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

COVID-19 pandemic had a devastating effect on both lives and livelihoods in 2020. The arrival of effective vaccines can be a major game changer. However, vaccines are in short supply as of early 2021 and most of them are reserved for the advanced economies. We show that the global GDP loss of not inoculating all the countries, relative to a counterfactual of global vaccinations, can be higher than the cost of manufacturing and distributing vaccines globally. We use an economic-epidemiological framework that combines a SIR model with international production and trade networks. Based on this framework, we estimate the costs for 65 countries and 35 sectors. Our estimates suggest that up to 49 percent of the global economic costs of the pandemic in 2021 are borne by the advanced economies even if they achieve universal vaccination in their own countries.

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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

The COVID-19 shock was unexpected and severe. The world was caught unprepared as countries hastily put together policies to curb the spread of the virus, contain the financial panic, and offset the economic contraction all at the same time. The entire 2020 was spent with lockdown policies that went on and off, as the countries learned from each others' experiences. Renewed upticks in countries through cross border travelling highlighted the limitations of country specific lockdowns in a global pandemic. In retrospect, it became evident that a globally coordinated lockdown in Spring and Summer of 2020 could have contained the pandemic much sooner. This would have earned time to invest in testing and contact tracing procedures.

Approximately one year after the outbreak, we are at the crossroads of a critical decision again, this time with respect to global coordination of manufacturing and distribution of the vaccines worldwide. COVAX facility, co-led by the Coalition for Epidemic Preparedness Innovations and the World Health Organization, aims to coordinate the efforts among advanced economies to collect the necessary funding to manufacture and distribute the vaccines in an equitable way, but currently lacks funding.

We show that advanced economies (AEs) cannot eliminate the economic costs of the pandemic entirely by having national access to the vaccine. The interdependencies of the economies in a globalized economy implies that there can be a sizable drag on the vaccinated countries due to their trade links with the unvaccinated countries, mainly emerging markets and developing economies (EMDEs). We show that even if AEs eliminate the domestic costs of the pandemic thanks to the vaccines, the costs they bear due to their international linkages would be in the range of 0.2 trillion USD and 2.6 trillion USD, depending on the strength of trade and production linkages. Overall, AEs can bear up to 49 percent of the global costs in 2021, despite the fact that they might vaccinate a sizable part of their populations by summer 2021.[1] By illustrating the sizable economic costs in the absence of equitable vaccine distribution, we demonstrate the importance of making the vaccine globally available, not from a moral standpoint but from an economic one. It is not an act of charity but an act of economic rationality for the advanced economies to get involved in the efforts for an equitable global vaccine distribution.

In order to estimate the economic costs of COVID-19 that are *solely* due to international linkages, we develop a framework that combines an epidemiological Susceptible-Infected-Recovered (SIR) model with international trade and production network. In our earlier work, Çakmaklı et al. (2020), we considered a similar framework focusing on how the *domestic costs* of the pandemic can be amplified for a given *small open economy* (EMDEs) due declining foreign demand and exports. Our current work builds on this set up and adds the production and supply side, which helps us to highlight the importance of the global trade and production networks in amplifying the costs of the pandemic *globally*. A country's own pandemic not only impacts its own production and employment as a pure domestic supply shock, but it also impacts the production of intermediate inputs imported by other countries. In order to capture these spillovers, we incorporate the global input-output linkages between sectors. This approach allows us to estimate the cascading effect of sectoral supply shocks in different countries via global value chains and international production network.

We introduce the vaccine as an immediate treatment of the virus, which reverts the sectoral demand and supply shocks in the vaccinated country right away. Consequently, the economic costs of the pandemic that arise due to negative domestic sectoral demand and supply shocks disappear in a given country, where the vaccine becomes available. However, the costs coming from the international linkages remain as long as foreign countries are not vaccinated. The reasons for the sub-par performance of a country with full inoculation are twofold: First, this country's exports cannot fully recover as long as there is weak external demand from the countries that are still suffering from the pandemic. Second, this country's imports of final and/or intermediate goods are also affected when the supplier countries are not fully recovered from the pandemic, which in turn decreases the country's production capacity.

[1] These numbers are far larger than the 38 billion USD cost of manufacturing 2 billion doses of vaccines to inoculate 20 percent of the world population by the end of 2021 as targeted by COVAX.

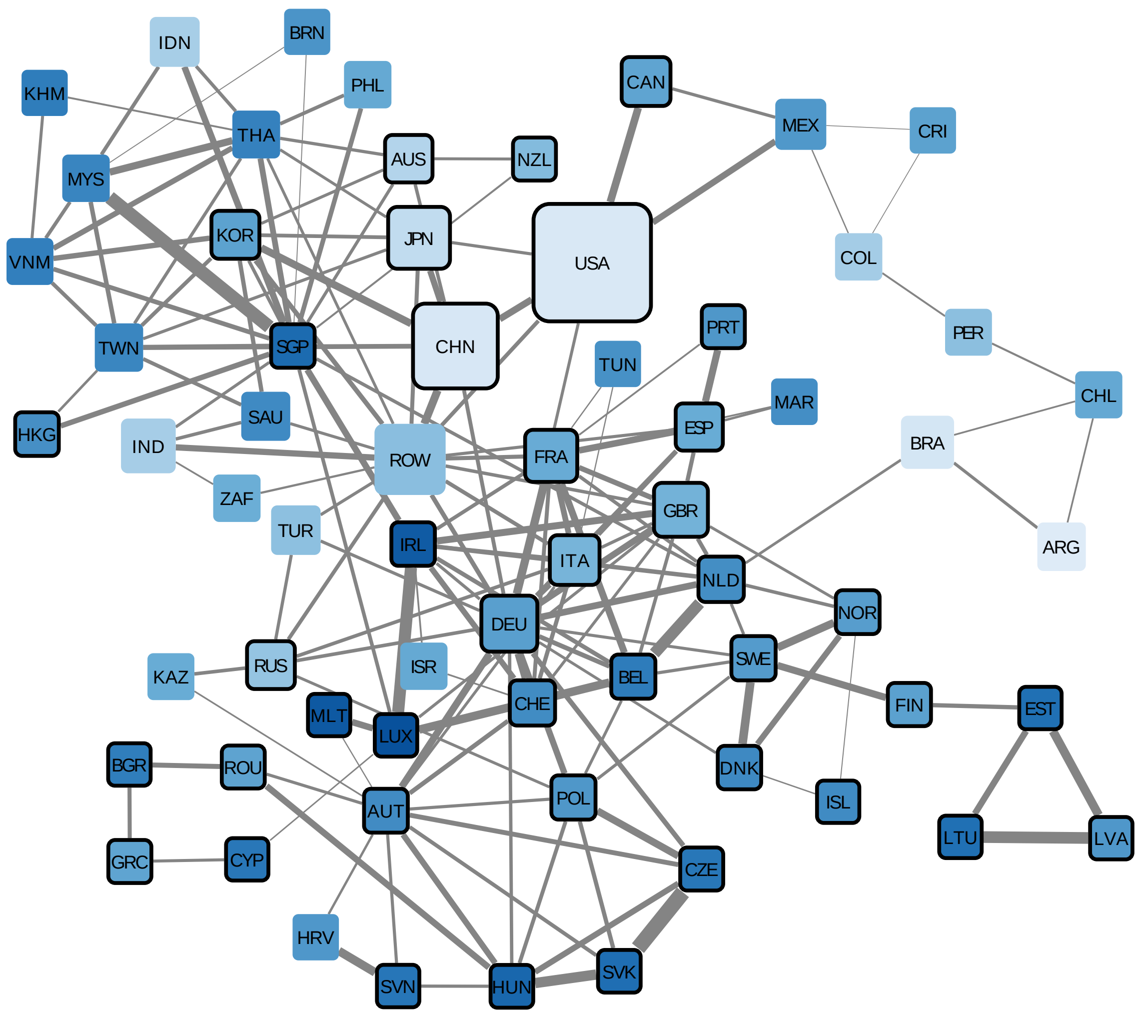
Given the extensive evidence on the disproportionate intensity of the COVID-19 shock on certain sectors, we follow a granular sectoral approach. Our approach allows us to combine the sectoral heterogeneity in infection dynamics with sectoral heterogeneity in global trade and production networks.[2] We estimate COVID losses for 65 countries and 35 sectors, using OECD's multi-industry multi-national input-output tables. Figures 1 and 2 show the importance of incorporating international and inter-sectoral trade linkages in the calculation of the economic costs of the pandemic. Figure 1 shows the trade networks. Each node represents a country. The larger the country's GDP, the bigger the node size. The darker blue nodes are more open countries measured by the ratio of imports and exports to GDP. In our calibration, we assume AEs have access to vaccination. These countries are marked with a black border around their nodes. Out of 65 countries, 41 countries are classified as AEs who have access to vaccination.[3] The remaining 25 countries (including a residual entity called the "Rest of the World") belong to the set of EMDEs who are assumed to be unvaccinated. The thicker is the line between any two countries, the higher is the intensity of trade between those countries.

These international linkages are comprised of sectoral links. Industries use inputs from a variety of other industries. These inputs can be supplied either domestically or internationally. In Figure 2 we show a glimpse of the global inter-industry production network. In this network, each node represents an industry. The node size indicates the total intermediate input usage of the industry. The node color shows the share of imported inputs in the industry such that the industries with darker shades of red use more international inputs. It is clear that an industry with a relatively larger node size and a darker color (such as "Coke an Refined Petroleum" as opposed to "Real Estate") will be more exposed to the drag from the pandemic if its' imported inputs are obtained from unvaccinated trade partners and if the production of these inputs require more in-person contacts, increasing the fraction of sick workers. It is also the case that, the other industries who are not as open themselves but connected to these open industries, such as "construction and mining" will also be indirectly affected. The lines between the nodes show bilateral supply relationships, where the thicker lines represent stronger relations between the two sectors that source more from each other. The directed

[2]See Gourinchas et al. (2020) who uses heterogenetiy in sectoral shocks to identify business failures.

[3]Some countries in the AE group are essentially emerging markets. We still classify these countries, including China and Russia, among AEs, because they have access to vaccines.

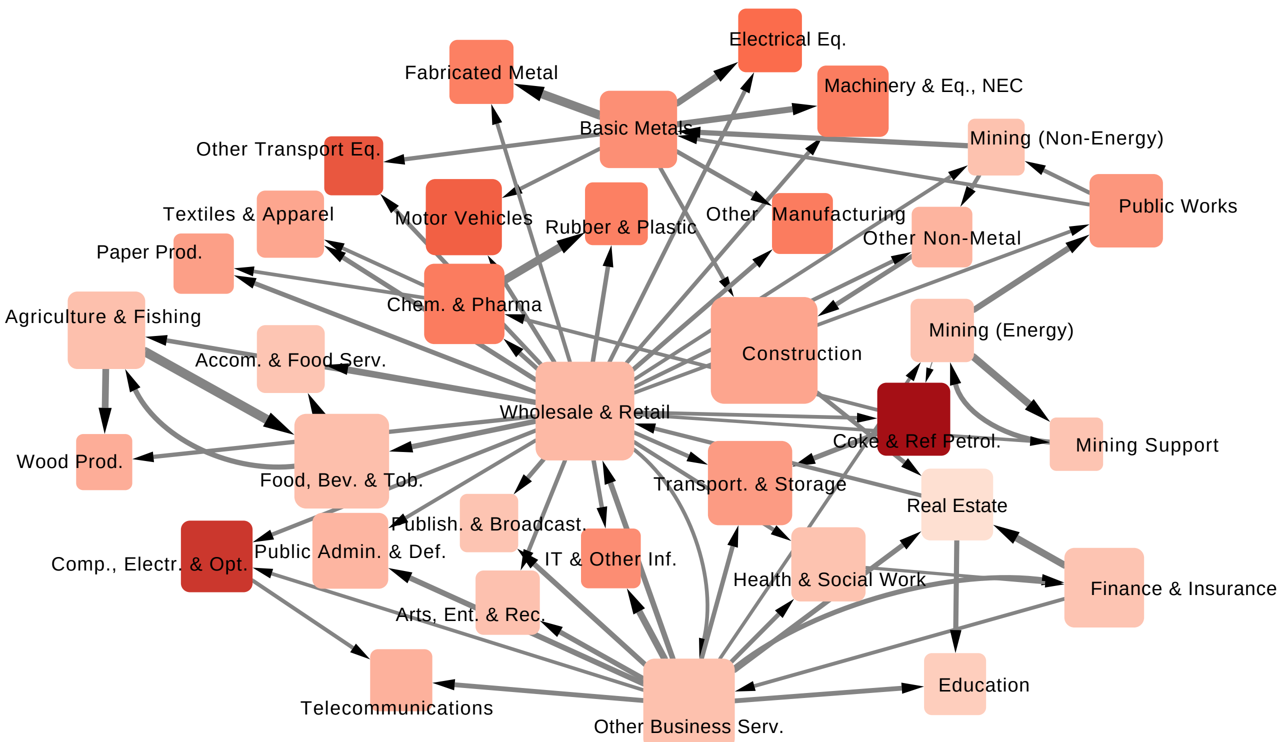
Figure 1: International Trade Linkages



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. 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.

line points from the supplier to the target industry. 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 in 2015. Such a high prevalence of intermediate products reflects increasing prominence of global value chains (The World Bank, 2020).

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.

