{F}} \chi_c \Omega^{0c}_{jm}(\sigma-1)\Omega^{0c}_{iv}\Psi_g^{iv} d\log w_g \Psi_f^{jm}/\lambda_f \\
\textit{Line 6:} \quad & + \sum_{jm\in\mathcal{N}}\sum_{kc\in\mathcal{N}}\sum_{g\in\mathcal{F}} \lambda_{kc}\Omega^{kc}_{jm}(1-\xi_j)\Psi_g^{jm} d\log w_g \Psi_f^{jm}/\lambda_f \\
\textit{Line 7:} \quad & + \sum_{jm\in\mathcal{N}}\sum_{v\in\mathcal{C}}\sum_{kc\in\mathcal{N}}\sum_{g\in\mathcal{F}} \lambda_{kc}\Omega^{kc}_{jm}\left(\frac{\xi_j-\varepsilon}{\Omega s_j^{kc}}\right)\Omega^{kc}_{jv}\Psi_g^{jv} d\log w_g \Psi_f^{jm}/\lambda_f \\
\textit{Line 8:} \quad & + \sum_{jm\in\mathcal{N}}\sum_{kc\in\mathcal{N}}\sum_{iv\in\mathcal{N}}\sum_{g\in\mathcal{F}} \lambda_{kc}\Omega^{kc}_{jm}\left(\frac{\varepsilon-\phi}{1-\alpha_{kc}}\right)\Omega^{kc}_{iv}\Psi_g^{iv} d\log w_g \Psi_f^{jm}/\lambda_f \\
\textit{Line 9:} \quad & + \sum_{jm\in\mathcal{N}}\sum_{kc\in\mathcal{N}}\sum_{g\in\mathcal{F}} \lambda_{kc}\Omega^{kc}_{jm}(\phi-1)\Psi_g^{kc} d\log w_g \Psi_f^{jm}/\lambda_f \\
\textit{Line 10:} \quad & + (1-\phi)d\log w_f + (\phi-1)\sum_{g\in\mathcal{F}}\Psi_g^{i_f} d\log w_g - d\log L_f
\end{aligned} \tag{25}
$$

where

- $\lambda_f \equiv \frac{w_f L_f}{E}$ *is the income share (i.e., Domar weight) of factor* f *in the world income,* E*;*
- $\Psi \equiv [I-\Omega]^{-1}$ *is the Leontief Inverse matrix and* I *is the identity matrix;*
- $\chi_c \equiv \sum_{f\in\mathcal{F}_c}\lambda_f$ *is the income share of country* c*.*

The proof of this proposition is provided in the online Appendix and requires careful differentiation at each step, combined with the Shepard's Lemma. The intuition behind each line is as follows:

Line 1: This line comes from the direct effect of the sectoral demand shock on prices, which is further translated into a factor price change via Leontief inverse.

Line 2: This line captures the consequences of changes in income shares of countries on the wages of other countries from the demand side.

Line 3: This line captures the substitution between two factors that are used in same industry in consumption. Since our factors are sector-specific, only the term with $g = f = f_{jm}$ would survive for every $jm \in \mathcal{N}$ where f_{jm} is the factor used in industry jm.

Line 4: This line captures the substitution between two varieties coming from different countries in same industry in the consumption bundles.

Line 5: This line captures the overall substitution between any two industries in the consumption.

Line 6: This line captures the substitution between two factors that are used in same industry in production. Since our factors are sector-specific, only the term with $g = f = f_{jm}$ would survive for every $jm \in \mathcal{N}$ where f_{jm} is the factor used in industry jm.

Line 7: This line captures the substitution between two varieties coming from different countries in the same industry in industry bundles in production.

Line 8: This line captures the substitution between two industries in intermediate bundles.

Line 9: This line captures the substitution between two industries in overall production.

Line 10: First term in this line captures the direct effect of wage changes. The second term comes from the substitution between two factors in production. The last term captures the effect of labor loss on the wages.

Given the supply and demand shocks, unknowns in this equation are $d \log w_f$ terms. These 10 lines can be combined to form:

$$d \log w = A \, d \log w + B.$$

However, all the equations are not independent of each other. To solve the system, we impose the fact that the overall world expenditure levels do not change, i.e., $d \log E = 0$. This specification can be written as:

$$\sum_f \lambda_f (d \log w_f + d \log L_f) = 0.$$

Hence, we can solve for $d \log w_f$ using this linear system. From the changes in log-wages, we can calculate all other log-changes in prices, Ω matrix, Leontief-inverse matrix and real GDP.

3 Data and Parameters

3.1 Data

We use OECD ICIO Tables as of 2018 for 65 countries and 35 sectors.[10] These tables report expenditure shares of each sector to/from other sectors across countries. Hence they capture global input-output links or sectoral exports/imports. We obtain sectoral employment data from OECD's Trade in employment (TiM) database Horvàt et al. (2020).[11]

To calculate the industry level teleworkable share and the physical proximity measures, we use the occupational composition of the industries. We use the list provided by Dingel and Neiman (2020) for the occupations which can fulfill their tasks remotely. Dingel and Neiman (2020) use several measures from O*NET to identify which occupations are teleworkable. For the workers that continue to perform their jobs on-site, we assume that the infection rate depends on the physical proximity that is required in their workplace. To calculate the proximity requirements for the occupations, we use the self-reported Physical Proximity values available in the Work Context section of the O*NET database. O*NET collects the physical proximity information through surveys with following categories: (1) I don't work near other people (beyond 100 ft.); (2) I work with others but not closely (e.g., private office); (3) Slightly close (e.g., shared office); (4) Moderately close (at arm's length); (5) Very close (near touching). We divide the category values by 3 to make category (3) our benchmark. Specifically, a proximity value larger than 1 indicates a closer proximity than the 'shared office' level and a value smaller than 1 corresponds to less-dense working conditions. We create a single physical proximity value for each occupation by computing a weighted average of the normalized category values. We calculate the proximity values at the industry level after removing the

[10] As the industrial classification, OECD uses an aggregation of 2-digit ISIC Rev 4 codes to 36 sectors. The last sector, "Private households with employed persons," does not have any linkages with other industries. We drop that sector from our analysis when we measure international inter-industry linkages. This leaves us with 35 sectors. Throughout our analysis, we will make use of this classification labeled as OECD ISIC Codes.

[11] For 14 countries that have missing data in TiM, we obtained the total employment data from the World Development Indicators database of the World Bank. We then gathered the value added per employer data from the closest geographical aggregation and used this information to distribute the employment to industries for these 14 countries.

teleworkable portion from the employees. We create a single proximity value for each occupation by weighting the normalized score with the percentage of the answers in each category.

To obtain industry-level teleworkable share and proximity values, we calculate the weighted average of the values corresponding to the occupations in each industry using the Occupational Employment Statistics (OES) provided by the U.S. Bureau of Labor Statistics (BLS). OES data follows four-digit NAICS codes to classify industries. In order to convert proximity data to OECD ISIC codes, we make use of the correspondence table between 2017 NAICS and ISIC Revision 4 Industry Codes, provided by the U.S. Census Bureau. We provide the teleworkable share and the proximity index for the industries in Table B.2 of the Appendix.

3.2 Consumption, Production and Trade Elasticities

As depicted in Figure 6 we use same elasticities as in Baqaee and Farhi (2019) and di Giovanni et al. (2022). Producing "Good (Varieties)" requires combining labor and intermediate goods, which are complements. We set this elasticity to $\theta = 0.6$. The "intermediate bundle" captures the aggregation of alternative inputs such as steel and textiles, which are also complementary to each other. This elasticity is set to be $\varepsilon = 0.2$. This value is consistent with the estimates in the literature (Atalay, 2017; Boehm et al., 2019, 2020) who find strong complementarities at this stage. The "sector bundle" captures substitution of input varieties from different countries, such as Turkish steel, Chinese steel and the US steel from the perspective of the US. We experiment with the substitution rates between country varieties while forming the sector bundles. At one extreme, we use industry-specific trade elasticities measured by Caliendo and Parro (2015), in which all varieties are substitutes. At the other extreme, we take the elasticities to be complements. By doing so, we aim to capture both the short-term (when it is hard to substitute between varieties) and long-term dynamics. Note that our specification is different than a single layered production function combining all inputs and varieties simultaneously (e.g., not only cotton and steel are substitutes, but also cotton from different countries are also substitutes). Instead we use nested CES functions to separate between consumption of Turkish vs German cars by US consumers ("consumption bundle" in Figure 6), and steel inputs from China vs Germany for US construction sector ("sector bundle" in Figure 6).

3.3 Sectoral Demand Shocks

In order to account for the changes in total demand of each sector, we need to consider not only domestic but also foreign sectoral demand. We utilize OECD Inter-Country Input-Output (ICIO) Tables, which provides us with input demand of industry i in country c from any industry in any country. The final demand vector has 2340 entries indexed by (c, i), corresponding to each country-industry combination. By dividing the rows of ICIO matrix with the total output of industry (c, i), we obtain the direct requirements matrix Ω. This matrix summarizes the usage of each intermediate input to generate \$1 worth of output. Output of each industry is either used as an intermediate input or consumed as final demand.

To calibrate the sector specific demand shifter, $\delta_j^{0c}(I_{c,t})$, in (24) that evolves according to the trajectory of the pandemic, we use publicly available monthly sectoral personal consumption data for US from the Bureau of Economic Analysis (BEA) starting from March until the end of 2020. The availability of sectoral personal consumption data sets are limited for countries other than the US. Therefore, we first compute the parameters obtained using the projection of the US sectoral personal consumption on the US number of infections from a second order polynomial. Using these sector specific parameters, we extrapolate these projections to other countries-sectors to generate infections related demand shock across sectors and countries. For curbing sizable estimation errors that might result due to parameter estimation uncertainty in our computations, we restrict the sectoral shocks not to exceed the observed range of changes in the data.[12]

3.4 SIR Parameters

Each of the 65 countries in our sample have a distinct experience regarding the course of the pandemic. In the SIR model, the two fundamental structural parameters, the resolution, and the infection rates, define the pandemic's trajectory. The resolution rate is a disease-specific structural parameter that does not vary much across the countries. According to the report by the WHO [13], the median recovery time for the mild cases is approximately two weeks. The mean recovery time

[12] Our robustness checks and comparisons using credit card spending data for selected countries reveal similar demand patterns for these countries.

[13] https://www.who.int/docs/default-source/coronaviruse/who-china-joint-mission-on-covid-19-final-report.pdf

could be longer when we include severe cases. In this paper, we err on the optimistic side and set $\gamma = 1/14 \approx 0.07$ to establish a mean recovery time of 14 days. However, the infection rate might vary across countries depending on each country's success in containing it. Furthermore, since the onset of the pandemic, the infection rate exhibits a varying pattern over time. This time variation arises because of the various lockdown measures adopted by the countries to reduce the transmission rate of the virus.