Our approach is data-driven. We do not allow firms to optimize and change their positions in global value chains in response to labor supply shocks. We assume that the COVID-19 shock is temporary and maintain the assumption that prices of goods and inputs are sticky at that horizon. As argued by Shih (2020) and Carvalho et al. (forthcoming), the time needed to rebuild these networks is longer than the average duration of price stickiness. Furthermore, there might be a reluctance on the firms' part to rebuild their networks in response to temporary shocks. Our analysis is meant to capture the first-round effects of an unequal vaccine distribution throughout 2021, where the COVID-19 shock is now perceived to be temporary given the presence of the vaccines. In this sense, our approach can be viewed as a special application of the general framework presented by Baqaee and Farhi (2020a,b). Similar to their framework, we assume strong complementarities between intermediate inputs and do not allow labor adjustments within or across sectors. Both in Baqaee and Farhi (2020b) and Guerrieri et al. (2020), these strong complementarities lead the supply shock to generate an even larger decline in aggregate demand, where in the latter paper goods are complements in demand. Our paper is an empirical application of these models that allows amplification of both demand and supply shocks through the global trade and production networks.[4]

In order to show the key channels of our model, we consider several specifications. In the best case that gives the lowest costs for the AEs, we solely focus on the foreign demand shocks that affect exports. That is, if country A is fully vaccinated and wants to export to country B, which is not fully vaccinated, the exports of country A will be lower compared to the counterfactual where country B was also inoculated. In the worst case with the highest costs, we employ fully integrated inter-country inter-industry input-output matrices, where inputs from different country-sectors cannot be distributed across the sectors of country A. For example, suppose the construction industry in country A imports steel from unvaccinated country B, and the manufacturing industry in country A imports steel from a vaccinated country such as D. Then, when steel imports from B goes down, construction industry cannot borrow steel from the manufacturing industry.[5]

We consider these specifications under three vaccination and lockdown scenarios. In our first and second scenarios, AEs are inoculated immediately, but the EMDEs are not. Hence the dynamics of the pandemic in the unvaccinated EMDEs feed back into the economic recovery of the AEs. In the second scenario we add lockdowns in EMDEs, different from the first scenario. The lockdown decisions are endogenous to infection dynamics. A lockdown is put into place when the number

[4]In the long-run prices will rise and labor will adjust which might lead to lower estimates. See for example Bonadio et al. (2020).

[5]We consider a hybrid case, where total inputs are imported at the country level, regardless of where they came from. The inputs are then distributed among the domestic sectors proportional to their initial shares. This treatment is analogous to building a country level input-output table, similar to the Bureau of Economic Analysis' practice of building the well-established US I-O matrices. For example, the steel imports of the United States from Germany and China constitute the total imports of steel that is distributed across US' sectors based on each industry's share of the input.

of severe cases exceeds the given country's ICU bed capacity.[6] In the third scenario, we allow for a gradual distribution of the vaccines in both AEs and EMDEs, keeping the endogenous lockdowns.

In the first scenario, we find that the global aggregate GDP losses range from 2.9 to 4.3 trillion USD, depending on our specifications described above. Out of these aggregate costs, a range of 0.5 to 1.6 trillion dollars are suffered by the AEs. Once we incorporate endogenous lockdowns in the second scenario, the supply of inputs produced by EMDEs will decline further while their export demand from AEs will strengthen as the lockdowns reduce the number of infections in EMDEs. Hence, even though the costs that stem from the export channel decline, the costs that stem from the import channel will increase. In this scenario, the overall losses range from 1.5 to 6.1 trillion USD, with 0.2 to 2.6 trillion USD of the costs borne by the AEs. In our final scenario, the losses are mitigated as the vaccines are also available in EMDEs. The aggregate losses in this scenario are 1.84 to 3.8 trillion USD, of which 0.4 to 1.9 trillion USD of the losses are borne by the AEs. Overall, AEs may bear somewhere from 13 percent to 49 percent of the global losses arising from an unequal distribution of vaccines in 2021. This range corresponds to 0.3 to 3.7 percent of their pre-pandemic GDPs.

The remainder of this paper is organized as follows: In Section 2, we provide an overview of the literature. In Section 3, we present the conceptual framework. In Section 4, we describe the data and the parameters for calibration. Section 5 presents results and includes a premier on possible global supply chain disruptions in 2021. Section 6 concludes.

2 Literature

There is a rapidly growing literature that aims to capture the economic impact of COVID-19 crisis. Many papers utilize SIR models or its extensions to incorporate the infection dynamics into their analysis. However, most of this literature focuses on closed economies, excluding the international production and trade linkages that we consider. Papers such as Stock (2020), Alvarez et al. (2020), and Acemoglu et al. (2020) consider the trade-off between the lives and the livelihoods. They reach the conclusion that full lockdowns during the early stages of the pandemic is the optimal policy for

[6] This is motivated by the observation that COVID-19 overwhelmed health systems through sharp increases in ICU bed occupancies (Mendoza et al. (2020)).

advanced closed economies. Alon et al. (2020) and Alfaro et al. (2020) take a developing country perspective, focusing on the informal sector and small firms. They reach the opposite conclusion in terms of lockdowns, arguing that lockdowns harm the livelihoods at a greater scale in these countries.

A separate group of papers focus on the endogenous response of demand or supply to the infection rates. Papers such as Farboodi et al. (2020), Eichenbaum et al. (2020), Krueger et al. (2020), and Eichenbaum et al. (2020) model the endogenous response of consumption or employment to the pandemic, that is missing from the SIR models. These papers aim to capture the interplay between infection dynamics and the determinants of demand or supply in closed economies.

The recent 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 heterogenous 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 (2020) 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.

To be consistent with this evidence, we model both sectoral demand and supply shocks for an open economy, which is missing in the above cited literature. Furthermore, these shocks are linked to the other countries through trade and production networks. We model the epidemiological part similar to the closed economy literature as in Acemoglu et al. (2020), Alvarez et al. (2020), Farboodi et al. (2020), and Eichenbaum et al. (2020).[7]

[7] There is also a closed economy literature with rich input-output and network dynamics, similar to us, but this literature omits the epidemiology part. See Barrot et al. (2020), Bonadio et al. (2020), and Baqaee et al. (2020), Baqaee and Farhi (2020a,b) and Guerrieri et al. (2020).

3 Conceptual Framework

We present an open economy framework combined with a SIR model with multiple sectors. We then combine this model with data on international and inter-sectoral input-output linkages on 65 countries and 35 sectors, composing the global international trade and production network. We incorporate both supply and demand shocks to the model through the epidemiological part. These shocks directly impact exports and imports of final and intermediate goods.

Ability to work from home, physical proximity requirements and lockdowns are all domestic factors that pin down the sectoral supply shock in our epidemiological model. Most infection dynamics models, including Acemoglu et al. (2020), Alvarez et al. (2020), Farboodi et al. (2020), and Eichenbaum et al. (2020), do not use the sectoral heterogeneity in disease dynamics. To the best of our knowledge, Baqaee et al. (2020) is the only paper with a similar sectoral heterogeneity to us. The novelty of our model is to introduce yet another factor that affects sectoral supply though international linkages. For instance, the car industry requires steel, plastics, textiles, electronics, and numerous other inputs to make its final product. Critically, many of these inputs are provided internationally. Depending on the infection rates of the country that they are imported from, they constitute a further sectoral supply shock for our small open economy. Similarly, demand shocks move with the infection rates. Once infections reach a certain threshold, demand stalls and remains rather sluggish. In our model, even if the domestic infection rates are reduced, countries still suffer from weak external demand if other countries' infection rates are not improved simultaneously.

We calibrate our model to analyse the consequences of a hypothetical distribution of vaccination. We assume that when AEs have access to the vaccine, local demand and supply shocks in AEs due to high infection rates disappear. Nevertheless, AEs still suffer from the economic costs of the pandemic as they are still affected from the foreign demand and supply shocks transmitted from EMDEs. Specifically:

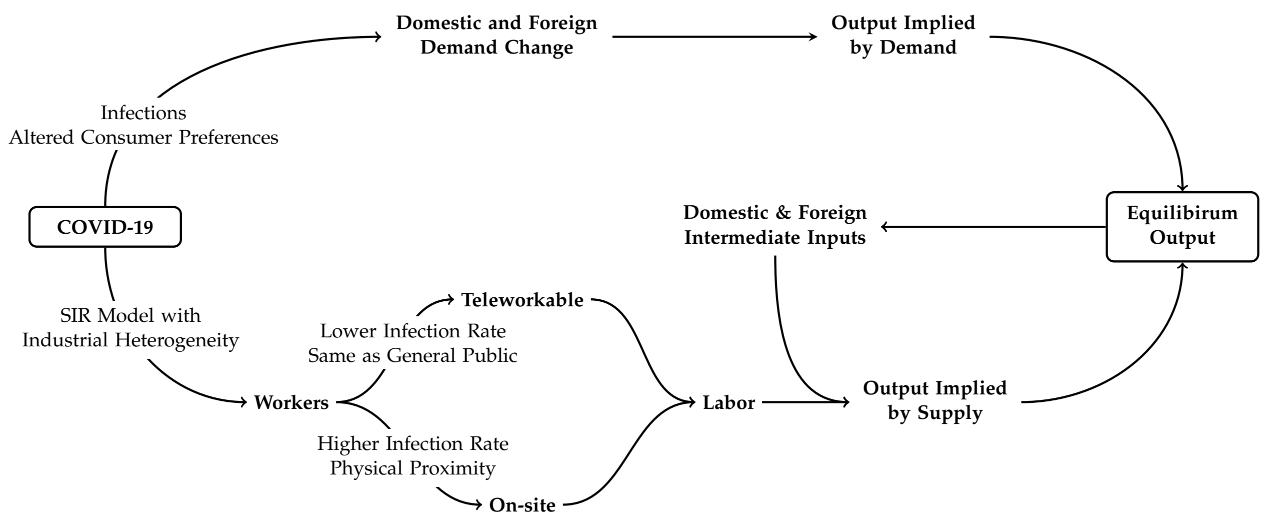
i Exports of final goods: In EMDEs where the pandemic is still ongoing, aggregate demand will not fully recover. Hence, the exports of AEs would not return to pre-pandemic levels.

ii Exports of intermediate goods: Intermediate inputs produced by the AEs would not be demanded as much because of weaker overall growth in EMDEs.

iii Imports of intermediate goods: Intermediate inputs produced by EMDEs for industries in AEs would fall short of meeting total demand in AEs as the supply in EMDEs is subject to domestic and international supply shocks due to the pandemic.

iv Imports of final goods: The goods and services produced and sold by EMDEs to AEs would decline as well.

Figure 3: Modelling the effects of the COVID-19 shock in a multi-country multi-sector open economy



NOTES: This figure presents a schematic of our model to illustrate the effects of the COVID-19 shock in a multi-country multi-sector open economy framework. 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 A.2 for the list of essential industries) and the workers in the non-essential sectors stay at home. Thanks to strict lockdown restrictions, the infection rates are lowered for almost everyone. The lockdowns affect the supply channel directly via workers as well as the disruptions in the global supply chain. They affect the demand channel by mitigating the number of infected individuals, which in turn change the consumption profiles.

Figure 3 summarizes our 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 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. We model demand as a reduced form function where demand deviates from its normal pattern as a function of the number of infected people. Hence, the demand profile changes depending on the infection levels in the population, which, in turn, is mitigated by the lockdown decisions and vaccines.

3.1 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. 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 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:

$$\Delta S_t = -\beta S_{t-1}\frac{I_{t-1}}{N} \quad (1)$$

$$\Delta R_t = \gamma I_{t-1} \quad (2)$$

$$\Delta I_t = \beta S_{t-1}\frac{I_{t-1}}{N} - \gamma I_{t-1} \quad (3)$$

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

[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.

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. 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 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:

$$L_i = TW_i + N_i. \tag{4}$$

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,:

$$N_0 = N_{NW} + \sum_{i=1}^{K} TW_i. \tag{5}$$

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:

$$\beta_i = \beta_0 \text{Prox}_i \qquad \text{for} \quad i = 1, \ldots, K \tag{6}$$

where Prox_i is the proximity index for industry i that we obtain from O*NET database.[10] It is plausible to think that the decline in demand during COVID-19 in a particular industry would lead to a decline in proximity (see Eichenbaum et al. (2020)). Nevertheless, we do not incorporate this in our model and take the proximity rates as exogenous.

[10] https://www.onetcenter.org/database.html. See Section 4.1 for the details on this measure.

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:

$$\Delta S_{0,t} = -\beta_0 S_{0,t-1} \frac{I_{t-1}}{N} \tag{7}$$

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:

$$\Delta S_{i,t} = -\beta_i S_{i,t-1} \frac{I_{i,t-1}}{N_i} - \beta_0 S_{i,t-1} \frac{I_{t-1}}{N} \tag{8}$$

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

$$\Delta R_{i,t} = \gamma I_{i,t-1} \tag{9}$$

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

$$\Delta I_{i,t} = -\left(\Delta R_{i,t} + \Delta S_{i,t}\right) \tag{10}$$

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 $(\beta_0 + \beta_i)$. [11] For a non-working individual, this parameter is only β_0. Using Equation (6), we impose:

$$\beta_0 \frac{N_0}{N} + \sum_{i=1}^{K} (\beta_0 + \beta_i) \frac{N_i}{N} = \beta_0 + \beta_0 \sum_{i=1}^{K} \text{Prox}_i \frac{N_i}{N} = \beta \tag{11}$$

[11] A report by DISK labor union in Turkey claims a three-fold increase in infection rates among workers: http://disk.org.tr/2020/04/rate-of-covid-19-cases-among-workers-at-least-3-times-higher-than-average/. Here, we take a moderate stance and set the rate to be 2 times higher on average for the workers.

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

$$\beta_0 = \beta\left(1+\sum_{i=1}^{K}\frac{\text{Prox}_i N_i}{N}\right)^{-1}. \tag{12}$$

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

$$\Delta\mathcal{I}_t \quad = \quad F\mathcal{I}_{t-1} - \gamma\,\mathbb{I}_{\mathbb{K}}\,\mathcal{I}_{t-1} \tag{13}$$

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 $F^{-1}v$. Given the initial size of the groups based on employment numbers, the eigenvalue would approximately correspond to the normalization present in Equation 12.

3.2 The Effects of Infection Dynamics on the Production

As shown in the lower half of Figure 3, the pandemic affects production through labor supply and inputs. First, the labor supply declines due to those workers who get infected or put under lockdown by the governments. Second, decreased labor force in a country's trade partners result in reduced availability of intermediate inputs, albeit with a delay. The combined impact of the labor supply and intermediate inputs result in a decline in production through the supply side in the short run.

In the short run, firms have little time to adjust for the shocks. We assume a Leontief production function to capture these short run dynamics. In this framework, countries need to combine inputs in fixed ratios to produce a single unit of output. These ratios are determined by the present technology and the combination of inputs available in the country. All these inputs, including labor, are assumed to be complementary to each other in the short run (see Atalay (2017) and Baqaee and Farhi (2020a)). For instance, to produce a single unit of an automobile, after setting up its factory for a specific type of production process, a car company requires inputs in certain ratios such as 4 workers, 100 kilograms of steel, 4 tires, 4 seats, a microprocessor, a car battery, etc. (These numbers are for illustrative purposes). Thus, disruptions in certain countries and industries during the pandemic regarding the production of any of these inputs may spill over to other sectors and countries through input linkages. This amplification mechanism allows us to estimate the full impact of the pandemic in the worst case scenario where unvaccinated countries experience supply shocks.

Focusing on periods of natural disasters, Barrot and Sauvagnat (2016) show that the Cobb-Douglas production function that allows for among inputs may break down in the short run when the existing value chain relationships make it more difficult to substitute among inputs or among different suppliers in the short run. Furthermore in our set up of 35 industries, sectors that produce similar products are already aggregated into a common sector. Hence, any potential substitution among similar inputs within a given industry is implicitly present in our framework. The Leontief production function that we utilize implies that any remaining substitution between more distant industries is not feasible and not allowed in our modelling. This argument is in line with the 66-sector input-output model of Baqaee and Farhi (2020a,b) where the authors use an elasticity of substitution among inputs that is close to 0 following Atalay (2017). Utilizing input-output data from the US, Atalay (2017) obtains an elasticity of input substitution that is at most 0.2. Evidence for complementarity among inputs is further reinforced by Boehm et al. (2019) who focus on the Japanese earthquake of 2011 and find a one-to-one impact in the US affiliates of the Japanese multinationals. This implies an elasticity of substitution close to zero. Carvalho et al. (forthcoming) extend this analysis further to investigate the propagation of the Japanese earthquake onto indirectly connected firms. Our 65-country and 35-sector framework allows for such non-linearities as well, in order to capture the full amplification of disruptions in supply chains. Specifically, we not only capture how the COVID shock in one country or "sector x" spills over to another "sector y" that has an immediate trade relationship with sector x, but we also capture how consequent changes in sector y affect other sectors that it is connected through input-output linkages.

Let's denote the set of industries that are used by industry i in country c with $\mathscr{S}_{ci}$. The industry subscript j refers to another industry. We can write the unit output requirement in industry i in country c in terms of its inputs as:

$$y_{ci} = \left\{ l_{ci}, \{z_{j,ci}\}_{j \in \mathscr{S}_{ci}} \right\} \tag{14}$$

where l_{ci} denotes the unit labor requirement of industry i in country c and $z_{j,ci}$ denotes the amount of intermediate inputs that should be used in industry i from industry j to produce a single unit of i. Going back to our automobile example, with 400 workers, 10 tons of steel, 400 tires, 400 seats, 100 microprocessors and 100 batteries, a car company would be able to produce 100 automobiles. Increasing the number of tires to 500, or number of workers to 1000 would not change the number of automobiles produced. However, in the long run, given an increase in wages, the car company may want to readjust its manufacturing technology to require less workers. We focus on the short-run effects, where this mechanism is absent.

Formally, with these assumptions, we can write the output in industry i in country c as a Leontief production function:

$$Y_{ci} = \min \left\{ \frac{L_{ci}}{l_{ci}}, \left\{ \frac{Z_{j,ci}}{z_{j,ci}} \right\}_{j \in \mathscr{S}_{ci}} \right\} \tag{15}$$

where L_{ci} captures the amount of labor allocated by country c to industry i and $Z_{j,ci}$ denotes the amount of output of industry j used in industry i of country c. The j could capture an industry from another country as well a domestic industry. In our car company example, one of js would correspond to tires, that can either be supplied domestically or internationally. It is important to note that this production function also captures the network effects. In particular, taking the minimum in Equation 15 requires considering all inputs to the industry.

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

$$L'_{ci} = (N_{ci} - I_{ci}) + TW_{ci} \left(1 - \frac{I_{c0}}{N_{c0}} \right) \tag{16}$$

where N_{ci} is the number of on-site workers in industry i in country c, I_{ci} is the number of infected workers among on-site workers, and TW_{ci} is the number of at-home workers (i.e., those who can work remotely) in industry i. The ratio I_{c0}/N_{c0} 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. Overall changes in output in country c in industry i will be Y'_{ci}. Hence, we denote the change in the total sectoral output level with:

$$\hat{Y}_{ci} \equiv \frac{Y'_{ci}}{Y_{ci}} = \min \left\{ \frac{L'_{ci}}{L_{ci}}, \left\{ \frac{Z'_{j,ci}}{Z_{j,ci}} \right\}_{j \in \mathscr{S}_{ci}} \right\} = \min \left\{ \hat{L}_{ci}, \left\{ \hat{Z}_{j,ci} \right\}_{j \in \mathscr{S}_{ci}} \right\}. \tag{17}$$

Continuing with the example of the car manufacturer above, let's assume that the car company produces 100 automobiles a day. Let's further assume that out of 400 workers, 50 of them got infected and cannot report to work. Moreover, the tire company who supplies for this car company was also affected by the pandemic and could only produce 300 tires. Suppose all the other inputs remain at their normal levels. In this example, the automobile production decreases to 75 that day because the binding constraint (minimum) is the available tires for production.

The shocks propagate through input-output linkages. In our model, we assume that the production is daily. 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. We assume that the propagation of an imported input shock is not simultaneous, assuming that it would take some time for the disrupted input to arrive at the production location. To capture the travel time, we use the intermediate inputs that are produced two weeks prior to the production of the final good. From a practical point of view, incorporation of this two-week delay eliminates the estimation of a rather complicated system of 65 countries with simultaneous trade flows. Instead, we take the supply shock in a particular country as given and analyze its impact on the other countries rather than a simultaneous feedback between the countries.

3.3 The Effects of Infection Dynamics on Demand

During the pandemic period, consumer priorities and preferences change dramatically due to many reasons. First, there is the fear of infection which leads to voluntary social distancing. The fear of infection is related to the number of infected individuals in the society. In order to minimize the risks of getting infected, individuals alter their behavior and change their consumption patterns, such as refraining from public events, restaurants or malls. These pandemic-related changes in demand patterns affect the sectors that require closer proximity more than the others. There is also the fear of transmitting the disease to others. Individuals may choose to minimize their social interactions with a precautionary motive, in order to avoid infecting others inadvertently. In addition to the fear factor, there is uncertainty about the duration of the pandemic and the related economic outlook which affects aggregate demand. Aggregate expenditure typically declines during times of elevated uncertainty.

In order to capture the change in demand patterns during the pandemic, we consider two demand profiles for each industry, one corresponding to normal times and the other one corresponding to the brunt of the pandemic. We determine the demand for each industry during normal times from the consumption data in national accounts. As for the COVID-19 period, we estimate changes in the expenditure levels during the pandemic using credit card spending data. For the sectors where we do not have the credit card data, we use industry reports and expert opinions.[12] The progression of the pandemic and the normalization of demand as the pandemic fades is a gradual process. In order to capture this steady adjustment, we assume that the individuals move between these two profiles smoothly, as a function of the number of infected individuals in the country.

The demand structure we employ here is similar to Çakmaklı et al. (2020). The demand is a function of the number of infections. The number of infections is proportional to the population of the given country. The severity of infections is measured by the incidence rate out of 100,000 individuals

[12] Expected final demand changes and the resources we use in this estimation are presented in Table A.1 of the Appendix.

to make the numbers comparable across countries. We measure the infections as a function of $I/\bar{I}$ where $\bar{I}$ is proportional to the population.

We express the utility function of a representative agent who maximizes her utility by optimally allocating her income on the expenditure of different goods from each industry. Following the literature, (see, for example Acemoglu et al. (2012), among others), we assume that the representative agent has a Cobb-Douglass utility function:

$$U(e_1, \ldots, e_K) = \prod_{i=1}^{K} e_i^{\alpha_i}, \tag{18}$$

with e_i denoting the level of expenditure in industry i, and α_i representing the share of industry i in total expenditure with $\sum_{i=1}^{K} \alpha_i = 1$ and $0 < \alpha_i < 1$ for all $i = 1, \ldots, K$. The utility function in Equation 18 incorporates a budget restriction which implies that the total income (w) equals total expenditure, i.e., $w = \sum_{i=1}^{K} e_i$. With the Cobb-Douglass utility function, α_i determines the share of industry i in the expenditure so that $e_i = \alpha_i w$ for $i = 1, \ldots, n$.

During times of the pandemic, demand patterns change. For the sake of simplicity, we assume that changes in demand come from two channels. First, the pandemic changes preferences and priorities, which implies an adjustment in sectoral weights. Second, sectoral demand also changes due to the income effect, which is a function of aggregate output (demand). Consequently, these two effects lead to a change in the expenditure structure. To capture this change, we construct a ratio, $\hat{e}_i(I/\bar{I})$, that is directly linked to the number of active infections. This shows the expenditure in industry i when the infection level is $(I/\bar{I})$, relative to the expenditure during normal times. During the pandemic, the expenditures change as function of infections:

$$\hat{e}_i(I/\bar{I}) \equiv \frac{e_i'}{e_i}$$

As the demand ratio approaches 1, it signals that the number of infections decline and demand normalizes. As the demand ratio approaches 0, it reflects that the number of infections increase and demand shrinks due to the pandemic. Using this ratio, we write the limiting cases for $\hat{e}_i(I)$. For small I (i.e., $(I/\bar{I}) \leq 0.1$), $\hat{e}_i(I) = 1$. Thus, for a small number of infections, demand remains intact such that the ratio of demand during normal times equals demand during the pandemic. For large I, which corresponds to the peak of the pandemic, $\lim_{I\to\infty} \hat{e}_i(I/\bar{I}) \equiv \bar{e}_i$. If the demand for an industry i completely collapses during the pandemic (e.g., the airline industry), then $\bar{e}_i = 0$. If there is no change in demand during the pandemic (e.g., food industry), then, $\bar{e}_i = 1$. We assume that $\bar{e}_i$ is the utmost demand change in a particular sector that is globally valid under a fully developing pandemic. In this framework, we assume that the ratio of demand, $\hat{e}_i(I/\bar{I})$, smoothly fluctuates between 1 when nobody is infected and $\bar{e}_i$ when a very large number individuals get infected using the following functional form:

$$\hat{e}_i(I/\bar{I}) = \begin{cases} 1 & \text{if} \quad (I/\bar{I}) \leq 0.1 \\ \bar{e}_i \frac{1+(I/\bar{I}-0.1)}{\bar{e}_i+(I/\bar{I}-0.1)} & \text{if} \quad (I/\bar{I}) > 0.1 \end{cases} \tag{19}$$

It is important to note that the overwhelming uncertainty about the course of the virus may suppress economic confidence for a longer period of time. To the extent that the actual normalization is slower than what is implied by Equation (19), we err on the conservative side by assuming a faster recovery.

In our simulations, we let the pandemic take its course in each country separately and use the number of infected patients in each country as the determinant of demand change in a particular industry. Given the smooth transition function, we model the changes in the final demand levels using $\hat{e}$ values.

Let's illustrate the expenditure of country m in industry i with e_{mi}. Consumers in country m can consume both domestic and imported goods in industry i. We denote the goods coming from industry i of country c to be consumed in country m by $e_{mi,c}$. Consumers in country m can consume both domestic and imported goods in industry i. Denote goods in industry i coming from any country c to be consumed in m by $e_{mi,c}$. Then:

$$e_{mi} = \sum_c e_{mi,c}$$

Hence, the output of industry i of country c that is consumed as the final good globally is:

$$F_{ci} = \sum_m e_{mi,c}$$

During the pandemic, the demand for these goods will also drop by $\hat{e}_i(I_m/\bar{I}_m)$. Hence, the final good consumption level changes to: final good changes to:

$$F'_{ci} = \sum_m e_{mi,c}\hat{e}_i(I_m/\bar{I}_m) \tag{20}$$

where F'_{ci} represents the revised demand during the pandemic.

In order to account for the 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 $\mathbf{A}$. 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. Using matrix notation, we decompose the total output into intermediate and final usage as:

$$Y = \mathbf{A}Y + F \tag{21}$$

Here, Y denotes the output vector and F denotes the final demand vector whose entries are Y_{ci} and F_{ci} respectively.[13] Therefore, we can solve for the output to satisfy the final demand as:

$$Y = (\mathbf{I} - \mathbf{A})^{-1}F \tag{22}$$

From this equation, we write the total output of country c as:

$$Y_c = \sum_{i=1}^{n} Y_{ci} \tag{23}$$

Using the demand change from Equation 20 during the infection, the demand channel changes the output as:

$$Y' = (\mathbf{I} - \mathbf{A})^{-1}F'(I). \tag{24}$$

[13] With a slight abuse of the notation, we drop the subscript to refer to vectors or matrices of the variables.

where Y represents the output and $F'(I)$ represents the vector of demand as a function of the number of infections, I. Relative change in the output, is therefore,

$$\hat{Y} = \frac{(\mathbf{I} - \mathbf{A})^{-1} F'(I)}{(\mathbf{I} - \mathbf{A})^{-1} F} \tag{25}$$

where the fraction represents element-by-element division.

3.4 Equilibrium

In equilibrium, production declines by the largest magnitude that is implied by either the supply or the demand sides. In other words, during the pandemic, we expect the change in the output vector to be:

$$\hat{Y}^{\text{EQ}} = \min\left(\hat{Y}^{\text{Supply}}, \hat{Y}^{\text{Demand}}\right) \tag{26}$$

where min represents element by element minimum function for two vectors, that is, $\hat{Y}^{\text{Supply}}$ and $\hat{Y}^{\text{Demand}}$.

The change in value-added of the output in industry i in country c under the pandemic is calculated from adjusting the initial shares of value added in each industry during normal times by output under COVID shock as:

$$\widehat{\text{VA}} = \hat{Y}^{\text{EQ}} \tag{27}$$

Therefore, the change in GDP of the country c under the pandemic can be obtained through:

$$\widehat{\text{GDP}}_c = \frac{\sum_{i=1}^{n} \widehat{\text{VA}}_{ci} \text{VA}_{ci}}{\sum_{i=1}^{n} \text{VA}_{ci}} \tag{28}$$

We calculate the output on a daily basis. Therefore, the yearly declines we report are the average of all the daily declines.