For the calibration of β, we make use of publicly available data sets to trace this variation across countries and across time.[14] For each country, we estimate a SIR model described in equations (9)-(11) using official data to reproduce the variation in the trajectory of the pandemic across countries. In order to capture the variation within each country over time, we extend the SIR model to allow for time variation in the infection rate, i.e., β_t. Specifically, we employ the methodology proposed in Çakmaklı and Şimşek (2020) to capture the changes in the rate of infection throughout the pandemic for the countries in our sample. This methodology involves estimating a SIR model with time-varying parameters in a statistically coherent way to accommodate various non-pharmaceutical interventions, including lockdowns.

There are abundant studies that estimate the SIR model using fixed parameters (See, for example, Wu et al. (2020); Hortaçsu et al. (2021); Zhang et al. (2020)). In contrast, models that allow for time variation in parameters are scarce. Kucharski et al. (2020) uses a variant of the SIR model framework allowing the infection rate to follow a geometric random walk. Similarly, Yang et al. (2020), and Fernández-Villaverde and Jones (2022) allow for time variation in the rate of infection. The advantages of the time-varying parameters SIR model of Çakmaklı and Şimşek (2020) are twofold. First, the framework is statistically consistent with the typical count data structure related to the pandemic. This contrasts with the models that either employ least-squares or likelihood-based inference using Normal distribution. Second, it is computationally easier, unlike the models that are statistically consistent but computationally costly, such as the particle filter. Because we exploit a wide number of countries with typically daily data, this computational efficiency is critical in our estimation process. For each country, the data spans the period from the day the number of active infections exceeds 1000 until the end of December 2020. Consequently, we use the parameter val-

[14]The data is obtained from GitHub, Covid-19 Data Repository by the Center for Systems Science and Engineering (CSSE), at Johns Hopkins University.

ues, country-specific β_t, and γ estimated as of the end of December 2020 to simulate the pandemic's evolution over the next year in each country. Except for Australia, New Zealand, and China, which have been relatively successful in suppressing the infections, we imposed an R_0 between 1.1 and 1.3 for all countries. These values are reported in Table B.4 of the Appendix.

In our simulations, we allow for endogenous lockdown when the number of critical cases exceed the ICU capacities of the countries. The data for ICU is capacities are obtained from various sources including the WHO, the JHU data repository and the health ministries of the countries depending on the availability. In the case of full lockdowns, the infection rate becomes zero during the lockdown reflecting the containment of the virus. Each lockdown is imposed for 14 days. This implies that during this time, the number of Covid-19 patients decline to 36% of the number before the lockdown was imposed. Once the lockdown is removed, we assume that it takes 90 days for the infections to reach the reproduction number prior to the lockdown. Under full lockdown, only a few industries are active. We construct the list of industries that are closed during lockdowns based on international examples of government decrees. The list of these sectors is given in Table B.3 of the Appendix. From these industries and using the employment data at 4 digits, we calculated the share of each OECD ISIC industry that would remain active during the lockdown. Finally, we calculated the share of public employees that are not affected by the lockdown using the publicly available information.

3.5 Reduced Form Evidence on Infections and Sectoral Shocks

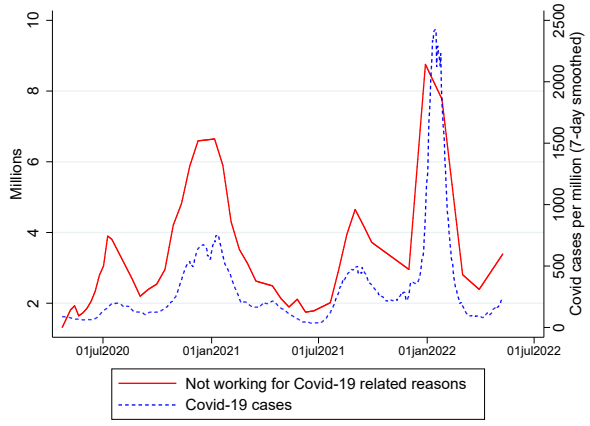
Before we go over our model calibration results, we present reduced form evidence on the relation between infections dynamics and sectoral demand and supply shocks.

On the labor supply side, Figure 8 shows the number of people who reported that they cannot work due to "pandemic-related reasons" in red in both panels. As we document in Appendix, most important of these reasons are being sick or taking care of someone who is sick/has long Covid. The left panel plots this data together with the actual number of infections (the blue line). The high correlation of 0.84 indicates that the progression of the pandemic directly affects the labor supply. As we show in Figure A.1 in Section A.1 the share of US households who reported "pandemic-related" reasons for not working is 47 percent. The blue line on the right panel shows the labor supply shocks

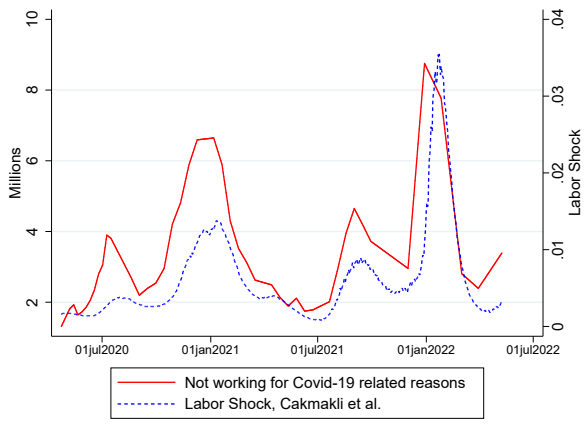
for the US derived from our sectoral epidemiological model, where the correlation of these supply shocks with the reported reason of not working being pandemic is 0.84.

Figure 8: Effects of COVID-19 on the US Labor Market

(a) Covid-19 Cases and Related Time Off, Correlation 0.84



(b) Covid-19 Cases and Labor Supply Shock, Correlation 0.82



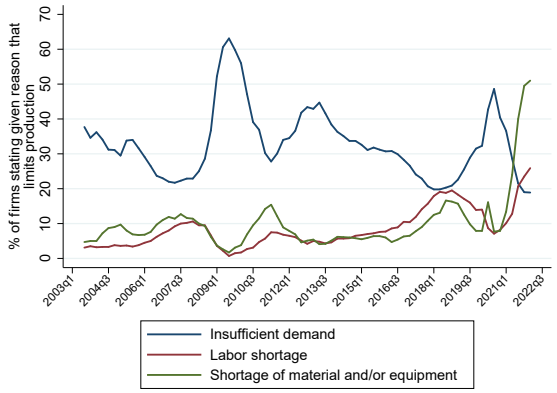
NOTES: The U.S. Census Bureau Household Pulse Survey asks the respondents the reason for not working at a weekly or bi-weekly frequency over the period 23 April, 2020 and May 9, 2022. See Section A.1 for the details on the construction of these series.

The EU Commission's Business and Consumer Survey provides time series data from business managers on the factors limiting production.[15] Panels (a)–(c) of Figure 9 plot these factors as a weighted average of all EU countries for manufacturing, construction, and services sectors respectively. Historically, , especailly during 2008–2009 crisis, we observe that insufficient demand (blue line) is the mist important factor limiting production and when demand goes down there is no issue of labor and/or material shortage. This is consistent with when demand goes down, all sectors become demand constrained with a limited role for supply chain bottlenecks. What is unique about the Covid-19 shock is that shortage of material and equipment (the green line) and labor (red line) both became the key reasons for limiting production in all sectors, including services for labor.

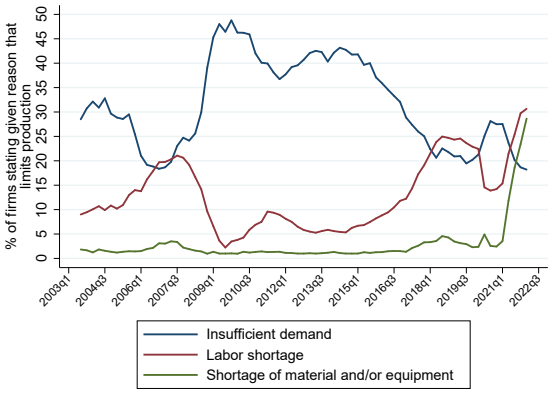
Figure 10 plots the period after 2019Q4 to zoom-in on the asymmetric dynamics across sectors.

[15] See https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/business-and-consumer-surveys_en for more information about business and consumer surveys.

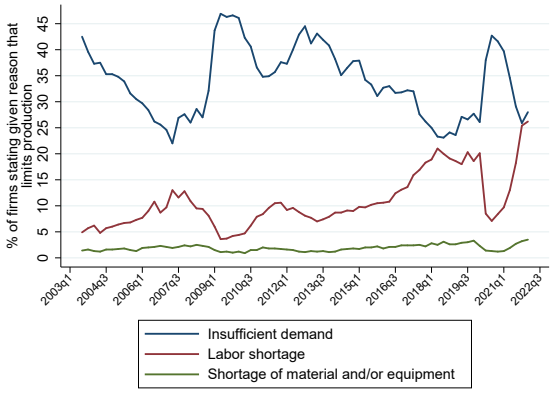
Figure 9: Factors Limiting Production in Europe (2003Q3-2022Q1)



(a) Manufacturing



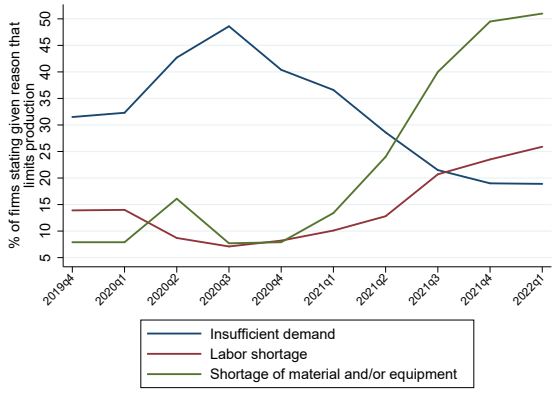
(b) Construction



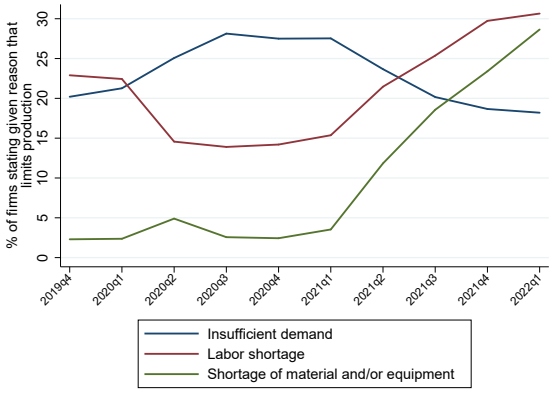
(c) Services

NOTES: Figure 9 plots the replies of business managers to the question "What main factors are currently limiting your production?" as a weighted average using country shares in EU's total gross-value added. These series are smoothed by calculating a two-year moving average and are seasonally adjusted.