4 Data and Calibration

4.1 Data

We use OECD ICIO Tables. 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.

To calculate the industry level teleworkable share and the physical proximity measures shown in the lower part of Figure 3, 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 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 A.1 of the Appendix.

We obtain employment by sector data from OECD's Trade in employment (TiM) database Horvàt et al. (2020). For 14 countries that have missing data in TiM, we obtained the total employment from the World Development Indicators database of the World Bank. We use the value added per employer information from the closest geographical aggregation and use this information to distribute the employment to industries for these 14 countries.

4.2 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 [14], the median recovery time for the mild cases is approximately two weeks. The mean recovery time 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 datasets to trace this variation across countries and across time.[15] For each country, we estimate a SIR model described in (1)-(3) 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 Cakmakli

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

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

and Simsek (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. (2020); 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 (2020) allow for time variation in the rate of infection. The advantages of the time-varying parameters SIR model of Cakmakli and Simsek (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 November 2020. Consequently, we use the parameter values, country-specific β_t, and γ estimated as of the end of November 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 A.3 of the Appendix.

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 A.2 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.

4.3 Demand Shock

Turning to the demand side that is depicted in the upper half of Figure 3, we use publicly available credit card spending data to calculate the estimated demand changes during the pandemic in each industry. To that end, we use data from Turkey, which is a representative EMDE. We particularly choose an EMDE to capture the demand changes during the pandemic because the demand effect is particularly pronounced for the unvaccinated countries. The demand effect essentially disappears in AEs once the vaccine becomes available. Nevertheless, as a robustness check, a comparison with the US credit card data reflects that the changes in demand patterns are rather similar between EMDEs and AEs.[16] Armed with this evidence, we assume that the changes in demand arising from the "fear factor" can be generalized around the globe.

The list of OECD ISIC industries, and the expected changes are listed in Table A.1 of the Appendix along with explanations. The data on credit card spending is not available for the full set of sectors. In this case, we use projections based on sectoral reports, experiences of other countries and historical data on the specific sector as well as the whole manufacturing sector. While the aggregate demand shock is computed as 23% when we focus only on the sectors with credit card spending data, it is 16% when we consider the full set of sectors. Therefore, our sensitivity analysis indicate little or no change in our qualitative findings.

Demand is a function of the number of infections and this relationship is governed by the $\bar{I}$ parameter of Equation 19 that determines the speed at which the public approaches the maximum decline in demand. We select this parameter to be country specific. In particular, we set $\bar{I}$ = population/2000 to capture a relevant range for the number of infections (see below for our simulations). This limit implies that the utility function returns to normal times if the number of infections remain below population/20000. This approach is consistent with the levels observed dur-

[16]Considering Turkey and the US as representative EMDE and AE countries respectively, we compare their credit card spending data, focusing on two industry groups, namely "Accommodation," and "Gasoline Stations." We obtained the underlying data from the Central Bank of the Republic of Turkey and the Bureau of Economic Analysis that group weekly credit card transactions into various expenditure categories. To avoid a misleading comparison between Turkey and the US, we consider these two expenditure categories that are defined in the same manner by these agencies. To illustrate, two weeks after Turkey and the US were hit by COVID-19 pandemic, the weekly estimates of percentage differences from the typical spending suggest rather similar demand patterns in these countries: The corresponding declines in the accommodation sector for the week of March 25 are 40.1% for Turkey and 43.6% for the US. In the gasoline industry, the numbers are 81.1% decline in Turkey and 85.6% decline in the US. Thee corresponding estimates for the week of April 1 are -41.5% in Turkey and -46.8% in the US for Accommodation; -82.2% in Turkey and -85.2% in the US for the gasoline industry respectively.

ing the summer of 2020, when the number of infections decreased and the consumption rebounded back to relatively normal levels as observed from the credit-card spending data in Turkey and the US.

4.4 Supply Shock

Recall from Equation 17 that the supply is affected from the inputs during the pandemic with the following relationship:

$$\hat{Y}_{ci} = \min\left\{\hat{L}_{ci}, \left\{\hat{Z}_{j,ci}\right\}_{j\in\mathscr{S}_{ci}}\right\}.$$

where $\hat{Y}_{ci}$ denotes the change in supply, "$'$" sign denotes the levels of the inputs and the output during the course of pandemic and $\mathscr{S}_{ci}$ represents the set of intermediate inputs used by industry ci.

We consider three different specifications to incorporate the supply shock. With the help of these alternative specifications, we highlight the importance of both labor and intermediate input channels as well as the amplification through domestic and international sectoral linkages.

In the first specification, we ignore potential interruptions in the delivery of intermediate inputs. Our goal is to solely focus on the decline in the final demand of EMDEs. The export demand in EMDEs can decline either through labor supply shocks due to infections and lockdowns or through final demand changes. Hence, labor is the only limiting factor on the supply side. This gives us the following relationship for the output implied by supply under the first specification:

$$\hat{Y}_{ci} = \hat{L}_{ci}. \tag{29}$$

Starting with the second specification, we incorporate the drag coming from the intermediate inputs channel into our calculations. In specification 2, we assume that the inputs are aggregated at the country level, wherever they come from, and then distributed to the specific industries within the country. This is akin to building national input-output matrices, such as the U.S. input-output matrices build by the Bureau of Economic Analysis (BEA). For instance, suppose the particular input is steel and the country in question is Germany. We assume that the total imported steel in Germany is distributed proportionately among the different industries in Germany, such as automotive and appliance, in accordance with demand conditions. Essentially, we impose that the firms within a country can adjust to an outside shock more easily and redistribute the inputs among themselves. With this assumption, a fixed proportion of industry j present in country c is allocated to industry i. We can write the fixed proportion term as:

$$r_{j,ci} \equiv \frac{\sum_x Y_{xj,ci}}{\sum_x \sum_k Y_{xj,ck}} \tag{30}$$

where $Y_{xj,ci}$ denotes the output of industry j produced in country x and exported to country c to be used in industry i. Therefore,

$$Z_{j,ci} = r_{j,ci} \sum_x \sum_k Y_{xj,ck} \tag{31}$$

During the pandemic, the available intermediate input from industry j in country c to be used in industry j changes to:

$$Z'_{j,ci} = r_{j,ci} \sum_x \sum_k \hat{Y}_{xj} Y_{xj,ck}. \tag{32}$$

Hence, the change in output in the second specification becomes:

$$\hat{Y}_{ci} = \min \left\{ \hat{L}_{ci}, \left\{ \frac{\sum_x \sum_k \hat{Y}_{xj} Y_{xj,ck}}{\sum_x \sum_k Y_{xj,ck}} \right\}_{j \in \mathscr{S}_{ci}} \right\}. \tag{33}$$

In effect, with this specification we keep track of the changes in the level of an industry within a country.

In the third specification, we utilize the inter-country inter-industry matrix. Here, we assume that supply shocks can also be specific to the importing sector. Going back to the example of German automotive industry and appliance industry, in this specification we assume that the steel inputs used in the automotive industry cannot be transferred to the appliance industry. Furthermore, if the imported steel for these two industries are coming from different countries, then the heterogeneity in the infection rates of those countries will come into picture. This specification is our most stringent case. Specifically, a particular input imported by industry j can be put into use only by industry i. Therefore, we can combine all the inputs that come from different countries, indexed by x, to be used in industry i to obtain:

$$Z_{j,ci} = \sum_x Y_{xj,ci}. \tag{34}$$

When supply shocks to intermediate inputs are industry specific, pandemic driven decline in imported inputs in each industry is:

$$Z'_{j,ci} = \sum_x \hat{Y}_{xj} Y_{xj,ci}. \tag{35}$$

Therefore, the output in this specification can be written as:

$$\hat{Y}_{ci} = \min \left\{ \hat{L}_{ci}, \left\{ \frac{\sum_x \hat{Y}_{xj} Y_{xj,ci}}{\sum_x Y_{xj,ci}} \right\}_{j \in \mathscr{S}_{ci}} \right\}. \tag{36}$$

In specifications 2 and 3, we use the minimum function, which is sensitive to outliers. To be on the conservative side and prevent these outliers from driving our results, we focus on sizable inputs. Therefore, when we calculate the minimum, we impose the following two filters: (i) *Filter small values*: We do not consider an input industry in the supply side if the value of that input is less than 10 thousand USD, daily. (ii) *Filter small industries*: For a given industry, we only consider input industries that constitute at least $(1/35)^{\text{th}}$ of the total inputs of that industry. We choose this threshold because we have 35 industries that are used as inputs.

The summary of these specifications is provided in Table 1. In our empirical analysis, we use these specifications under different vaccination scenarios to get a range of the economic impact in the absence of equitable vaccine distribution.

Table 1: Alternative Supply Shock Specifications

Specification	Demand Domestic and Foreign	Intermediate Inputs Domestic and Foreign	Health Shock
1	Yes	No	Labor
2	Yes	Yes	Amplification via Domestic I-O
3	Yes	Yes	Amplification via Inter-country / Inter-industry I-O

5 Results

In this section, we report the economic costs arising from cross country heterogeneity in vaccine availability under different scenarios. Table 2 summarizes these scenarios. In the first scenario, we assume that the AEs are fully vaccinated but the EMDEs are not vaccinated. The pandemic still persists in EMDEs and, yet, we do not impose any lockdowns. In scenario 2, we maintain the same vaccine allocation as in scenario 1, but add endogenous lockdowns, which are determined by the ICU capacities of countries. In scenario 3, we make the vaccine available in both AEs and EMDEs, distributed in a gradual manner. We assume a relatively slower vaccine distribution in EMDEs compared to AEs. For each of the 3 scenarios, the results are computed for all 3 specifications explained in Section 4.4.

Table 2: Vaccination Scenarios

Scenarios	AEs	EMDEs	Endo. Lockdowns
1	Immediate Vaccination	No Vaccination	No
2	Immediate Vaccination	No Vaccination	Yes
3	Fast Vaccination	Slow Vaccination	Yes

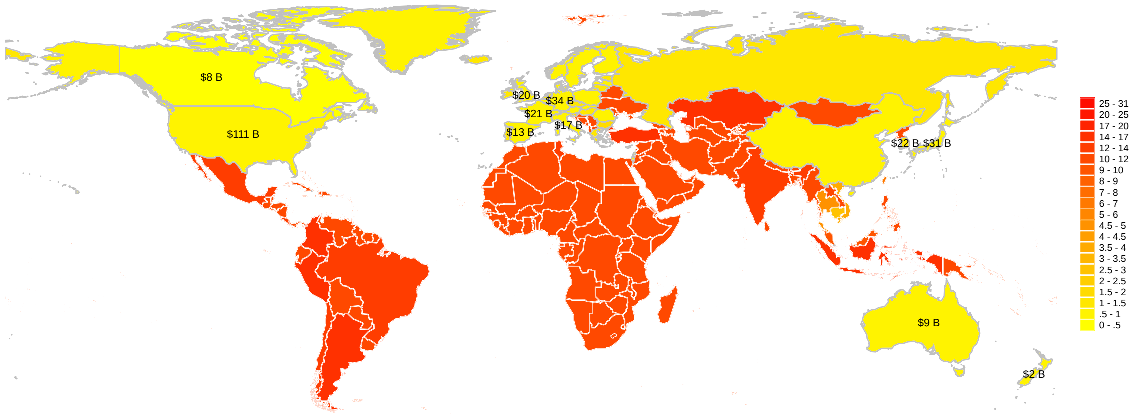
5.1 Scenario 1: Vaccination only in AEs, No Lockdowns in EMDEs

In this scenario, we assume that the pandemic is fully contained in AEs thanks to countrywide vaccinations. In EMDEs the pandemic evolves at its natural course in the absence of any lockdown measures and vaccines. Figure 4 displays the relative reduction in countries' annual GDPs —relative to the counterfactual of global vaccinations— under this scenario in percentage terms. As it is shown by the scale on the right, larger costs are indicated by the darker shades.

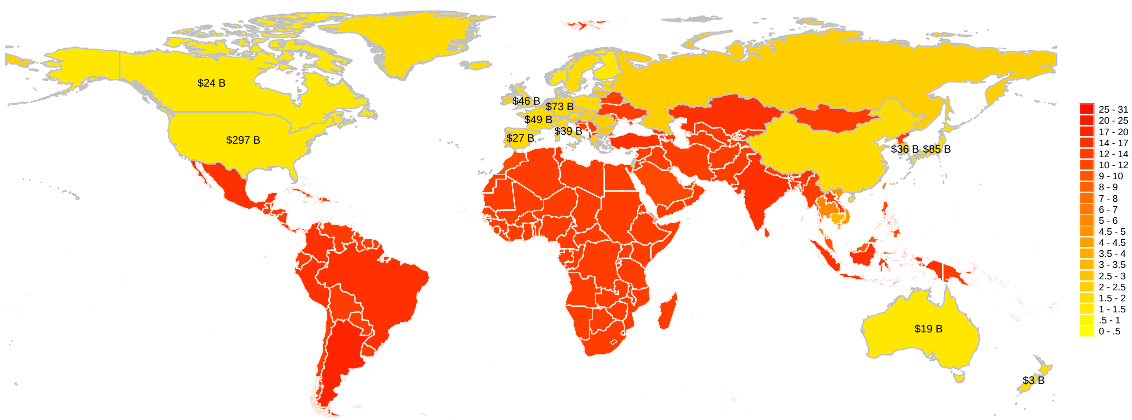
Figure 4 relays several critical messages. First, the severe domestic effects of the pandemic can be immediately noticed for the EMDEs which correspond to darker shades of red on the map. The overall negative drag is far more pronounced in all three specifications compared to AEs. In Morocco and Malaysia, for example, the economic costs amount to at least 9% of the GDP in specification 1 due to higher number of infections and higher R0 in these countries (Figure 4a). The striking finding

Figure 4: Relative Decline in GDPs under Scenario 1: No Lockdowns (%)

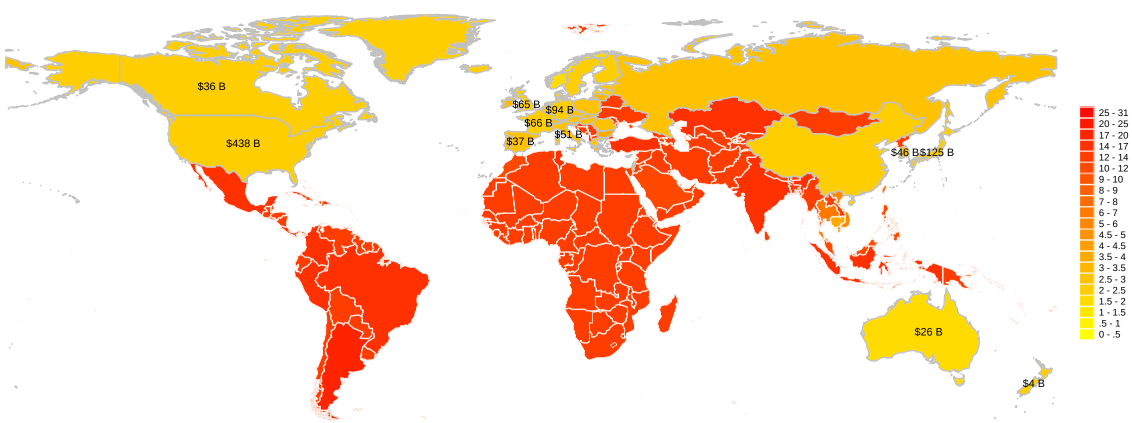
(a) Specification 1 – Only Demand



(b) Specification 2 – Country Level Intermediate Inputs



(c) Specification 3 – Country-Industry Level Intermediate Inputs



NOTES: This figure shows the relative reductions in GDP under Scenario 1, where the unvaccinated countries do not impose lockdowns. Vaccinated countries are highlighted with light gray borders. Shades of yellow correspond to relatively lower costs while shades of red correspond to higher relative losses. GDP loss values are shown on the map for a few selected countries.

is the fact that AEs still suffer from the economic costs of the pandemic even if they fully contain it at home. In specification 1, AEs are affected by the pandemic only through the decline in their exports to EMDEs. We note that the corresponding hit on their economies is on average 1%, where the size is proportional to the share of exports in each AE. For example, Russia as a major oil exporter is harder hit compared to other AEs due to the decline in oil demand during the pandemic.

When we incorporate the supply chains into our calculations, the overall costs increase dramatically. As we move from specification 1 to specifications 2 and 3, we note that the overall map gets darker, consistent with higher economic costs. In specification 2, the costs are still lower compared to specification 3 because we allow for more flexibility in distributing the imported intermediate goods across sectors of a given economy (Figure 4b). AEs are hit on average by %2 percent of their GDPs. For extensively open economies that heavily rely on trade such as Ireland, this reduction in GDP is as high as %2.5. In contrast, for relatively closed economies such as the US where the domestic demand is the major driver of the economy, this GDP loss is around %1.4.

In specification 3, the losses are higher because imported intermediate goods are country-sector specific and cannot be obtained from another country-sector (Figure 4c). In this setting, the GDP losses in AEs soar to %2.7 on average. For instance, the cost for the US is close to 438 billion USD and the cost for China is 47 billion USD under this specification.

The important takeaway from this analysis is that although non vaccinated EMDEs suffer the most, AEs will bear a non-negligable cost from the pandemic so long as an equitable distribution of the vaccines is not present. These costs are proportional to the extent of trade openness.

We present the monetary equivalent of these aggregate GDP losses for the world and AEs in terms 2019 USD in the first four rows of Table 3.As shown in rows 1-3, under scenario 1, costs incurred by AEs vary from 509 billion USD to 1.6 trillion USD, where AEs might bear more than 37 percent of the global costs. Rows 5-7 show the relative declines as a percentage of GDP. Accordingly, the world GDP declines by 4.9% and the GDP of AEs declines by 2.7%.

Table 3: Total Cost for the World, AEs and EMDEs in terms of 2019 USD (billions)

	Scenario 1			Scenario 2			Scenario 3		
	(1)			(2)			(3)		
	Spec. 1	**Spec. 2**	**Spec. 3**	**Spec. 1**	**Spec. 2**	**Spec. 3**	**Spec. 1**	**Spec. 2**	**Spec. 3**
	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
(1) World	2,946	3,768	4,273	1,479	4,297	6,144	1,844	3,287	3,763
(2) AEs	509	1,144	1,589	204	1,287	2,584	399	1,491	1,855
(3) EMDEs	2,437	2,625	2,685	1,275	3,009	3,561	1,445	1,796	1,908
(4) Share of AEs (%)	17.3	30.4	37.2	13.8	30.0	42.0	21.7	45.4	49.3
				Relative Declines					
(5) World	3.81	4.87	5.53	1.91	5.56	7.94	2.38	4.25	4.87
(6) AEs	0.75	1.68	2.33	0.30	1.89	3.79	0.59	2.19	2.72
(7) EMDEs	12.06	12.99	13.29	6.31	14.89	17.62	7.15	8.89	9.44

NOTES: This table presents total economic cost associated with COVID-19 pandemic for the World, AEs, and EMDEs calculated under three scenarios. In the first scenario, we assume that the pandemic is fully contained in AEs thanks to universal vaccinations, whereas in EMDEs the pandemic evolves at its natural course in the absence of any lockdown restrictions and vaccines. The second scenario is similar to the first one with the exception of endogeneous lockdowns in EMDEs that impose multiple 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 third scenario, AEs and EMDEs follow two different vaccination calendars and can implement lockdowns if required. We estimate total economic cost of each of these scenarios under three different specifications: In specification 1, the countries are affected only through the changes in final demand in the world; In specification 2, the countries are also constrained by the supply of intermediate goods by the foreign countries, and the substitution of intermediate goods across sectors and countries is allowed; In specification 3, the countries are still constrained by the supply of intermediate goods by the foreign countries (as in specification 2), and the substitution of intermediate goods is allowed only across the imported countries.

5.2 Scenario 2: Vaccination only in AEs, Endogeneous Lockdowns in EMDEs

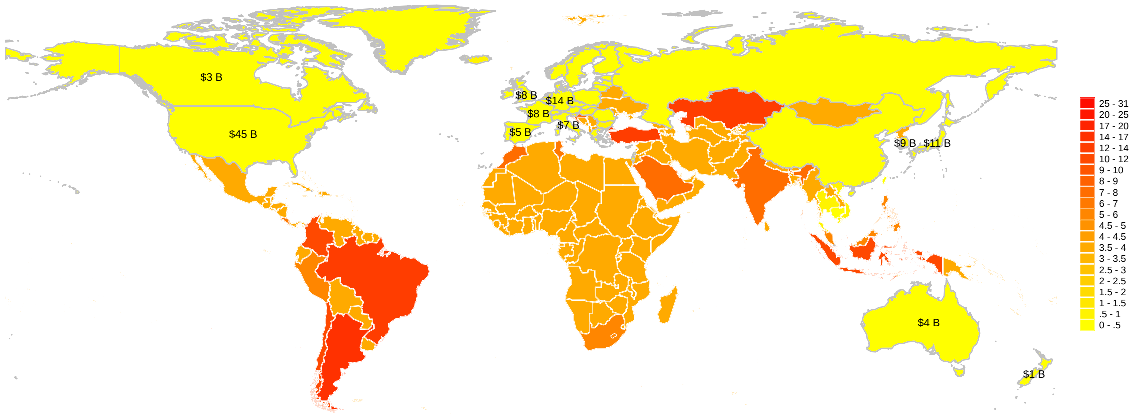
The second scenario is similar to the first scenario with the exception of endogenous lockdowns in EMDEs. In this scenario, the countries impose multiple lockdowns when the number of COVID-19 patients that require intensive case units (ICUs) exceed the number of ICUs that are reserved for COVID-19 patients. Lockdowns result in a more substantial labor shock because only workers in 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 number 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. Figure 5 displays the relative reductions in countries' annual GDPs under this scenario in percentage terms (The numerical estimates for AEs are reported in Table A.4).

As we move from the first scenario to the second scenario, we note that total costs decline for specification 1 (column 1a vs. 2a in Table 3) and increase for specification 2 (column 1b vs. 2b in Table 3). On the one hand, the lower number of infections in EMDEs improve their export demand, contributing to lower costs (specification 1). On the other hand, the lockdowns in EMDEs limit production and hence restrict available imports to AEs, contributing to higher costs (specification 2). Within Scenario 2, we note that the overall costs increase as we move from specification 1 to specification 3, similar to scenario 1 as shown in Figure 4. When we move to the last specification, AEs are also hit more fiercely like EMDEs (Figure 5c). In this case, the cost of the pandemic to the AEs is as high as 4.1% on average, which reaches 6.5% for the most open countries such as Singapore. In terms of 2019 USD, these costs amount to a total loss ranging from 0.2 to 2.6 trillion USD for the AEs depending on the specification (column 2a-c, row 2). AEs bear 14% to 42% of this cost. [17]

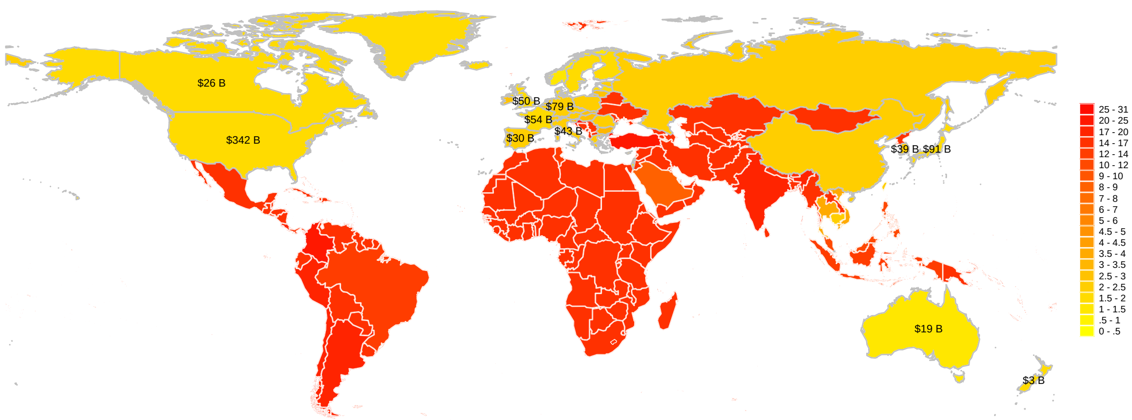
[17] Table 3 uses a conservative setting where we filter out small industries from our calculations as explained at the end of section 4.4. As a robustness check, if we bring these small industries back into our calculations –i.e., consider input industries even if their share is lower than 2.85%– the overall costs are higher. Indeed, total global costs reach 9.2 trillion USD under scenario 2, specification 3. AEs bear up to half of these global costs.

Figure 5: Relative Decline in GDPs under Scenario 2: Endogeneous Lockdowns (%)

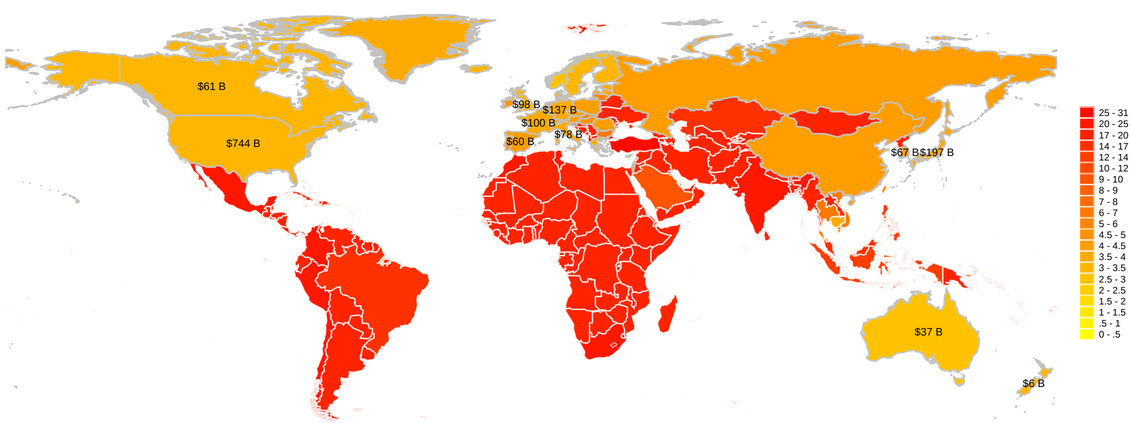
(a) Specification 1 – Only Demand



(b) Specification 2 – Country Level Intermediate Inputs



(c) Specification 3 – Country-Industry Level Intermediate Inputs



NOTES: This figure shows the reductions in relative GDP under Scenario 2, where we model endogenous lockdowns in unvaccinated countries. Shades of yellow correspond to relatively lower ratios and shades of red correspond to higher relative losses. Vaccinated countries are highlighted with light gray borders. GDP loss values are shown on the map for selected countries.