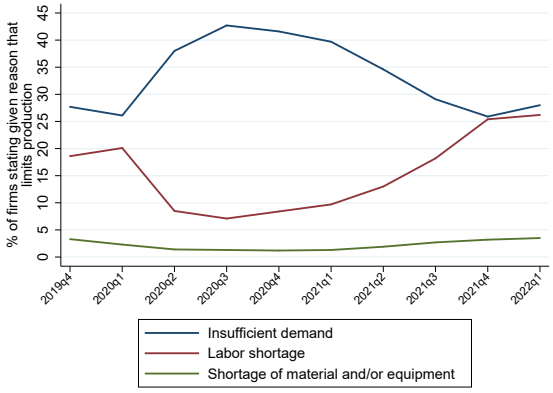
Figure 10: Factors Limiting Production during the Pandemic in Europe (2019Q4-2022Q1)



(a) Manufacturing



(b) Construction



(c) Services

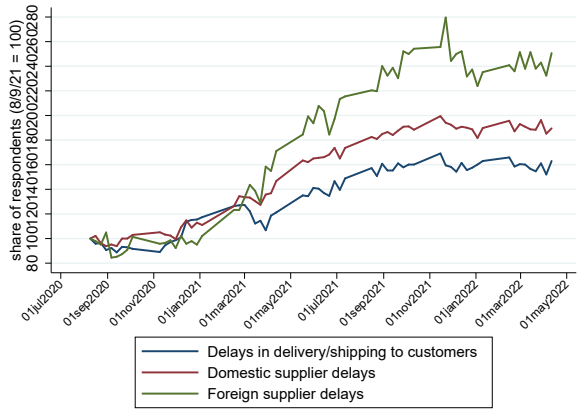
Clearly, demand recovery due to vaccines and economic stimulus made the shortages worse, both material and labor throughout 2021. This is consistent with the framework depicted in Guerrieri et al. (2022) who note that the asymmetric nature of the pandemic and associated spillovers among sectors. Trade-able sector of manufacturing registered higher shortages of inputs given the supply chain bottlenecks and recovery in demand intersecting with the fact that most of those inputs are imported, whereas non-tradeable sectors such as construction and services is going to suffer from labor shortages more. Given the complementary between intermediate inputs and labor in our framework, our estimates can capture this notion of switching from a mostly demand constrained to a mostly supply constrained world under Covid-19 shock.

An analogous survey for the US illustrates the factors limiting production in the US as shown in Figure 11. This figure makes the importance of global supply chain bottlenecks for the production in the US clear even for the non-tradeable sectors of construction and services in panels (b) and (c) with the most important delays coming from foreign suppliers.

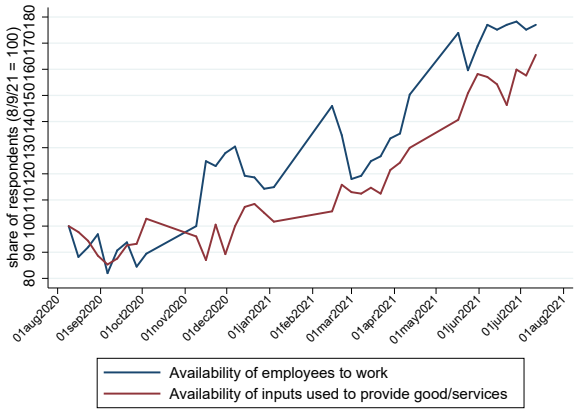
Figure 11: Factors Limiting Production during the Pandemic in US (August 2020-May 2022)

Panel A: Manufacturing

(a1) Supplier Delays

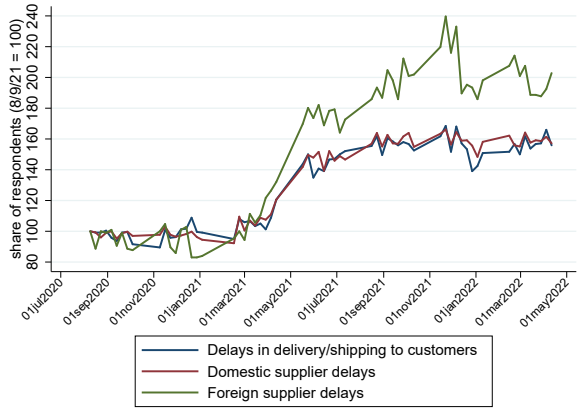


(a2) Material and Labor Shortage

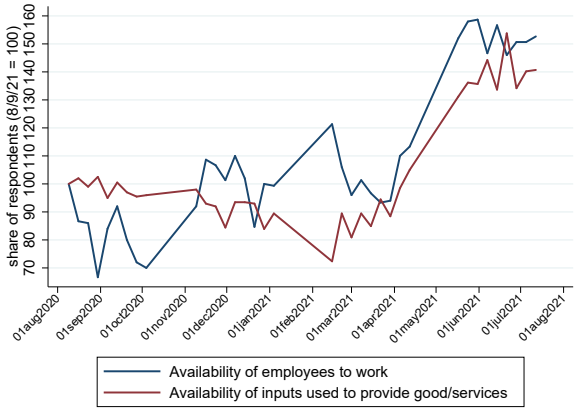


Panel B: Construction

(b1) Supplier Delays

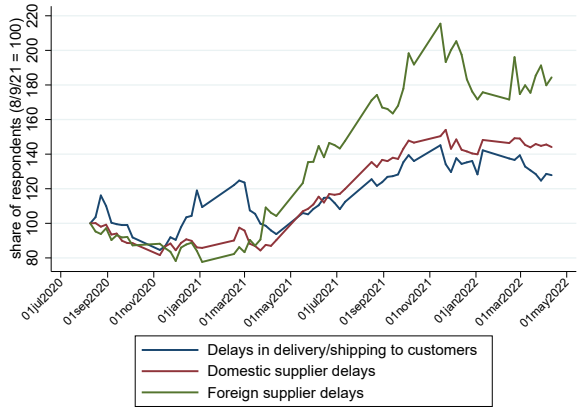


(b2) Material and Labor Shortage

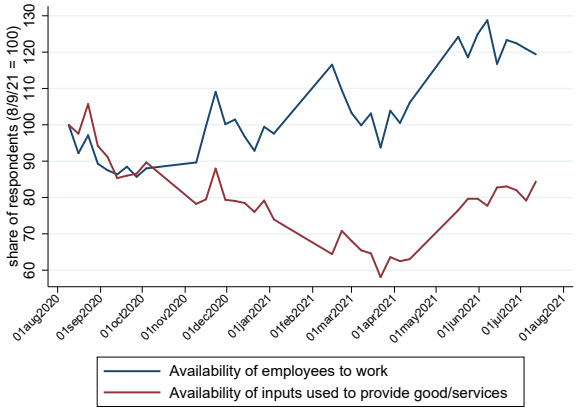


Panel C: Services

(c1) Supplier Delays



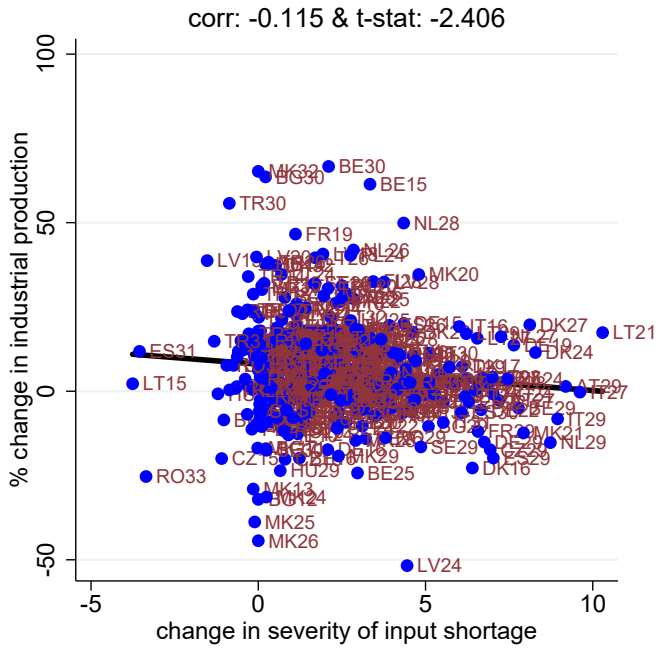
(c2) Material and Labor Shortage



NOTES: Figure 11 plots the replies of small business managers in the US Pulse Survey to the question "In the last week, was this business affected by any of the following?" This figure provides a cross-sectoral comparison of the factors that limit US production during the Covid-19 era.

Using full sector-country heterogenetiy, the figure below plots the strong negative correlation between the severity in input shortage and the decline in industrial production.

Figure 12: The Relationship between Severity of Shortage of Inputs and Industrial Production



NOTES: Figure 12 plots the change in severity of input shortage against the percentage change in industrial production from december 2020 to december 2021. We label each country-sector pair as the first two letters corresponding to ISO country code and the latter corresponding to Eurostat NACE Revision 2 two digit industry codes.

4 Model Calibration Results

In this section, we report the real GDP losses arising from cross country heterogeneity in vaccine availability under different vaccine scenarios.

Table 1 summarizes the two scenarios that we examine. The scenarios differ in terms of speed of vaccination in both AEs and EMDEs, with scenario two being closer to the real life vaccine roll-out. Notice that, different speeds in vaccination translate into having heterogeneity in sectoral demand and supply shocks in different countries within the second period that we divide into 365 days to mimic the heterogeneity during 2021. We calculate real GDP losses based on the model at the sectoral level and aggregate to country level for presenting the results in a succint way to highlight

the effect of sectoral heterogeneity in shocks on country level economic costs.

Table 1: Vaccination Scenarios

Scenario	AEs	EMDEs
I	Immediate Vaccination	No Vaccination
II	Fast Vaccination	Slow Vaccination

4.1 Scenario I: Immediate Vaccination in AEs

In this scenario, we assume that the pandemic is fully contained in AEs thanks to countrywide vaccinations. Thus there are no sectoral demand and supply shocks in AEs. In EMDEs the pandemic evolves without access to any vaccine. It can only be contained by means of endogenous lockdowns. In this scenario, the countries impose lockdowns when the number of Covid-19 patients that require intensive case units (ICUs) exceed the number of ICUs that are reserved for Covid-19 patients. Lockdowns generate a substantial labor shock because only workers in the essential sectors are allowed to be on-site. Each lockdown is imposed for 14 days. During this time, the number of Covid-19 patients decline to 36% of the value before the lockdown was imposed. Once the lockdown is removed, we assume that it takes 90 days for the infection to reach the reproduction number prior to the lockdown. This is clearly an extreme scenario. We calibrate this scenario to have an upper bound estimate on the real GDP losses for AEs due to their international linkages with EMDEs.