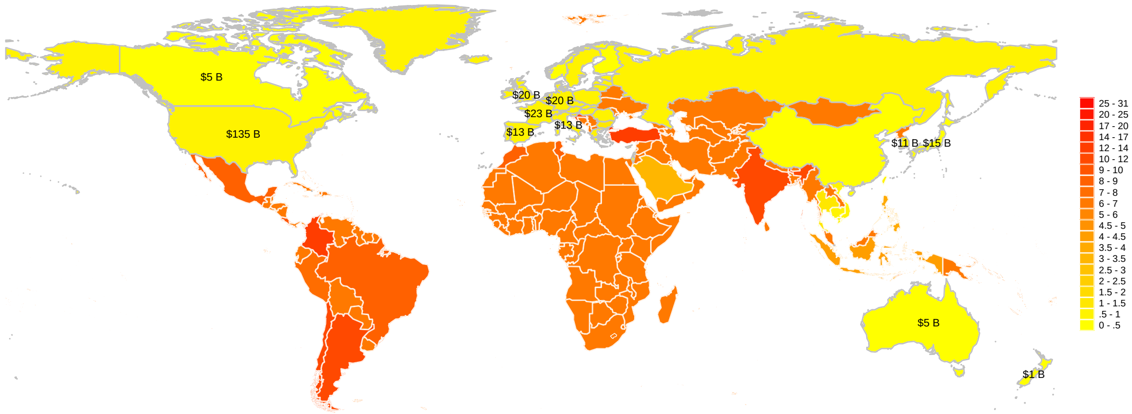
5.3 Scenario 3: Gradual Vaccination in EMDEs and in AEs, Endogenous Lockdowns in EMDEs and AEs

The final scenario aims to replicate the actual vaccination plans in real life more closely. Under this scenario AEs and EMDEs follow two different vaccination calendars. Specifically, 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 2 apply in scenario 3 as well. Technically, AEs can be put under lockdown in this scenario as well as EMDEs because the vaccination is not immediate in AEs. Figure 6 displays the relative reduction in countries' annual GDPs under this scenario in percentage terms. The numerical values for AEs are reported in Table A.4.

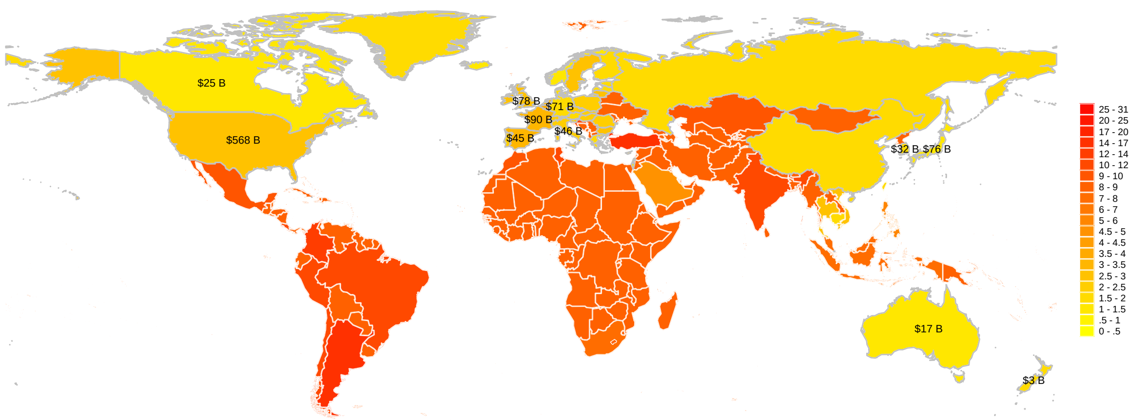
While the cost incurred by the advanced AEs is on average 2% for the second specification (Figure 6b), it increases to 3% on average under the third specification (Figure 6c). When we compare the total economic costs in Table 3, we observe that the costs increase for both AEs and EMDEs under the first specification as we move from scenario 2 to scenario 3 (column 2a vs. column 3a). This could reflect the slower vaccination schedule in AEs which increases their domestic costs as well as their export demand from EMDEs. As we move to the second and the third specifications, we observe a noticeable decline in the costs of EMDEs (row 3, column 3b and 3c) thanks to the availability of vaccine in these countries. The net impact on AEs is less trivial. On the one hand, there is an increase in their domestic costs due to the slower vaccination schedule at home. On the other hand, the faster recovery of the EMDEs support the growth in AEs through stronger exports and provision of intermediate goods. We note that these factors more or less offset each other for the second specification (row 2, column 2b vs. 3b). However, overall costs decline by over 700 billion USD for the AEs under the third specification (row 2, column 2c vs. 3c). This indicates that the positive impact coming from the faster recovery in EMDEs dominate the drag coming from slower vaccination in AEs. That being said, total global costs are still rather sizable (column 3, row 1), suggesting that a

Figure 6: Relative Decline in GDPs under Scenario 3: Gradual Vaccination (%)

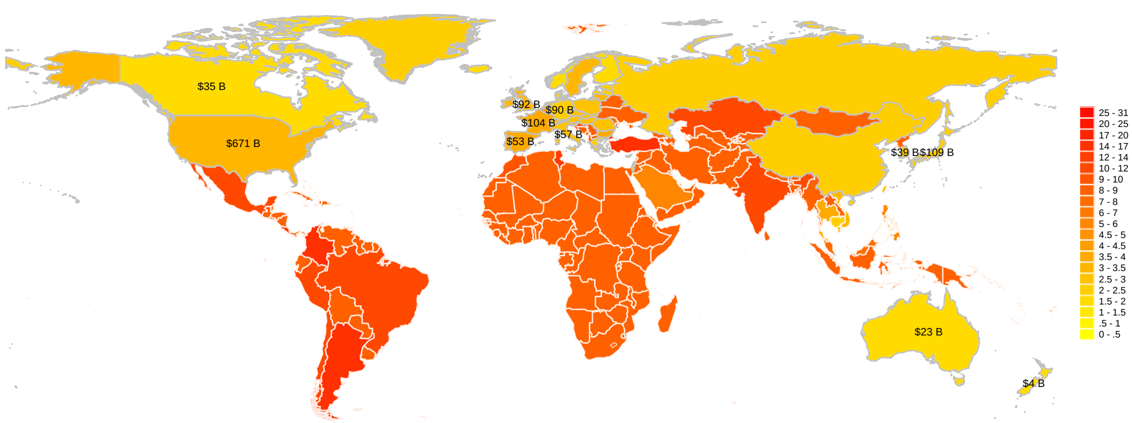
(a) Specification 1 – Only Demand



(b) Specification 2 – Country Level Intermediate Inputs



(c) Specification 3 – Country-Industry Level Intermediate Inputs



NOTES: This figure shows the reductions in relative GDP under Scenario 3, where we model the gradual vaccination. The shades of yellow correspond to relatively lower ratios and the shades of red correspond to higher relative losses. Vaccinated countries are highlighted with light gray borders. GDP loss values are shown on the map for selected countries.

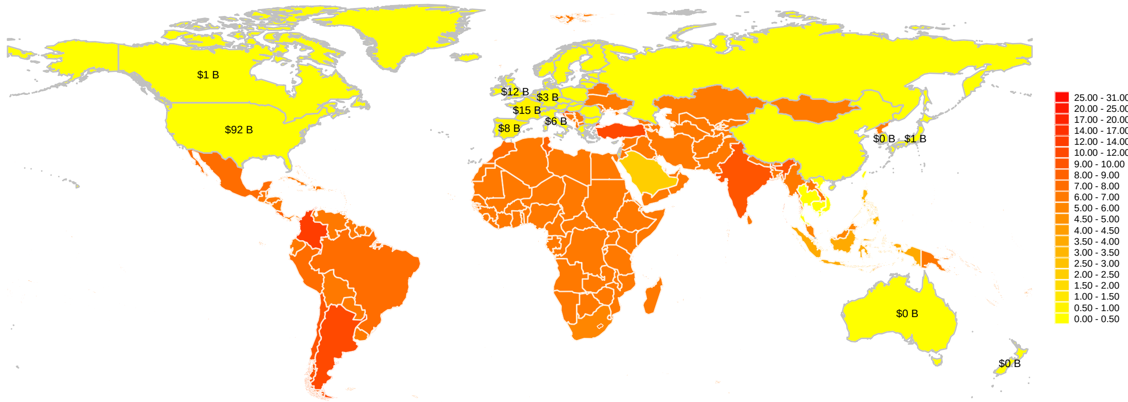
slow inoculation calendar such as the one depicted in scenario 3 is "too little, too late." Under this relatively more realistic scenario, the total cost for the world varies between 1.8 and 3.8 trillion USD depending on the availability of the intermediate goods. Strikingly, for the third specification, the absolute costs for the AEs is almost as high as the costs for EMDEs (column 3c, row 2 vs. row 3). Under all three scenarios and all three specifications, the GDP costs dwarf the 38 billion USD cost reported by Access to COVID-19 Tools (ACT) Accelerator partnership to manufacture 2 billion doses of vaccines to vaccine 20 percent of the global population by the end of 2021.

We consider the framework that is depicted in Figure 6c as the most realistic case that mimics the actual developments during the pandemic more closely. As of this writing in January 2021, there are delays in the implementation of the vaccine in AEs while such delays are far more noticeable for the EMDEs. Consequently, lockdowns and vaccinations are simultaneously observed both in AEs and EMDEs at the same time. Thus, the assumptions that are valid for this scheme seem to match the real world the best. Figure 7 filters out the costs that arise from international costs and only focuses on the domestic costs for this baseline specification. To that end, for a given country, we assume that the course of pandemic follows the same pattern as specification 3 of scenario 3 within the country. Meanwhile, the rest of the world is devoid of the pandemic, and, hence, is back to normal. We run this simulation separately for 65 countries. As expected, compared to Figure 6c, the losses are subdued. The costs borne by the EMDEs are not significantly different from those observed in Figure 6c because the bulk of the costs incurred by the EMDEs are domestically driven. For the AEs, however, we observe that the domestic costs are far less important compared to those that arise from international linkages. For the US, for example, while the domestic costs of the pandemic are 92 billion USD, when we add the costs due to trade linkages the toll rises to 744 billion USD. Countries like China, Australia, and New Zealand, which have the pandemic under control, have negligible domestic costs where most of their costs shown in Figure 6c are driven by international linkages. This figure corroborates the importance of international linkages in the disease toll.

5.4 Sectoral Heterogeneity

Recall from Figure 3 and our eloborate discussion of the model that the economic costs that we estimate for each country are calculated at the sectoral level. Sectoral aggregates yield the country-

Figure 7: Relative Decline if GDP due to Domestic Costs (% GDP)



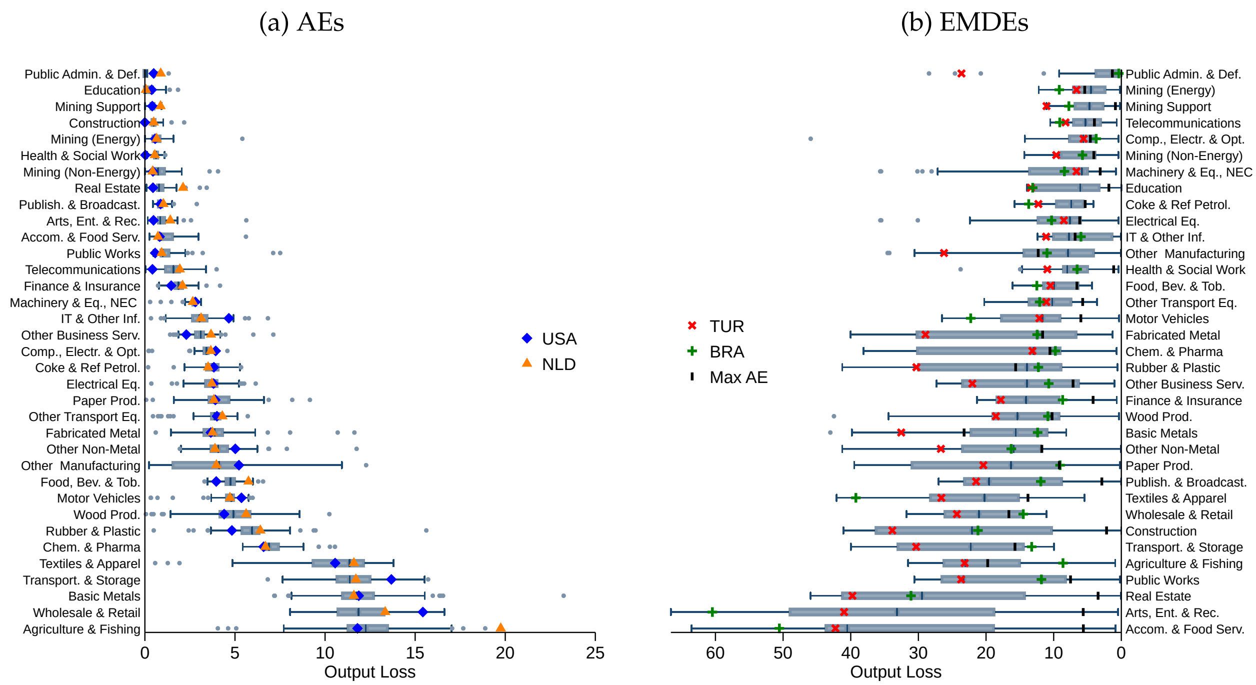
NOTES: This figure illustrates the domestic shocks under specification 3 of scenario 3. Here, we eliminated all the shocks associated with the pandemic except within a given country. We run our simulations for 65 countries separately. The shades of yellow correspond to relatively lower ratios and the shades of red correspond to higher relative losses. Vaccinated countries are highlighted with light gray borders. GDP loss values are shown on the map for selected countries.

level economic costs that we reported in the previous section. In this section, we shed light onto sectoral costs to illustrate the heterogenous impact of the pandemic on different sectors.

Sectoral heterogeneity can be driven by demand or supply factors. On the demand side, heterogeneity arises due to a disproportionate decline in demand for those goods that necessitate a violation of voluntary social distancing measures. The harder the pandemic hits a particular country, the more severe will be the decline in demand for these pandemic-sensitive sectors both for domestic goods and for exports. In addition to exports, trade exposures further amplify sectoral heterogeneity through supply of intermediate goods. The more severe the pandemic is, the more difficult it is for a country to produce the intermediate goods that are imported by other countries.

To illustrate the extent of cross-country heterogeneity in terms of sectoral economic costs, Figure 8 shows horizontal box-plots for the distribution of sectoral economic costs, measured by sector-level output loss in percentages across AEs (Panel (a)) and EMDEs (Panel (b)) using scenario 2 specification 3. In both panels, the main box of data for each industry shows the range of the 25–75 percentiles and the vertical line in this box corresponds to the median of the given sector-level distribution. On the y-axis of both panels, the sectors are ranked according to the median output loss in AEs. In the horizontal box-plot distribution of each industry, light blue dots mark the values that lie out of the given range. In both panels, we highlight two countries, namely the Netherlands and the United States in (a), and Turkey and Brazil in (b). These countries are chosen based on their trade openness to make the illustration more vivid. In addition, we show the maximum of AEs' values from Panel (a) on Panel (b) with a black mark to highlight the scale differences.