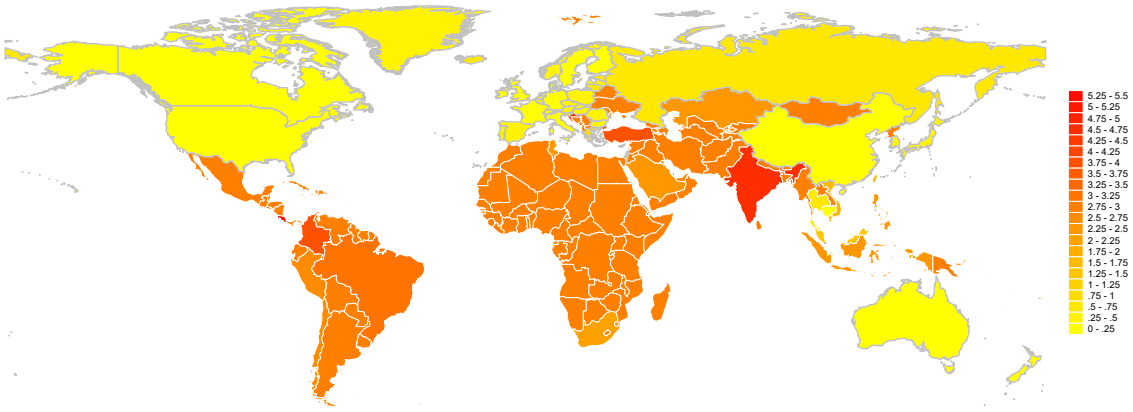
Figure 13 displays visually the relative reductions in countries' annual real GDPs for 2021 under this scenario in percentage terms, where we report the country-specific estimates for AEs in Table B.5. These estimates are relative to the counterfactual of global vaccinations that are immediate for all countries.

Here, we report two sets of estimates with a low and high trade elasticity for the countries to emphasize the resulting change in the economic cost of the pandemic when the international production networks do not properly operate (low trade elasticity) on the one hand or they operate well on the other hand (high trade elasticity) in response to pandemic induced demand and supply shocks.

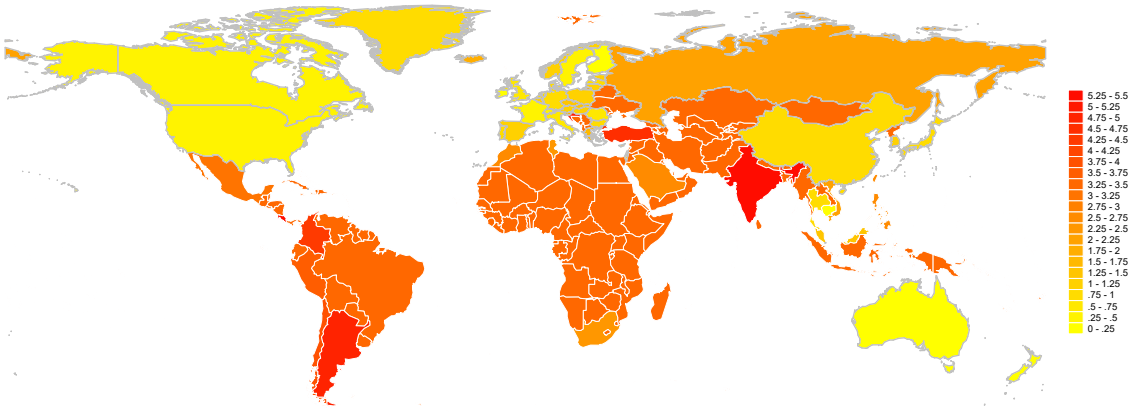
The results are presented for two alternative trade elasticities. As we move from a high trade elasticity (panel (a)) to a relatively low trade elasticity (panel (b)), we observe that the costs of the pandemic increase, reflected by darker shades. This is consistent with the intuition that lower trade elasticity reflects less flexibility in production and more exposure to supply chain disruptions. Hence, even if AEs contain the pandemic at home, they still suffer larger losses to the extent that they are exposed to supply chain disruptions through their trade partners.

Figure 13: Relative Decline in GDPs under Scenario I (%)

(a) $\xi_i = 0.9$



(b) $\xi_i = 0.6$



NOTES: This figure shows the reductions in relative GDP under Scenario 1 for two alternative trade elasticities in Panels (a)–(b), respectively. In Scenario 1, AEs follow a vaccination schedule whereas in EMDEs pandemic evolves without a vaccination campaign. In this scenario, both AEs and EMDEs impose potentially multiple lockdowns when the number of Covid-19 patients that require ICUs exceed the number of ICUs that are reserved for Covid-19 patients. Darker shades correspond to higher relative losses. Vaccinated countries are highlighted with light gray borders.

4.2 Scenario II: Gradual Vaccination in EMDEs

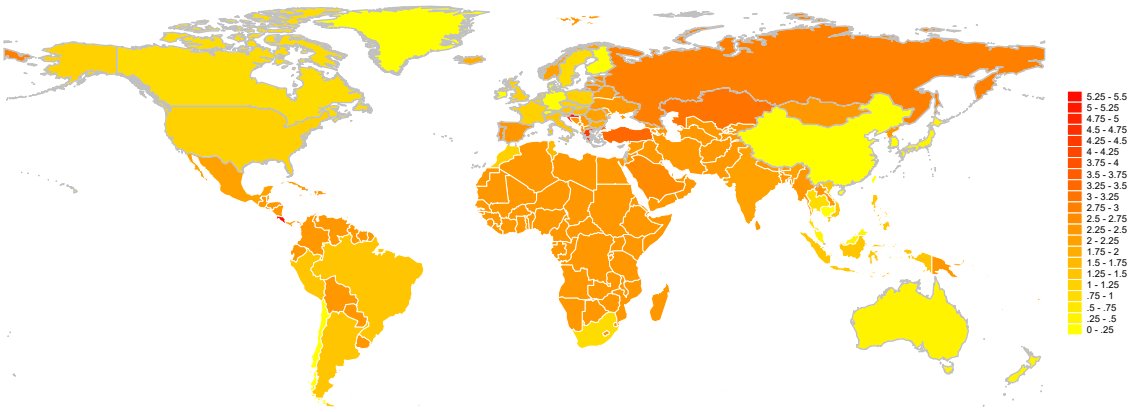
This scenario aims to replicate the actual vaccination roll out in real life more closely. In this scenario, AEs are not fully vaccinated immediately. In addition, EMDEs also have access to the vaccine although at a slower rate. AEs start vaccination quite early with the half of the susceptible population getting vaccinated in the first 30 days and the remaining half getting vaccinated in the following 90 days. Therefore, we assume that the vaccination of all susceptible population will be accomplished within 120 days in AEs. In contrast, EMDEs are not able to inoculate their susceptible populations fully, but they can only vaccinate half of it. The vaccination program starts at the same time as the AEs, but it takes a full year to vaccinate half of the susceptible population. Furthermore, the lockdown conditions elaborated in scenario 1 apply in scenario 2 as well.

Figure 14 displays the relative reduction in countries' real GDPs under this scenario in percentage terms, with estimates being reported in Table B.5. Compared to scenario 1, AEs face two offsetting effects. On the one hand, their vaccination calendar is now slower, which increases their domestic losses. On the other hand, their EMDE trade partners now have access to the vaccine, which reduces their losses that are coming from international linkages. As we compare the AES from Figure 13 to Figure 14, we observe that AEs are generally darker, indicating that the slower the pace of the domestic vaccinations at home outweigh the trade partners' access to the vaccine, yielding a net negative impact for AEs as we move from scenario 1 to scenario 2.

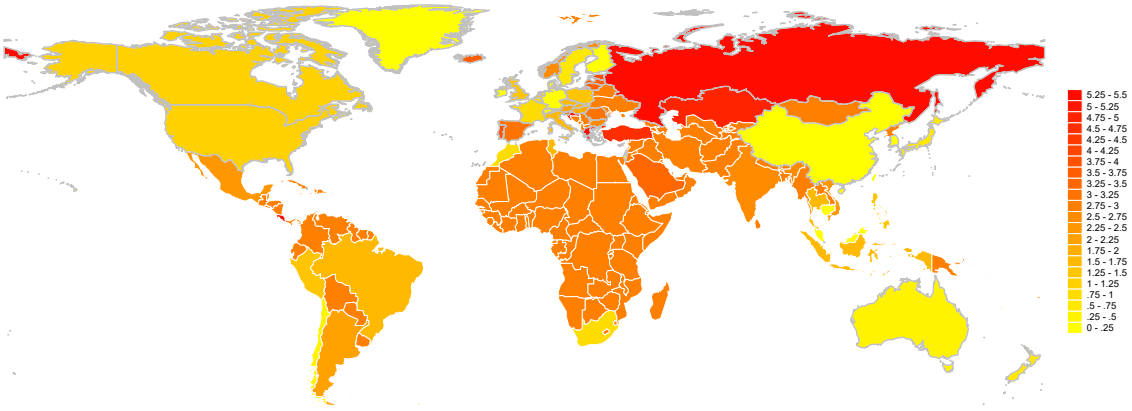
Turning to the EMDES, the sharp reduction in the costs borne by EMDEs is immediately noticeable . This is because EMDEs also have access to the vaccine in this scenario, albeit at a slower pace. The two exceptions are Turkey and Russia. Both of these countries are major exporters to AEs. Hence, when the AEs are subject to a slower pace of vaccinations, the economies of Turkey and Russia are also adversely affected from lower demand in AEs even though they now have partial access to the vaccine.

Figure 14: Relative Decline in GDPs under Scenario II (%)

(a) $\xi_i = 0.9$



(b) $\xi_i = 0.6$



NOTES: This figure shows the reductions in relative GDP under Scenario 2 for two alternative trade elasticities in Panels (a)–(b), respectively. In Scenario 2, AEs follow immediate vaccination schedule whereas EMDEs follow gradual vaccination schedule. In this scenario, both AEs and EMDEs impose potentially multiple lockdowns when the number of Covid-19 patients that require ICUs exceed the number of ICUs that are reserved for Covid-19 patients. Darker shades correspond to higher relative losses. Vaccinated countries are highlighted with light gray borders.