Figure 8: Cross-Country Heterogeneity in terms of Sectoral Economic Costs



NOTES: For a given sector listed in the y-axis, this figure illustrates horizontal box-plots of output loss across AEs, and EMDEs in Panel (a) and Panel (b), respectively, using scenario 2 specification 3. The sectors are ranked according to the median of output loss in AEs in both panels. We measure the sector-level economic costs as the percentage change in GDP of the corresponding country for a given sector during the pandemic relative to the counterfactual of global vaccinations. Sectors are classified following the 2-digit OECD ISIC codes and their broad definitions are given in Table A.1. In the horizontal box-plot distribution of each industry, light blue dots show the values that lie outside the corresponding range. Specifically, a value that is smaller than the lower quartile minus 1.5 times the interquartile range or larger than the upper quartile plus 1.5 times the interquartile range is marked by a light blue dot. In both panels, we highlight two countries each, namely the Netherlands and the United States in (a), and Turkey and Brazil in (b). In addition, we show the maximum of AEs' values from Panel (a) on Panel (b) with a red mark to highlight the scale differences.

Figure 8 illustrates the following key highlights:

(i) In terms of the overall economic costs between AEs and EMDEs, the sectoral costs are in accordance with the aggregated costs that we had reported at the country level. In particular, we observe that the sectoral costs borne by the EMDEs are significantly larger than AEs in each sector. The black mark in panel (b), which shows the maximum sectoral cost in AEs, is typically lower than the average sectoral costs borne by the EMDEs.

(ii) There is substantial sectoral heterogeneity within both AEs and EMDEs.

(iii) The sectoral costs for the EMDEs are the highest for those sectors that are more severely affected from the domestic pandemic conditions such as accommodation and food services, arts and entertainment, or real estate (Panel (b)). The economic costs in these sectors primarily reflect the decline in demand due to the fear factor in these countries where the pandemic is not contained.

(iv) When we turn to AEs that are vaccinated at a faster pace, we observe a different sectoral breakdown. Because the domestic drag from the pandemic is eliminated in these countries, the sectors that bear the highest economic costs are those that are more exposed to trade with unvaccinated countries such as textiles and apparel, transportation and storage, basic metals, wholesale and retail or agriculture and fishing. Recall from Figure 2 that all of these sectors are either sizable importers of inputs (shown by the node color) or they are connected to other industries that are major importers of inputs, such as the thick edge connecting the mining sector (which is mostly based in EMDEs) to basic metal sector. Thus, our findings are strongly supportive of our predictions from the discussion of Figure 2.

(v) Within the hardest hit sectors for AEs, wholesale and retail or transportation and storage are non-tradable sectors. A closer look into wholesale and retail sector reflects that this sector uses oil as a major input. As shown by the darkest node in Figure 2, Coke and Refined Petroleum sector relies heavily on imported inputs and a fair share of these inputs come from the unvaccinated countries, particularly through mining (not shown). Furthermore, there are evident nonlinearities detected where the oil industry is connected to chemicals and pharmaceuticals, which itself is one of the hardest hit sectors during the pandemic. Turning to transportation and storage, which is another nontradable sector, the costs borne by this sector are largely explained by the sizable contraction in the motor vehicles sector.

(vi) In order to give a glance about the sectoral costs with respect to trade exposure, we plot a couple of countries with different levels of trade openness. The idea is to visually illustrate whether those countries that are more open to trade suffer larger sectoral costs. Recall that the node color in Figure 1 illustrated trade openness. We observe that the countries that are represented by darker nodes in Figure 1 bear higher economic costs. More specifically, within two AEs such as the Netherlands and the US, we observe that the sectoral costs are generally higher in Netherlands compared to US, consistent with more trade exposure. A similar picture emerges when we compare the sectoral costs for two EMDE countries. Turkey is more open to trade relative to Brazil. Consequently, sectoral costs borne by Turkey, are generally higher than those of Brazil.

5.5 Global Supply Chain Disruptions: A Premier

Our worst case estimates rely on potential disruptions in the global supply chains due to ongoing pandemic in EMDEs that disrupts production, whereas the best case estimates only require a loss to export earnings of AEs due to slow normalization in demand in EMDEs. The intuition for amplification that delivers the large costs in the worst case comes from the short-run fixed price framework with complementarities in intermediate inputs and inelastic labor supply. Thus, a health shock in a given country leads to shortages of labor and intermediate inputs, together with low demand. This health shock is then amplified to have a cascading effect in the other countries through the global trade and production network, disrupting global supply chains.

Although this Leontief structure might be too stark, we believe it is a realistic setting easily mapped to data in order to calculate the first-round effects of an inequitable vaccine distribution for 2021. A more flexible approach might be preferable theoretically, however, with the country-sector granularity that we want to capture in the data, it would have been much harder to parameterize. We opt for realism relying on the fact that the global value chains involve billions of dollars of investment and well established supplier relationships that are hard to change in the short run. Re-optimizing alternate trade partners is not a trivial decision given that most of the potential trade partners are also hit by the pandemic and the vaccination schedules are far from being complete. The feasibility of identifying alternative suppliers might be further limited due to differences in domestic policies regarding travel restrictions or government guidance on lockdown requirements. With annual exports of intermediate goods exceeding 10 trillion USD, the hefty supply chain networks may not adopt to short run shocks very well, leading to supply chain disruptions.[18] It is further noted that supply chain disruptions may have a lagged effect as well, because production may not start as smoothly after periods of lockdowns.[19]

It is hard to capture these disruptions in real time data and hence we put a narrative together combining different pieces of information. On the anectodal evidence side, there have been several complains that exports could not be shipped to western ports in the second half of 2020.[20] In 2021, these complains increase with the normalization in demand.[21, 22] More recently, there are articles that note that the container crisis evolved into a more general problem that involves shortages of skilled workers due to COVID-19.[23] There are also articles that highlight strains in supply chains due to the global semiconductor shortage triggered by Taiwan. [24] Overall, there have been over 30 articles in FT and NYT alone between February and April of 2021 on the disruptions in global supply chains. Most recently, the CEOs of Maersk and Hapag-Lloyd, the two largest shipping companies, have argued that COVID-19 related disruptions combined with the Suez Canal event cannot be smoothed out right away and lead to disruptions in supply chains until the last quarter of 2021.[25]

The real-time aggregate trade data, however, shows an improvement in world trade in early 2021.[26] Such trade data combines prices, quantities, and inventories so it is hard to pin down why it registers an improvement and why it cannot pick up the real-time supply chain disruptions on the ground. Figure 9 shows the growth in exports and imports for the US, Euro Area, and China, taken from CPB World Trade Monitor. We observe that China plays a leading role in trade recovery.

[18] See https://www.project-syndicate.org/commentary/emerging-economies-supply-chain-resilience-by-jonathan-woetzel-and-mekala-krishnan-2021-02?utm_source=twitter&utm_medium=organic-social&utm_campaign=page-posts-february21&utm_post-type=link&utm_format=16:9&utm_creative=link-image&utm_post-date=2021-02-13.

[19] See https://www.wsj.com/articles/consumer-demand-snaps-back-factories-cant-keep-up-11614019305?mod=searchresults_pos3&page=1.

[20] See e.g. https://www.wsj.com/articles/covid-19-shipping-problems-squeeze-chinas-exporters-11609675204

[21] IHS Markit report on December 11, 2020 ”Global supply chains face heavy disruption amid freight slowdown and port gridlock”, https://ihsmarkit.com/research-analysis/global-supply-chains-face-heavy-disruption-amid-freight-slowdown-Dec20.html.

[22] The Economist article on January 23, 2021 refers to a survey of small and medium size importers where one-third of the 77 percent of the respondents who reported supply chain disruptions raised their prices as a result. https://www.economist.com/finance-and-economics/2021/01/21/supply-bottlenecks-are-pushing-up-costs-for-manufacturers

[23] See e.g. https://www.ft.com/content/ef937903-ed1d-4625-b2ba-d682318a314f or https://www.nytimes.com/2021/03/06/business/global-shipping.html

[24] See e.g. https://www.ft.com/content/74038c71-f0a2-41e0-8cc3-5f61a6157931?desktop=true&segmentId=7c8f09b9-9b61-4fbb-9430-9208a9e233c8

[25] https://www.ft.com/content/de6d56f6-699e-49ee-b71a-fac29ffb3687?desktop=true&segmentId=d8d3e364-5197-20eb-17cf-2437841d178a#myft:notification:instant-email:content

[26] See IMF, January 2021 WEO.

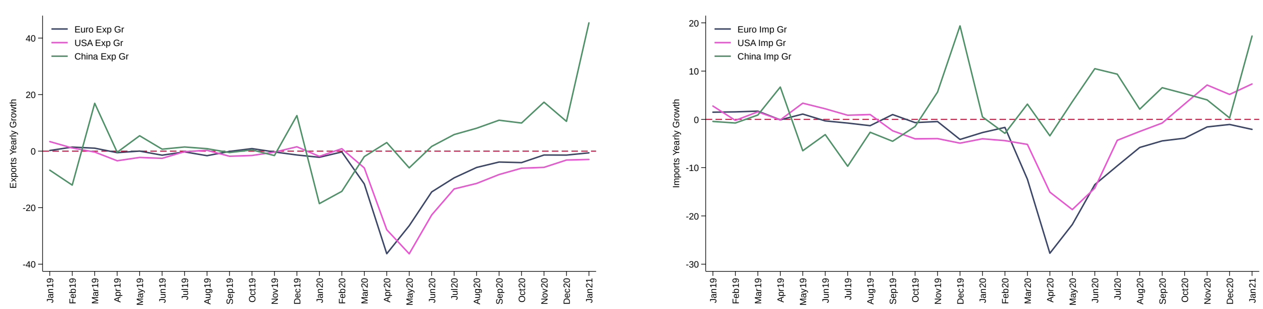
In its latest report as of March 25, 2021, CPB notes that the world merchandise trade is driven by China and developed Asia. [27] The recovery in trade in China and developed Asia is consistent with early and strict lockdown policies that enabled a faster economic recovery in this region. A more modest recovery is observed in the US and the Euro area, where the export performance particularly loses momentum through the end of our sample. The US imports pick up, mimicking the export performance of China, which is one of the major trade partners of the US.

Figure 10 plots the Euro area trade volumes utilizing two different data sources: CPB and Eurostat. It is striking that the two datasets for exactly the same set of countries show different trade trends in the recent period. This is odd, given that their data source should be the same, coming from the countries' own statistical offices. Clearly, there is a pronounced dip in trade in January 2021 in Eurostat data, but not in CPB data. [28]

Figure 9: Changes in Trade

(a) Growths in Exports

(b) Growths in Imports



NOTES: This figure plots the growth in exports (a) and imports (b) for the US, Euro Area, and China over the period January 2019-January 2021. We calculate growth rates based on the seasonally adjusted volumes (2010=100) that are obtained from CPB World Trade Monitor (See https://www.cpb.nl/en/worldtrademonitor).

One potential explanation for increasing trade might be inventories. A recent report highlights the importance of inventory management during the pandemic to minimize supply chain disruptions.[29] Survey evidence suggests that in response to the decline in overall demand during COVID-19, firms adjusted their inventories to support their operations in 2020.[30] Figure 11 shows the two

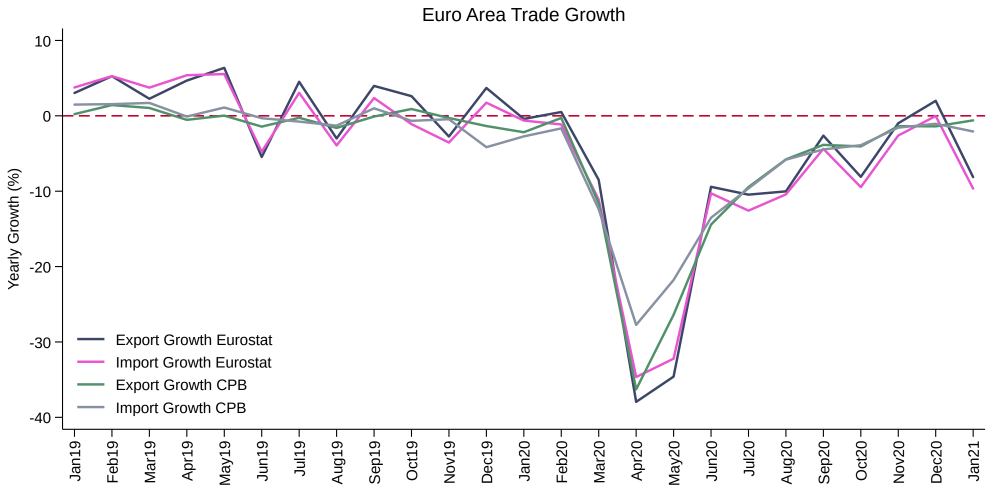
[27] https://www.cpb.nl/en/worldtrademonitor

[28] For details, see https://ec.europa.eu/eurostat/documents/2995521/11562995/6-18032021-BP-EN.pdf

[29] For details on the McKinsey&Company report, see https://www.mckinsey.com/business-functions/operations/our-insights/supply-chain-recovery-in-coronavirus-times-plan-for-now-and-the-future

[30] For details on the COVID-19 Survey conducted by the Institute for Supply Management (ISM), see https://www.prnewswire.com/news-releases/covid-19-survey-round-3-supply-chain-disruptions-continue-globally-

Figure 10: Discrepancies in the Trade Data



NOTES: This figure contrasts the growth rates in imports and exports using the data provided by Eurostat and CPB.