Table 2: Total GDP Loss of the World, AEs and EMDEs (percentage of 2019 World GDP)

		Scenario I				Scenario II			
	Trade elasticity	**World**	**AE**	**EMDE**	Share of **AEs (%)**	**World**	**AE**	**EMDE**	Share of **AEs (%)**
(1)	ξ_i', ξ_i =0.50	2.149	0.561	1.588	26.1	2.687	1.038	1.649	38.6
(2)	ξ_i', ξ_i =0.60	1.347	0.312	1.035	23.2	1.296	0.592	0.705	45.6
(3)	ξ_i', ξ_i =0.70	0.996	0.189	0.806	19.0	1.125	0.560	0.565	49.8
(4)	ξ_i', ξ_i =0.80	0.898	0.140	0.758	15.6	1.072	0.550	0.523	51.2
(5)	ξ_i', ξ_i =0.90	0.857	0.112	0.744	13.1	1.049	0.545	0.504	51.9

NOTES: This table presents total economic cost associated with Covid-19 pandemic for the World, AEs, and EMDEs calculated under various scenarios. In the first scenario, we assume that the pandemic is fully contained in AEs instantly, whereas in EMDEs the pandemic evolves at its natural course. In this scenario, we assume there are endogenous lockdowns when the number of Covid-19 patients that require ICUs exceed the numbers of ICUs that are reserved for Covid-19 patients. In the second scenario, AEs follow the a vaccination calendar to vaccinate the full population within four months, whereas EMDEs follow a more gradual vaccination calendar with only the half of the population getting vaccinated. We estimate total economic cost of each of these scenarios under different trade elasticities that range from 0.5 to 0.9 to capture the effect of substitutions. ξ denotes the trade elasticity for the production side and ξ' denotes the trade elasticity for the consumption side, see Figure 6 for details.

To highlight the important role of complementarities and non-linearities in global trade and production network, we present the aggregate real GDP losses as a percentage of 2019 real GDP in Table 2. We change the trade elasticity the same way for consumption and production side from rows (1) to (5). Columns 2-5 show the costs for scenario I, while columns 6-9 show the corresponding costs for scenario II.

Focusing on the costs incurred by the world when trade elasticity=0.5 (both for consumption good and intermediate input trade), we observe that the total costs can be as high as 2.1 percent of 2019 GDP. As the trade elasticities increase and the countries can substitute goods and inputs that are imported from different countries, overall costs decrease. The costs incurred by EMDEs are significantly higher compared to AEs under both scenarios because EMDEs are not vaccinated at the same speed. The exception to this is when elasticises are higher then 0.8 under scenario II. These results show that when both AEs and EMDE deal with their own domestic shocks, a higher degree of substitution decreases the losses for EMDE more than AEs given the larger role of exports and imported inputs for those exports for EMDEs' GDP. This is why the share of world GDP loss by AEs increase under scenario II with lower degree of complementarity in global trade and production network under scenario II, whereas the relative costs that are borne by the AEs go down from 26

percent to 13 percent when the elasticity of substitution is higher under scenario I.This means that when there are no domestic sectoral shocks (no domestic pandemic), the loss to AEs coming from international linkages can be smaller if AEs can substitute between international suppliers of goods and inputs. The is not the case when they have their own domestic demand and supply shocks. Even they can substitute between international suppliers of goods and inputs, the positive effect they obtain is less than EMDEs. This is an important result highlighting the interaction between international linkages and domestic shocks and points to the fact that nationalizing supply chain may not be panacea.[16]

To dig deeper, we present our results separating consumption and production side in terms of elasticity of substitution. These results are presented in Table 3.

Table 3: Total GDP Loss of the World, AEs and EMDEs Under Supply Chain Bottlenecks: The Role of Complementarity in Global Production

		Scenario II			
	Parameter Setup	**World**	**AE**	**EMDE**	Share of **AEs (%)**
(1)	No IPN	1.045	0.556	0.490	53.2
(2)	$\xi_i' = 1.1, \xi_i$ =0.50	1.607	0.726	0.881	45.2
(3)	$\xi_i' = 1.1, \xi_i$ =0.60	1.151	0.585	0.566	50.8
(4)	$\xi_i' = 1.1, \xi_i$ =0.90	1.039	0.541	0.498	52.1
(5)	CP	1.018	0.523	0.495	51.4
(6)	Cobb-Douglas	0.818	0.441	0.377	53.9
(7)	Leontief	3.448	1.675	1.773	48.6

NOTES: This table presents total economic cost associated with COVID-19 pandemic for the World, AEs, and EMDEs calculated under various scenarios. In the second scenario, AEs follow the a vaccination calendar to vaccinate the full population within four months, whereas EMDEs follow a more gradual vaccination calendar with only the half of the population getting vaccinated. We estimate total economic cost of each of these scenarios under different alternative setting for elasticity parameters for a robustness check. ξ denotes the trade elasticity for the production side and ξ' denotes the trade elasticity for the consumption side, see Figure 6 for details. ε denotes the elasticity of substitution for the sectoral inputs and σ denotes the elasticity of substitution for the consumption goods. We also show the case where there are no international production networks (No IPN). "CP" stands for the trade elasticity values that are estimated in Caliendo and Parro (2015). Cobb-Douglas refers to the setup where all elasticities are set as 1. Leontief refers to the setup where all elasticities are set close to 0.

We start with presenting a counterfactual case of no international production network (IPN). This exercise allows us to mimic the studies that focus on closed economies with within country production complementarity such as Baqaee and Farhi (2022). In this specification, we ignore the economic costs due to international linkages, that is both final good and intermediate good trade,

[16] A similar intuition underlines the result in Bonadio et al. (2021) who focuses on the welfare effects of nationalization of supply chains.

and only focus on the domestic pandemic related domestic sectoral shocks and domestic I-O links. The share of AEs is much larger, 53.2 % in the world GDP losses simply because of their size. This case is a useful counterfactual benchmark as results below will make it clear how globalization can both amplify and smooth the shocks at the same time for different country-sectors depending on the heterogeneity in shocks and intensity of international linkages and exposure to supply chains.

In rows (2) to (4) of Table 3 we display the results where we increase the elasticity of substitution on the production side for traded inputs in a similar way as before, but we leave the trade elasticity for the consumption of final goods at ξ_i' exceeding 1. This meant to capture that you can switch to consuming a domestic car instead of an imported car under shocks but if your domestic car production needs foreign parts you still have varying degrees of substitution on these parts. We obtain the same result as before that a higher degree of substitution of intermediate inputs trade helps EMDEs more than AEs and the share of AEs costs increase from rows (2) to (4).

Row (5) of Table 3 shows the results for the trade elasticity values that are estimated in Caliendo and Parro (2015). These values can be perceived as long run elasticities with a higher degree of substitution. We obtain a similar result in terms of AEs share in world GDP losses. Row (6) and (7) are also very telling. We show results for two extremes, Cobb-Douglas and Leontief for both consumption and production trade elasticities. Both AE and EMDE losses are much lower under Cobb-Douglas than Leontief with much higher degree of substitution under Cobb-Douglas. However the share of the world GDP losses borne out by AEs is higher under Cobb-Douglas, again as substitutability helps EMDEs more.

Table 4: Total GDP Loss of the World, AEs and EMDEs Under Supply Chain Bottlenecks: The Role of Complementarity in Global Production - II

		Scenario II			
	Parameter Setup	**World**	**AE**	**EMDE**	Share of **AEs (%)**
(1)	ζ_i', ξ_i =0.60, σ =1.5	1.387	0.658	0.730	47.4
(2)	ζ_i', ξ_i =0.60, σ =0.5	1.555	0.589	0.966	37.9
(3)	ζ_i', ξ_i =0.60, θ =1.5	0.928	0.469	0.460	50.5
(4)	ζ_i', ξ_i =0.60, ε =0.5	1.131	0.552	0.580	48.7
(5)	ζ_i', ξ_i =0.60, ε =1.5	0.411	0.233	0.177	56.8

NOTES: This table presents total economic cost associated with Covid-19 pandemic for the World, AEs, and EMDEs calculated under various scenarios. In the second scenario, AEs follow the a vaccination calendar to vaccinate the full population within four months, whereas EMDEs follow a more gradual vaccination calendar with only the half of the population getting vaccinated. We estimate total economic cost of each of these scenarios under different alternative setting for elasticity parameters for a robustness check. ξ denotes the trade elasticity for the production side and ξ' denotes the trade elasticity for the consumption side, see Figure 6 for details. ε denotes the elasticity of substitution for the sectoral inputs and σ denotes the elasticity of substitution for the consumption goods.

We display the results for alternative values of other elasticities in Table 4. In rows (1) and (2), we change the value of σ, which controls the elasticity of consumption between different sectors. As the elasticity declines, the costs increase for EMDE but decrease for AEs, lowering the share of AEs in world GDP losses. This is an important result reflecting the effect of harsher lockdowns in EMDEs. If it is difficult to switch from services to goods, from restaurants to online deliveries and so on, this is going to increase the costs as shown here for EMDEs. This shows that switching consumption between sectors was harder for EMDEs due to lockdowns even the substitutability governed by the same elasticity in both set of countries, reflecting again the interaction between the shocks and elasticity of substitution.

In row (3), we change the value of θ, which controls the substitution between labor and the intermediate bundle. In this case, when we increase the elasticity from 0.6 to 1.5, the costs decline for everyone as the negative labor supply shock is more easily substituted by intermediate inputs. When we increase ε, in rows (4) and (5), which is the elasticity of substitution between sector bundles forming the intermediate bundle, from 0.2 to 0.5 (row 4) and later to 1.5 (row 5), the costs decrease with higher substitutability but again increasing the share of AEs in world GDP losses.

5 Conclusion

A global distribution of vaccines in the face of a global pandemic is primarily a humanitarian responsibility. Our paper makes the economic case for it: providing estimates that show that increasing the production of vaccines in a speedy manner and providing it to the whole world produces significant economic benefits for the rich countries who had the early access to the vaccines. The return to investing in COVAX initiative that aims to deliver vaccines to the rest of the world, putting it in the arms of the worlds poorest citizens, is 120 times of rich countries' investments.

Our global epidemiological-multi-sector-open macro framework, calibrated to 65 countries-35 sectors highlights the important role of complementarities and non-linearities in the global trade and production network and intersection of these with heterogeneity in country-sector shocks. We incorporate sectoral heterogeneity in infections together with inter-industry and international trade and production linkages. In the short-run (a year), AEs may bear somewhere from 13 percent to more than 50 percent of the global real GDP losses arising from an ongoing pandemic in other countries even they eliminate the pandemic related sectoral shocks in their own economies.

Early in the pandemic, World Health Organization (WHO) Director Dr. Tedros Ghebreyesus and the President of the European Commission Dr. Ursula von der Leyen noted that "None of us will be safe until everyone is safe." Our findings extend this argument to the economies by showing that no economy fully recovers unless every economy recovers. The sufferings from other people's losses that we highlighted in this paper remind us of John Donne's eloquent expression that "No man is an island." Our findings in this paper reveal an economic counterpart to this expression where "No economy is an island."