PMI indices i.e., Stocks of Finished Goods Index–shown in panel (a)– and Suppliers' Delivery Times Index–shown in panel (b)– over the period from January 2018 to January 2021, focusing on the manufacturing industry.[31] The noticeable downwards trend in panel (a) throughout 2020 is consistent with inventory adjustments during the pandemic. With the pandemic expanding into its second year, we expect the mitigating effect of inventories to disappear. Panel (b) supports this intuition. Specifically, we observe that although suppliers' delivery times reflected a V-pattern in the third quarter of 2020, there is a noticeable increase in delivery times in the fourth quarter, which could reflect supply chain disruptions that are getting more pronounced as the inventories are depleted.[32] Consequently the adverse effects of disruptions in supply chains should be felt more severely in 2021, especially if vaccinations delay, pandemic remains, and the duration of lockdowns increases.[33]

301096403.html

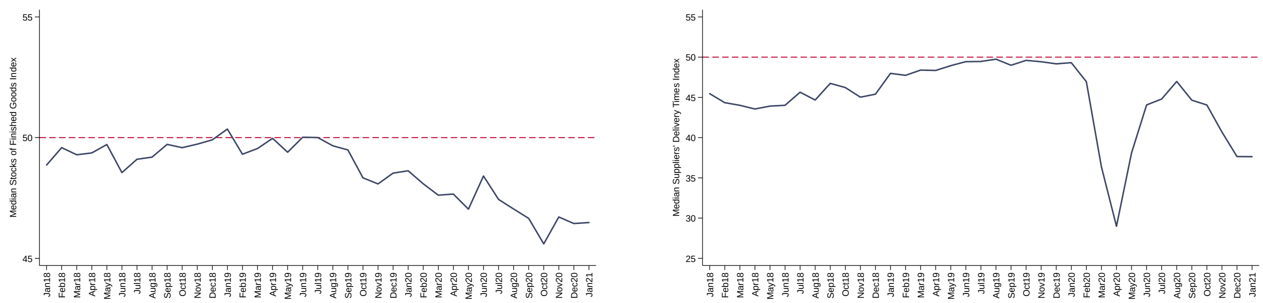
[31] For the surveys produced by IHS Markit, the interpretation of the Suppliers' Delivery Times Index is such that a reading above 50 signals shorter average lead-times, a reading below 50 signals longer average lead-times and a reading of 50 signals no change in average lead-times.

[32] This intuition is supported in a recent article where it is noted that supply chain disruptions are getting more pronounced in 2021 as the retail inventories are depleted during the lockdowns in 2020.https://www.ft.com/content/926c1dbe-e679-4783-975f-430c1d451ab8

[33] Another survey that is highlighted in the Financial Times on Jan 31, 2021, reports that 77 percent of the 900 global companies indicated that they have been experiencing supply chain disruptions in the last six months, see https://www.ft.com/content/40d23da5-c321-4b56-8ec7-551573a7a485.

Figure 11: PMI Manufacturing Data

(a) Stocks of Finished Goods Index (b) Suppliers' Delivery Times Index



NOTES: This figure plots the median values of two PMI indices i.e., Stocks of Finished Goods Index (a) and Suppliers' Delivery Times Index (b) over the period January 2018-January 2021, focusing on the manufacturing industry. Those indices are measured by IHS Markit. The first index that we use to proxy inventories measures the level of finished products, which has come off the production line and is awaiting shipment/sales. The latter measures the average time it takes for the suppliers to provide inputs to the manufacturers to use in the production process. In both panels, the horizontal dashed line stands for the normal level of the corresponding index that is equal to 50.

In order to understand the role of inventory adjustments under demand shocks (regular business downturns) and under both demand and supply shocks (COVID-19), we undertook an empirical analysis, using past data from January 2014 to November 2020. We estimate the following equation:

$$\text{INV}_{c,t} = \alpha + \beta_1 X_{c,t} + \beta_2 \text{COVID19}_t + \beta_3 \text{COVID19}_t \times \text{X}_{c,t} + \mu_c + \epsilon_{c,t}, \tag{37}$$

where $\text{INV}_{c,t}$ refers to stocks of finished goods (inventories), and $\text{X}_{c,t}$ refers to either new orders or backlogs of work for a given country-month pair. COVID19 is a dummy variable that equals 1 for the period after May 2020, and 0 otherwise. μ_c represents country fixed effects. The data is in panel format covering 23 countries.[34]

Backlogs reflect the buildup of new orders that have not been completed. It reflects a workload that is beyond the existing production capacity. During normal business cycles, both new orders and backlogs can be interpreted as a signal for strengthening demand and may prompt businesses to increase their production and pile up on their inventories ($\beta_1 > 0$). During the pandemic, however,

[34]The countries covered in our panel data are as follows: Australia, Austria, Brazil, Canada, Colombia, Czech Republic, France, Germany, Greece, India, Ireland, Italy, Japan, North Korea, Mexico, the Netherlands, Poland, Russian Federation, Spain, Switzerland, Turkey, United Kingdom, and the United States.

there is also a supply shock. If demand starts normalizing, then the difference between demand and supply can be met through inventories, leading to a decline in inventories, as shown in the above figures. If this is the case, then we should expect β_3 to be negative. The impact of the pandemic on inventory behavior can change from one month to the other. Accordingly, the COVID19 dummy can be positive or negative depending on whether it picks up the impact of demand or supply on inventories over the course of time.

Table 4: Inventory Adjustments during 2020 - I

		(1) Inventories	(2) Inventories	(3) Inventories
1	New Orders$_{ct}$	0.11**	0.13**	0.11**
		(0.05)	(0.05)	(0.05)
2	COVID19$_t$	-2.00***	7.22**	5.52
		(0.46)	(3.32)	(4.26)
3	COVID19$_t$ x New Orders$_{ct}$		-0.18**	-0.15*
			(0.07)	(0.08)
	Country FE	No	No	Yes
	Observations	1,881	1,881	1,881
	R-squared	0.10	0.12	0.30

NOTES: Robust standard errors in parentheses clustered by country. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Inventory Adjustments during 2020 - II

		(1) Inventories	(2) Inventories	(3) Inventories	(4) Inventories	(5) Inventories
1	Backlogs$_{ct}$	0.08	0.11*	0.11*	0.08	0.06
		(0.05)	(0.06)	(0.06)	(0.06)	(0.06)
2	COVID19$_t$	-2.07***	11.19***	9.24**	21.65	16.41
		(0.47)	(3.70)	(4.21)	(27.38)	(27.94)
3	COVID19$_t$ x Backlogs$_{ct}$		-0.27***	-0.23**	-0.19***	-0.16**
			(0.07)	(0.08)	(0.06)	(0.07)
4	Consumer Confidence$_{ct}$				0.24*	0.28***
					(0.13)	(0.09)
5	COVID19$_t$ x Consumer Conf.$_{ct}$				-0.14	-0.10
					(0.27)	(0.27)
	Country FE	No	No	Yes	No	Yes
	Observations	1,798	1,798	1,798	1,632	1,632
	R-squared	0.06	0.09	0.23	0.11	0.24

NOTES: Robust standard errors in parentheses clustered by country. *** p<0.01, ** p<0.05, * p<0.1.

We estimate this regression using IHS Markit PMI survey data on stocks of finished goods (inventories), new orders, and backlogs of work. Table 4 shows the regression results. Columns 1 and 2 show the results in the absence of country fixed effects while column 3 shows the results with those fixed effects. The results are highly significant and consistent with our expectations of inventory adjustments. Columns (1) and (2) show that an increase in our demand proxy, new orders is associated with beefing up inventories (row 1). This is consistent with a pro-cyclical adjustment of inventories. The pandemic has a net negative impact on inventories (row 2) as shown in column 1. However, this is no longer the case once we add the interaction term, which is negative and significant (column 2). This suggests a counter-cyclical inventory adjustment (See, Bernanke and Gertler (1995)) during the pandemic period. Once demand starts to normalize, however, inventories decline. The results are pretty similar with and without country fixed effects, as shown in column (3). This implies that the results are not driven by any unobserved heterogeneity across countries in terms of inventory adjustments.[35] The net impact of COVID-19 is negative and significant, which is captured by $\beta_2 + \beta_3 \times$ New Orders=-2.1, evaluated at the mean value of new orders.

Table 5 shows the corresponding results where new orders are replaced by our second demand proxy, backlogs. Similar to new orders, an increase in backlog is associated with beefing up inventories (row 1). When there is a backlog during the pandemic, however, inventories decline to meet the demand, consistent with our framework where firms are constrained in production due to disruptions in value chains (row 3). The net impact of COVID-19 is once again negative and significant, which is captured by $\beta_2 + \beta_3 \times$ Backlogs=-1.9, evaluated at the mean value of backlogs.

In order to check whether or not backlogs are also a good proxy for demand, we add consumer confidence index to capture the changes in demand. As shown in columns 4 and 5, the backlog variable itself becomes insignificant (row 1) while the consumer confidence becomes significant (row 4). During COVID-19, however, supply constraints come to surface. In fact, when demand increases, backlogs are associated with a decline in inventories, as shown by the interaction term (row 3).

It is too early to tell what will happen during the rest of 2021. As of the time of this writing (April 2021) aggregate trade data fails to pick up the ongoing global supply chain disruptions in the global economy, which play a key role in our 2021 estimates of the large economic effects of an inequitable global vaccine distribution.

[35] The evidence for the negative relationship between new orders and inventories is highlighted in an article in the Wall Street Journal on February 22, 2021: https://www.wsj.com/articles/consumer-demand-snaps-back-factories-cant-keep-up-11614019305.

6 Conclusion

An equitable global distribution of vaccines is primarily an ethical and humanitarian responsibility. Our paper makes the economic case for it by providing estimates that show that increasing the production and supply of vaccines produces significant economic benefits for the world economy as well and at a minimal cost. In order to fully eliminate the economic drag from the pandemic, rich countries have strong economic incentives to get involved in efforts such as COVAX that aims to increase the supply of vaccines to achieve an equitable global distribution, as such involvement will deliver high returns to these countries.

To estimate the costs of inequitable vaccine distribution, we develop a global SIR-multi-sector-macro framework and calibrate it to 65 countries-35 sectors. We incorporate sectoral heterogeneity in infections together with inter-industry and international trade and production linkages. Once we account for this economic interdependence of the economies, we reveal the substantial costs, up to 3 percent of advanced countries pre-pandemic GDPs, that will be borne by the vaccinated countries through their trade relationships with unvaccinated countries.[36] Our framework captures the short run. We find that AEs may bear somewhere from 13 percent to 49 percent of the global losses arising from an inequitable distribution of vaccines in 2021. Globalization might have amplified the effects of the pandemic but it is also imperative for an equitable distribution of the vaccines because this is the only way for open economies with international linkages to have a robust recovery.

There are substantial uncertainties ahead of us regarding the course of vaccine distribution. Our estimates are based on the available information about the pandemic. For example, we did not incorporate the recent developments on the variants into our analysis. To the extent that these variants threaten the efficacy of the current vaccines, there is even more urgency to make the existing vaccines globally available as soon as possible. Mutations that risk a prolonged pandemic would not

[36] These costs are an order of magnitude larger than those estimated by other studies that are in the range of 119 to 466 billion as in https://www.reuters.com/article/us-health-coronavirus-vaccine-gdp-trfn-idUSKBN28D217, https://www.who.int/docs/default-source/coronaviruse/act-accelerator/2020-summary-analysis-of-ten-donor-countries-11_26_2020-v2.pdf The reason for this discrepancy is twofold. Our estimates are based on an economic-epidemiological framework that incorporates the effects of infection dynamics through sectoral heterogeneity in exports and imports. Second, our calibration is based on a much larger set of countries and sectors. In contrast, the other studies' estimates only focus on the export part of trade by considering the loss in export revenue in main AEs from low-income countries for few selected sectors. The costs that we estimate do not include the costs on human health either. In contrast, Cutler and Summers (2020) focus entirely on health related costs and calculate the economic costs for the US due to COVID-19 related premature death, long-term health impairment, and mental health.

only have further health costs but also escalate the economic costs that we estimated in our analysis.

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." The economic interdependencies of countries imply that the economic drag in one country has immediate grave consequences for other countries.

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APPENDIX

A Additional Figures and Tables

List of Figures and Tables:

Figure A.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 A.1. 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 A.1: 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 A.2: 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 A.3: 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 A.5 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 A.4: RELATIVE REDUCTION IN GDP OF ADVANCED ECONOMIES (AEs) UNDER SCENARIOS 2 AND 3 (%)

	Scenario 2			Scenario 3		
	Spec 1	Spec 2	Spec 3	Spec 1	Spec 2	Spec 3
Australia	0.27	1.35	2.64	0.37	1.23	1.63
Austria	0.38	2.10	4.07	0.62	1.95	2.71
Belgium	0.38	2.20	4.23	1.18	3.85	4.73
Canada	0.18	1.52	3.49	0.30	1.44	2.00
Denmark	0.34	1.90	3.59	0.53	1.69	2.22
Finland	0.30	1.69	3.15	0.41	1.51	2.00
France	0.30	2.00	3.70	0.86	3.32	3.83
Germany	0.36	2.06	3.55	0.53	1.85	2.34
Greece	0.42	2.25	3.87	0.73	1.85	2.35
Iceland	0.56	1.60	3.21	0.53	1.42	1.94
Ireland	0.46	2.65	4.53	0.73	2.56	3.10
Italy	0.34	2.17	3.90	0.65	2.30	2.83
Japan	0.22	1.79	3.87	0.30	1.49	2.15
Luxembourg	0.53	1.88	3.44	0.83	2.32	2.85
Netherlands	0.52	2.42	4.57	0.91	3.13	3.76
New Zealand	0.34	1.67	3.09	0.47	1.51	1.97
Norway	0.35	1.45	2.70	0.49	1.41	1.82
Portugal	0.49	2.42	4.80	0.77	2.25	3.02
Spain	0.39	2.17	4.28	0.95	3.26	3.81
Sweden	0.34	1.83	3.45	0.74	2.63	3.15
Switzerland	0.37	2.15	4.09	0.63	2.21	2.82
United Kingdom	0.30	1.76	3.48	0.70	2.75	3.24
United States	0.21	1.60	3.48	0.63	2.66	3.14

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 2 and 3, as well as on the specifications 1,2 and 3 are provided in Section 4.4.

Table A.5: 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.