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APPENDIX

A Data

A.1 Household Pulse Survey

The U.S. Census Bureau designed the Household Pulse Survey (HPS) with the aim of understanding the individuals' experiences of Covid-19 as well as providing timely information essential in terms of employment status, food security, housing, physical and mental health, access to health care and educational disruption. The HPS uses a national representative sample to produce estimates at three geographic levels: (1) 15 largest Metropolitan Statistical Areas, (2) each of the 50 states plus the District of Columbia, and (3) the national level.[17]

For the purpose of our analysis, we focus on the national level information in terms of employment status that is available in the Employment Section.[18] This section asks the US households the reasons for not working and counts the responses for each reason reported. Using the counts available, we first linearly interpolate the weekly/bi-weekly series into daily series. We then group the reasons for not working into the following three categories, listed in the below.

(i) **Individual pandemic related reasons**

- I was caring for someone or sick myself with coronavirus symptoms
- I did not work because I am/was caring for children not in school or daycare
- I was concerned about getting or spreading the coronavirus
- I did not work because I am/was caring for an elderly person
- I am/was sick (not coronavirus related) or disabled

[17] The HPS has three phases: In Phase 1 US households were surveyed on a *weekly basis* over the time period from April 23, 2020 to July 21, 2020; In Phase 2 US households were surveyed households on a *bi-weekly basis* over the time period from August 19, 2020 to October 26, 2020; In Phase 3, US households were surveyed on a *bi-weekly basis* over the time period from October 28, 2020 to May 9, 2022.

[18] This information is accessible from https://www.census.gov/data/tables/2022/demo/hhp/hhp45.html.

(ii) **Business related reasons**

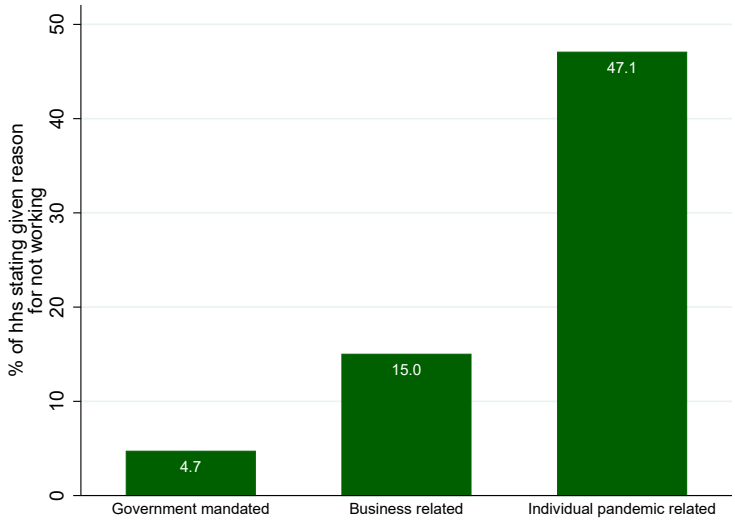
- I was laid off or furloughed due to coronavirus pandemic
- My employment went out of business due to the coronavirus pandemic

(iii) **Government mandated reasons**

- My employment closed temporarily due to the coronavirus pandemic

Figure A.1 displays the share of households in the US population aged 18 years and older who reported the reasons for not being employed in each of these three categories.[19] The numbers displayed on the bars are calculated as collapsing daily values into yearly values and taking the average of the resulting yearly responses over the period from 2020 to 2022.

Figure A.1: Main Reasons for Not Working



NOTES: Figure A.1 displays the fraction of households in each of the given three categories, based on their expressed reasons for not being employed. The numbers do not add up to 100 because the households stating the reason for not working as "Other" and "No response" are not considered in the computation.

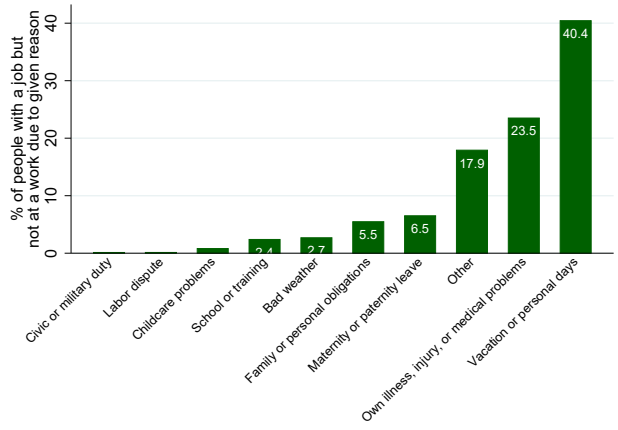
[19] We excluded from the total US population the households who stated the reason for not working as the retirement for not working at the time of survey.

A.2 Current Population Survey

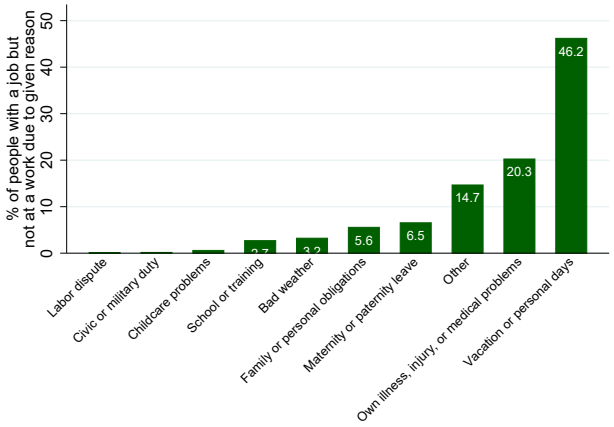
U.S. Bureau of Labor Statistics conducts the monthly household labor force survey, namely Current Population Survey (CPS) to track the number of employed people who missed work during the survey reference week. Specifically, this survey provides the following measures: i) people who did not work at all in the survey reference week, ii) people who usually work full time but were at work part time (1 to 34 hours) during the reference week.

Different from the HPS explained above, this survey provides time series data that goes until 2012. This feature enables us to compare post-Covid-19 employment figures with pre-Covid-19 ones. For the purpose of our analysis, we utilize the time series data on employed people with a job not at work by selected reasons. Figure A.2 displays the fraction of "employed" households in each of the given categories, based on their expressed reasons for not being at work.

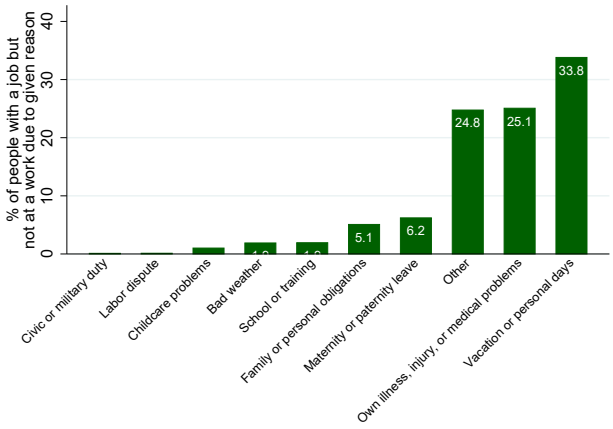
Figure A.2: Reasons for Not Working, 2012m1–2022m7



(a) averages over the sample period 2012m1-2022m7



(b) pre-Covid-19 averages



(c) post-Covid-19 averages

NOTES: Figure A.2 displays the fraction of "employed" households in each of the given categories, based on their expressed reasons for not being at work. The numbers may not be added up to 100 because of rounding in the computation of the corresponding averages.

B Additional Figures and Tables

List of Figures and Tables:

- **Figure B.1:** The Structure of OECD Inter-Country Input-Output (ICIO) Table
- **Table B.1:** Input-Output Matrix.
- **Table B.2:** Proximity Index, Teleworkable Share and Demand Changes Across Industries
- **Table B.3:** List of Essential Sectors during Lockdowns
- **Table B.4:** Country Settings for Various Scenarios
- **Table B.5:** Relative reduction in GDP of Advanced Economies (AEs) under Scenarios 2 and 3 (%).
- **Table B.6:** ICU Bed Capacities

Figure B.1: The Structure of OECD Inter-Country Input-Output Table

	Intermediate use country 1 x industry 1 [...] country 65 x industry 36	**Final Demand** country 1 x fd 1 [...] country 65 x fd 7	**Output**
country 1 x industry 1 country 1 x industry 2 ... ... country 65 x industry 1 ... country 65 x industry 36	**(Z)**	**(F)**	**(Y)**
Value added + taxes - subsidies on intermediate products	**(VA)**		
Output	**(Y)**		

NOTES: This table illustrates the structure of OECD Inter-Country Input-Output Table (ICIO), which represents the breakdown of output corresponding to 36 industries and 65 countries, giving us a matrix of 2340×2340 entries. In any industry-country combination, the output (Y) equals intermediate use (Z) plus final demand (F) of 36 industries in 65 countries. Industry list can be found in Table B.2. Further, in any industry-country combination, final demand sums the following components of expenditures over 65 countries. fd1: Households Final Consumption Expenditure (HFCE); fd2: Non-Profit Institutions Serving Households (NPISH); fd3: General Government Final Consumption (GGFC); fd4: Gross Fixed Capital Formation (GFCF); fd5: Change in Inventories and Valuables (INVNT); fd6: Direct purchases by non-residents (NONRES); fd7: Statistical Discrepancy (DISC).

Table B.1: INPUT-OUTPUT MATRIX

$$
\boldsymbol{\Omega} = \begin{array}{c} \\ E \\ \\ \\ \hline \\ G \\ \\ \\ \\ \\ \hline \\ L \\ \\ \\ \\ \\ \end{array}
\overbrace{\begin{array}{ccc} 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0 \\ \hline 0 & \cdots & 0 \\ \vdots & \vdots & \vdots \\ 0 & \cdots & 0 \\ \vdots & \vdots & \vdots \\ 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0 \\ \hline 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0 \\ \vdots & \vdots & \vdots \\ 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0 \end{array}}^{E \text{ (Size } C\text{)}}
\overbrace{\begin{array}{ccccccc} \Omega_{11}^{01} & \cdots & \Omega_{N1}^{01} & \cdots & \Omega_{1C}^{01} & \cdots & \Omega_{NC}^{01} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \Omega_{11}^{0C} & \cdots & \Omega_{N1}^{0C} & \cdots & \Omega_{1C}^{0C} & \cdots & \Omega_{NC}^{0C} \\ \hline \Omega_{11}^{11} & \cdots & \Omega_{N1}^{11} & \cdots & \Omega_{1C}^{11} & \cdots & \Omega_{NC}^{11} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \Omega_{11}^{N1} & \cdots & \Omega_{N1}^{N1} & \cdots & \Omega_{1C}^{N1} & \cdots & \Omega_{NC}^{N1} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \Omega_{11}^{1C} & \cdots & \Omega_{N1}^{1C} & \cdots & \Omega_{1C}^{NC} & \cdots & \Omega_{NC}^{NC} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \Omega_{11}^{NC} & \cdots & \Omega_{N1}^{NC} & \cdots & \Omega_{1C}^{NC} & \cdots & \Omega_{NC}^{NC} \\ \hline 0 & \cdots & 0 & \cdots & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & \cdots & 0 & \cdots & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & \cdots & 0 & \cdots & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & \cdots & 0 & \cdots & 0 & \cdots & 0 \end{array}}^{G \text{ (Size } C \times N\text{)}}
\overbrace{\begin{array}{ccccccc} 0 & \cdots & 0 & \cdots & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & \cdots & 0 & \cdots & 0 & \cdots & 0 \\ \hline \alpha_{11} & \cdots & 0 & \cdots & 0 & \cdots & 0 \\ \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & \cdots & \alpha_{N1} & \cdots & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & \cdots & 0 & \cdots & \alpha_{1C} & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & \cdots & 0 & \cdots & \alpha_{NC} \\ \hline 0 & \cdots & 0 & \cdots & 0 & \cdots & 0 \\ \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & \cdots & 0 & \cdots & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & \cdots & 0 & \cdots & 0 & \cdots & 0 \\ \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & \cdots & 0 & \cdots & 0 & \cdots & 0 \end{array}}^{L \text{ (Size } C \times N\text{)}},
$$

NOTES: In this table, we present the structure of the Input-Output table that we use.

Table B.2: PROXIMITY INDEX, TELEWORKABLE SHARE AND DEMAND CHANGES ACROSS INDUSTRIES

OECD ISIC Code	Definition	Proximity Index	Teleworkable Share	Demand Changes Percent
01T03	Agriculture, forestry and fishing	0,86	0,06	100
05T06	Mining and extraction of energy producing products	1,08	0,32	100
07T08	Mining and quarrying of non-energy producing products	1,06	0,14	100
9	Mining support service activities	1,21	0,2	100
10T12	Food products, beverages and tobacco	1,12	0,13	100
13T15	Textiles, wearing apparel, leather and related products	1,09	0,2	50
16	Wood and products of wood and cork	1,03	0,15	90
17T18	Paper products and printing	1,08	0,22	90
19	Coke and refined petroleum products	1,11	0,22	75
20T21	Chemicals and pharmaceutical products	1,06	0,25	90
22	Rubber and plastic products	1,1	0,18	90
23	Other non-metallic mineral products	1,08	0,18	90
24	Basic metals	1,09	0,14	90
25	Fabricated metal products	1,08	0,21	90
26	Computer, electronic and optical products	1,03	0,54	100
27	Electrical equipment	1,07	0,29	90
28	Machinery and equipment, nec	1,06	0,29	90
29	Motor vehicles, trailers and semi-trailers	1,09	0,19	70
30	Other transport equipment	1,06	0,31	70
31T33	Other manufacturing; repair and installation of machinery and equipment	1,07	0,32	90
35T39	Electricity, gas, water supply, sewerage, waste and remediation services	1,08	0,29	100
41T43	Construction	1,21	0,19	75
45T47	Wholesale and retail trade; repair of motor vehicles	1,13	0,37	110
49T53	Transportation and storage	1,18	0,21	80
55T56	Accommodation and food services	1,26	0,1	25
58T60	Publishing, audiovisual and broadcasting activities	1,11	0,69	85
61	Telecommunications	1,07	0,58	100
62T63	IT and other information services	1,01	0,88	100
64T66	Financial and insurance activities	1,02	0,79	100
68	Real estate activities	1,1	0,54	60
69T82	Other business sector services	1,09	0,46	85
84	Public admin. and defence; compulsory social security	1,16	0,39	125
85	Education	1,22	0,86	85
86T88	Human health and social work	1,28	0,35	100
90T96	Arts, entertainment, recreation and other service activities	1,18	0,34	25

NOTES: In this table, we present the physical proximity index, the share of teleworkable employees as well as demand changes in a given industry, which is categorized based on OECD ISIC Codes. In comparing proximity values across differential sectors listed in the first column, we use weighted average of occupation-specific proximity values in those sectors. Specifically, an occupation of a given industry is assigned with a proximity value that is smaller than 1 if it has sparse working conditions. An occupation of a given industry is assigned with a proximity value that is larger than 1 if it requires closer proximity than the "shared office" level. We calculate the proximity values for a given industry after removing the teleworkable share of the employees of that industry. Doing so, we follow Dingel and Neiman (2020)'s list of teleworkable occupations to determine the share of employees that can work remotely in each industry. In the last column, we present the demand changes at the sectoral level that we use to calculate the estimated demand change during the pandemic in each industry. For further details on the calculation of proximity index, teleworkable shares as well as demand changes, see Çakmaklı et al. (2020).

Table B.3: LIST OF ESSENTIAL SECTORS DURING LOCKDOWNS

NACE Rev. 2	Definition
01	Crop and animal production, hunting and related service activities
10	Manufacture of food products
1722	Manufacture of household and sanitary goods and of toilet requisites
1811	Printing of newspapers
1920	Manufacture of refined petroleum products
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
35	Electricity, gas, steam and air conditioning supply
36	Water collection, treatment and supply
463	Wholesale of food, beverages and tobacco
4646	Wholesale of pharmaceutical goods
4711	Retail sale in non-specialised stores with food, beverages or tobacco predominating
472	Retail sale of food, beverages and tobacco in specialised stores
4730	Retail sale of automotive fuel in specialised stores
4773	Dispensing chemist in specialised stores
4774	Retail sale of medical and orthopaedic goods in specialised stores
4781	Retail sale via stalls and markets of food, beverages and tobacco products
4920	Freight rail transport
4941	Freight transport by road
5224	Cargo handling
53	Postal and courier activities
60	Programming and broadcasting activities
61	Telecommunications
639	Other information service activities
75	Veterinary activities
86	Human health activities
87	Residential care activities

NOTES: This table provides the list of the essential sectors that we consider for the implementation of lockdowns under Scenario 2 & Scenario 3. The table is based on Çakmaklı et al. (2020) where authors use government decrees to identify these sectors.

Table B.4: COUNTRY SETTINGS FOR VARIOUS SCENARIOS

Country	ICU capacity reserved for Covid-19 patients	Reproduction rate R_0	GDP 2019 (Billion USD)	Share of population getting vaccinated	Duration of vaccination (days)	Openness Index
Australia	1665	0.7	1,393	100%	120 (30-90)	35
Austria	1000	1.1	446	100%	120 (30-90)	81
Belgium	2756	1.1	530	100%	120 (30-90)	164
Canada	2713	1.3	1,736	100%	120 (30-90)	52
Chile	1383	1.3	282	50%	330	49
Czechia	4151	1.1	247	100%	120 (30-90)	153
Denmark	925	1.2	348	100%	120 (30-90)	60
Estonia	338	1.2	31	100%	120 (30-90)	109
Finland	220	1.1	269	100%	120 (30-90)	55
France	8000	1.1	2,716	100%	120 (30-90)	45
Germany	28000	1.1	3,846	100%	120 (30-90)	71
Greece	704	1.1	210	100%	120 (30-90)	48
Hungary	1094	1.1	161	100%	120 (30-90)	151
Iceland	163	1.1	24	100%	120 (30-90)	49
Ireland	248	1.1	389	100%	120 (30-90)	69
Israel	4900	1.3	395	100%	120 (30-90)	34
Italy	7700	1.1	2,001	100%	120 (30-90)	50
Japan	3996	1.3	5,082	100%	120 (30-90)	28
Korea	5481	1.3	1,642	100%	120 (30-90)	64
Latvia	186	1.1	34	100%	120 (30-90)	102
Lithuania	451	1.1	54	100%	120 (30-90)	127
Luxembourg	91	1.1	71	100%	120 (30-90)	57
Mexico	4211	1.1	1,258	50%	330	74
Netherlands	1161	1.1	909	100%	120 (30-90)	148
New Zealand	585	0.7	207	100%	120 (30-90)	40
Norway	455	1.1	403	100%	120 (30-90)	47
Poland	3074	1.1	592	100%	120 (30-90)	89
Portugal	455	1.1	238	100%	120 (30-90)	66
Slovakia	570	1.1	105	100%	120 (30-90)	170
Slovenia	377	1.1	54	100%	120 (30-90)	166
Spain	4566	1.1	1,394	100%	120 (30-90)	51
Sweden	365	1.1	531	100%	120 (30-90)	60
Switzerland	1012	1.1	703	100%	120 (30-90)	84
Turkey	16850	1.3	754	50%	330	52
United Kingdom	7018	1.1	2,827	100%	120 (30-90)	41
US	84676	1.1	21,370	100%	120 (30-90)	20
Argentina	8404	1.1	450	50%	330	25
Brazil	43466	1.1	1,840	50%	330	22
Brunei	57	1.1	13	50%	330	90
Bulgaria	1347	1.1	68	100%	120 (30-90)	104
Cambodia	495	1.1	27	50%	330	131
China	50328	0.6	14,340	100%	120 (30-90)	32
Colombia	5286	1.3	324	50%	330	28
Costa Rica	136	1.1	62	50%	330	45
Croatia	277	1.3	60	50%	330	75
Cyprus	126	1.1	25	100%	120 (30-90)	51
India	32784	1.3	2,875	50%	330	28
Indonesia	7306	1.1	1,119	50%	330	30
Hong Kong	533	1.3	366	100%	120 (30-90)	304
Kazakhstan	3943	1.1	180	50%	330	53
Malaysia	1086	1.3	365	50%	330	122
Malta	70	1.1	15	100%	120 (30-90)	68
Morocco	2100	1.3	119	50%	330	67
Peru	943	1.1	227	50%	330	40
Philippines	2378	1.1	377	50%	330	49
Romania	1500	1.1	250	100%	120 (30-90)	69
Russia	17500	1.1	1,700	100%	120 (30-90)	40
Saudi Arabia	7813	1.1	793	50%	330	52
Singapore	650	1.2	372	100%	120 (30-90)	202
South Africa	2323	1.1	351	50%	330	56
Taiwan	6725	1.1	611	50%	330	101
Thailand	7241	1.1	544	50%	330	89
Tunisia	479	1.1	39	50%	330	94
Vietnam	251	1.1	262	50%	330	198
ROW	57225	1.1	7,276	50%	330	48

NOTES: This table reports the ICU capacities (see Table B.6 for details), estimated reproduction rates, GDP figures (obtained from World Development Indicators, 2019 current dollars), shared of population getting vaccine (for scenario 3), duration of vaccination days (for scenario 3) and openness index, which is defined as the ratio of imports and exports to GDP.

Table B.5: RELATIVE REDUCTION IN GDP OF ADVANCED ECONOMIES (AES) UNDER SCENARIOS 1 AND 2 (%)

	Scenario 1		Scenario 2	
	$\xi_i = 0.6$	$\xi_i = 0.9$	$\xi_i = 0.6$	$\xi_i = 0.9$
Australia	0.18	-0.03	0.33	0.25
Austria	1.02	0.33	2.02	1.41
Belgium	1.03	0.48	0.96	1.18
Canada	0.29	0.13	1.18	0.87
Denmark	0.83	0.32	0.04	0.05
Finland	-0.10	-0.05	-0.12	-0.06
France	0.42	0.16	0.95	1.05
Germany	0.83	0.18	-0.68	-0.23
Greece	1.73	0.97	6.53	4.30
Iceland	1.95	0.67	3.52	1.87
Ireland	0.15	-0.39	-2.34	-1.95
Italy	0.67	0.19	1.72	1.33
Japan	0.92	0.29	0.70	0.44
Luxembourg	1.18	0.22	-0.09	-0.09
Netherlands	0.98	0.37	1.01	1.18
New Zealand	-0.24	-0.29	0.58	0.34
Norway	1.19	0.47	2.67	2.15
Portugal	0.83	0.44	3.86	2.69
Spain	1.10	0.39	3.17	2.32
Sweden	0.32	0.07	0.60	0.77
Switzerland	0.37	0.01	-0.60	-0.20
United Kingdom	0.51	0.22	1.26	1.21
United States	0.31	0.15	1.20	1.19

NOTES: This table displays the percentage reduction in the GDP of the corresponding AEs relative to a counterfactual of global vaccinations. Details on the scenarios 1 and 2 are provided in Section 4.

Table B.6: ICU Bed Capacities

ISO-3	Country	ICU COVID	Reference
AUS	Australia	1665	https://www.mja.com.au/journal/2020/surge-capacity-australian-intensive-care-units-associated-covid-19-admissions
AUT	Austria	1000	https://www.covid19healthsystem.org/countries/austria/livinghit.aspx?Section=2.1%20Physical%20infrastructure&Type=Section
BEL	Belgium	2756	https://www.covid19healthsystem.org/countries/belgium/livinghit.aspx?Section=2.1%20Physical%20infrastructure&Type=Section
CAN	Canada	2713	https://www.covid19healthsystem.org/countries/canada/livinghit.aspx?Section=2.1%20Physical%20infrastructure&Type=Section
CHL	Chile	1383	https://www.oecd.org/coronavirus/en/data-insights/intensive-care-beds-capacity
CZE	Czech Republic	4151	https://www.covid19healthsystem.org/countries/czechrepublic/livinghit.aspx?Section=2.1%20Physical%20infrastructure&Type=Section
DNK	Denmark	925	https://www.sst.dk/-/media/Nyheder/2020/ITA_COVID_19_220320.ashx?la=da&hash=633349284353F4D8559B231CDA64169D327F1227
EST	Estonia	338	https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7472675/
FIN	Finland	220	https://www.covid19healthsystem.org/countries/finland/livinghit.aspx?Section=2.1%20Physical%20infrastructure&Type=Section
FRA	France	8000	https://www.covid19healthsystem.org/countries/france/livinghit.aspx?Section=2.1%20Physical%20infrastructure&Type=Section
DEU	Germany	28000	https://www.covid19healthsystem.org/countries/germany/livinghit.aspx?Section=2.1%20Physical%20infrastructure&Type=Section
GRC	Greece	704	https://www.covid19healthsystem.org/countries/greece/livinghit.aspx?Section=2.1%20Physical%20infrastructure&Type=Section
HUN	Hungary	1094	https://www.oecd.org/coronavirus/en/data-insights/intensive-care-beds-capacity
ISL	Iceland	163	https://europepmc.org/article/med/32796182
IRL	Ireland	248	https://www.thejournal.ie/icu-bed-numbers-5217685-Sep2020/
ISR	Israel	4900	https://www.covid19healthsystem.org/countries/israel/livinghit.aspx?Section=2.1%20Physical%20infrastructure&Type=Section
ITA	Italy	7700	https://apnews.com/article/international-news-virus-outbreak-italy-barcelona-france-d7a43368a17f0abaff4d563151b84127
JPN	Japan	3996	https://journals.lww.com/ccmjournal/Fulltext/2020/05000/Critical_Care_Bed_Capacity_in_Asian_Countries_and.6.aspx
KOR	Korea, Rep.	5481	https://journals.lww.com/ccmjournal/Fulltext/2020/05000/Critical_Care_Bed_Capacity_in_Asian_Countries_and.6.aspx
LVA	Latvia	186	https://www.covid-19.no/critical-care-bed-numbers-in-europe
LTU	Lithuania	451	https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7472675/
LUX	Luxembourg	91	https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7472675/
MEX	Mexico	4211	https://www.oecd.org/coronavirus/en/data-insights/intensive-care-beds-capacity
NLD	Netherlands	1161	https://www.oecd.org/coronavirus/en/data-insights/intensive-care-beds-capacity
NZL	New Zealand	585	https://www.nzherald.co.nz/nz/covid-19-coronavirus-new-zealands-intensive-care-unit-capacity-revealed/GYQ2FXOYHJECZAHU2YKHXYFWXI/
NOR	Norway	455	https://www.oecd.org/coronavirus/en/data-insights/intensive-care-beds-capacity
POL	Poland	3074	https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7472675/
PRT	Portugal	455	https://www.covid-19.no/critical-care-bed-numbers-in-europe
SVK	Slovak Republic	570	https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7472675/
SVN	Slovenia	377	https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7472675/
ESP	Spain	4566	https://www.covid-19.no/critical-care-bed-numbers-in-europe
SWE	Sweden	365	https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7472675/
CHE	Switzerland	1012	https://www.oecd.org/coronavirus/en/data-insights/intensive-care-beds-capacity
TUR	Turkey	16850	https://dosyasb.saglik.gov.tr/Eklenti/36164,siy2018en2pdf.pdf?0
GBR	United Kingdom	7018	https://www.oecd.org/coronavirus/en/data-insights/intensive-care-beds-capacity
USA	United States	84676	https://www.oecd.org/coronavirus/en/data-insights/intensive-care-beds-capacity
ARG	Argentina	8404	https://www.oecd-ilibrary.org/sites/63d94877-en/index.html?itemId=/content/component/63d94877-en
BRA	Brazil	43466	https://www.oecd-ilibrary.org/sites/63d94877-en/index.html?itemId=/content/component/63d94877-en
BRN	Brunei Darussalam	57	https://journals.lww.com/ccmjournal/Fulltext/2020/05000/Critical_Care_Bed_Capacity_in_Asian_Countries_and.6.aspx
BGR	Bulgaria	1347	https://www.covid19healthsystem.org/countries/bulgaria/livinghit.aspx?Section=2.1%20Physical%20infrastructure&Type=Section
KHM	Cambodia	495	Selected to be close to the minimum observed levels.
CHN	China	50328	https://journals.lww.com/ccmjournal/Fulltext/2020/05000/Critical_Care_Bed_Capacity_in_Asian_Countries_and.6.aspx
COL	Colombia	5286	https://www.oecd-ilibrary.org/sites/63d94877-en/index.html?itemId=/content/component/63d94877-en
CRI	Costa Rica	136	https://www.oecd-ilibrary.org/sites/63d94877-en/index.html?itemId=/content/component/63d94877-en
HRV	Croatia	277	https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7472675/
CYP	Cyprus	126	https://in-cyprus.philenews.com/coronavirus-seven-patients-in-intensive-care/
IND	India	32784	https://journals.lww.com/ccmjournal/Fulltext/2020/05000/Critical_Care_Bed_Capacity_in_Asian_Countries_and.6.aspx
IDN	Indonesia	7306	https://journals.lww.com/ccmjournal/Fulltext/2020/05000/Critical_Care_Bed_Capacity_in_Asian_Countries_and.6.aspx
HKG	Hong Kong SAR, China	533	https://journals.lww.com/ccmjournal/Fulltext/2020/05000/Critical_Care_Bed_Capacity_in_Asian_Countries_and.6.aspx
KAZ	Kazakhstan	3943	https://journals.lww.com/ccmjournal/Fulltext/2020/05000/Critical_Care_Bed_Capacity_in_Asian_Countries_and.6.aspx
MYS	Malaysia	1086	https://journals.lww.com/ccmjournal/Fulltext/2020/05000/Critical_Care_Bed_Capacity_in_Asian_Countries_and.6.aspx
MLT	Malta	70	https://www.covid19healthsystem.org/countries/malta/livinghit.aspx?Section=2.1%20Physical%20infrastructure&Type=Section
MAR	Morocco	2100	https://northafricapost.com/39786-covid-19-morocco-expands-hospital-capacity.html
PER	Peru	943	https://www.oecd-ilibrary.org/sites/63d94877-en/index.html?itemId=/content/component/63d94877-en
PHL	Philippines	2378	https://journals.lww.com/ccmjournal/Fulltext/2020/05000/Critical_Care_Bed_Capacity_in_Asian_Countries_and.6.aspx
ROU	Romania	1500	https://www.covid19healthsystem.org/countries/romania/livinghit.aspx?Section=2.1%20Physical%20infrastructure&Type=Section
RUS	Russian Federation	17500	https://tass.com/world/1162077
SAU	Saudi Arabia	7813	https://journals.lww.com/ccmjournal/Fulltext/2020/05000/Critical_Care_Bed_Capacity_in_Asian_Countries_and.6.aspx
SGP	Singapore	650	https://journals.lww.com/ccmjournal/Fulltext/2020/05000/Critical_Care_Bed_Capacity_in_Asian_Countries_and.6.aspx
ZAF	South Africa	2323	https://www.samrc.ac.za/news/covid-19-surge-investing-heavily-icu-capacity-not-only-option
TWN	Taiwan	6725	https://journals.lww.com/ccmjournal/Fulltext/2020/05000/Critical_Care_Bed_Capacity_in_Asian_Countries_and.6.aspx
THA	Thailand	7241	https://journals.lww.com/ccmjournal/Fulltext/2020/05000/Critical_Care_Bed_Capacity_in_Asian_Countries_and.6.aspx
TUN	Tunisia	479	https://www.medrxiv.org/content/10.1101/2020.06.02.20120147v1.full.pdf
VNM	Vietnam	251	https://www.who.int/docs/default-source/wpro---documents/countries/viet-nam/covid-19/vnm-moh-who-covid-19-sitrep4.pdf
ROW	Rest of the World	57225	Selected to be close to the minimum observed levels.

Notes: This table provides the resources from which we built the ICU capacities dedicated for Covid-19 patients in each country. If there is a direct number for the ICU beds for Covid-19 in a resource, we used that number. Otherwise we assigned 70% of the total ICU beds to Covid-19 patients. We estimated this ratio from the countries that we have the information about dedicated ICU beds to Covid-19 patients.