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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, is 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 global output is expected to contract 4.4 percent in 2020, as a result.[1] 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 year 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. This would have earned time for the policy makers to invest in testing and contact tracing procedures.

Approximately one year after the outbreak, the policymakers are at the crossroads of a critical decision again, this time with respect to global coordination of manufacturing and distributing the vaccines worldwide. In this paper, we demonstrate the importance of making the vaccine globally available, not from a moral standpoint but from an economic one, by illustrating the large economic costs in the absence of global vaccinations. Ironically, a significant portion of these costs will be borne by the advanced countries, despite the fact that they might vaccinate most of their citizens by the summer of 2021. This is because advanced economies (AEs) are tightly connected to unvaccinated trading partners which consist of a large number of emerging markets and developing economies (EMDEs). Thus, the devastating economic conditions in these countries under the ongoing pandemic can cause a non-negligible drag on the AEs as well. Even though AEs relative costs are less than that of EMDEs as a percentage of their GDPs, their larger sizes imply that they bear a large

[1] IMF World Economic Outlook, October estimate: https://www.imf.org/en/Publications/WEO/Issues/2020/09/30/world-economic-outlook-october-2020.

fraction of the total global costs. Within the group of AEs, the relative costs increase proportional to their exposure to unvaccinated trade partners. Regarding the pandemic, World Health Organization (WHO) Director Dr. Tedros Ghebreyesus and the President of the European Commission Dr. Ursula von der Leyen noted that "None of us will be safe until everyone is safe." Our findings extend this argument to the economies by showing that no economy fully recovers until every economy recovers.

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.[2] In this framework, external demand for each country's sectoral output changes with its trade partners' specific infection rates. This approach captures how the "global fear factor" can reduce the domestic output as a result of changes in foreign consumption due to voluntary social distancing abroad. The pandemic also acts as a negative shock to supply because the production patterns in all countries are affected from sick workers and lockdowns. We link the production in each country to other countries' infection dynamics through international production networks. We take a granular approach and consider demand and supply shocks at the two-digit sectoral level. Given the extensive evidence on the disproportionate intensity of the COVID-19 shock on certain sectors, our approach allows us to combine the sectoral heterogeneity in infection dynamics with sectoral heterogeneity in global trade networks.[3]

We introduce the vaccine as an immediate treatment of the virus, which improves the sectoral demand and supply conditions in a vaccinated country. 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 due to the international factors remain as long as foreign countries are not vaccinated. We show that even if a given country has access to the vaccine, it experiences a sombre recovery with a drag on its GDP when its trading partners do not have access to vaccines. The reasons for this 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

[2]See Çakmaklı et al. (2020) for a similar framework focusing on the *domestic costs* and the importance of financing of these costs through capital flows, highlighting the interplay between external finance and fiscal space in EMDEs. In that work, we focus on the role of foreign demand shocks as a function of infection dynamics.

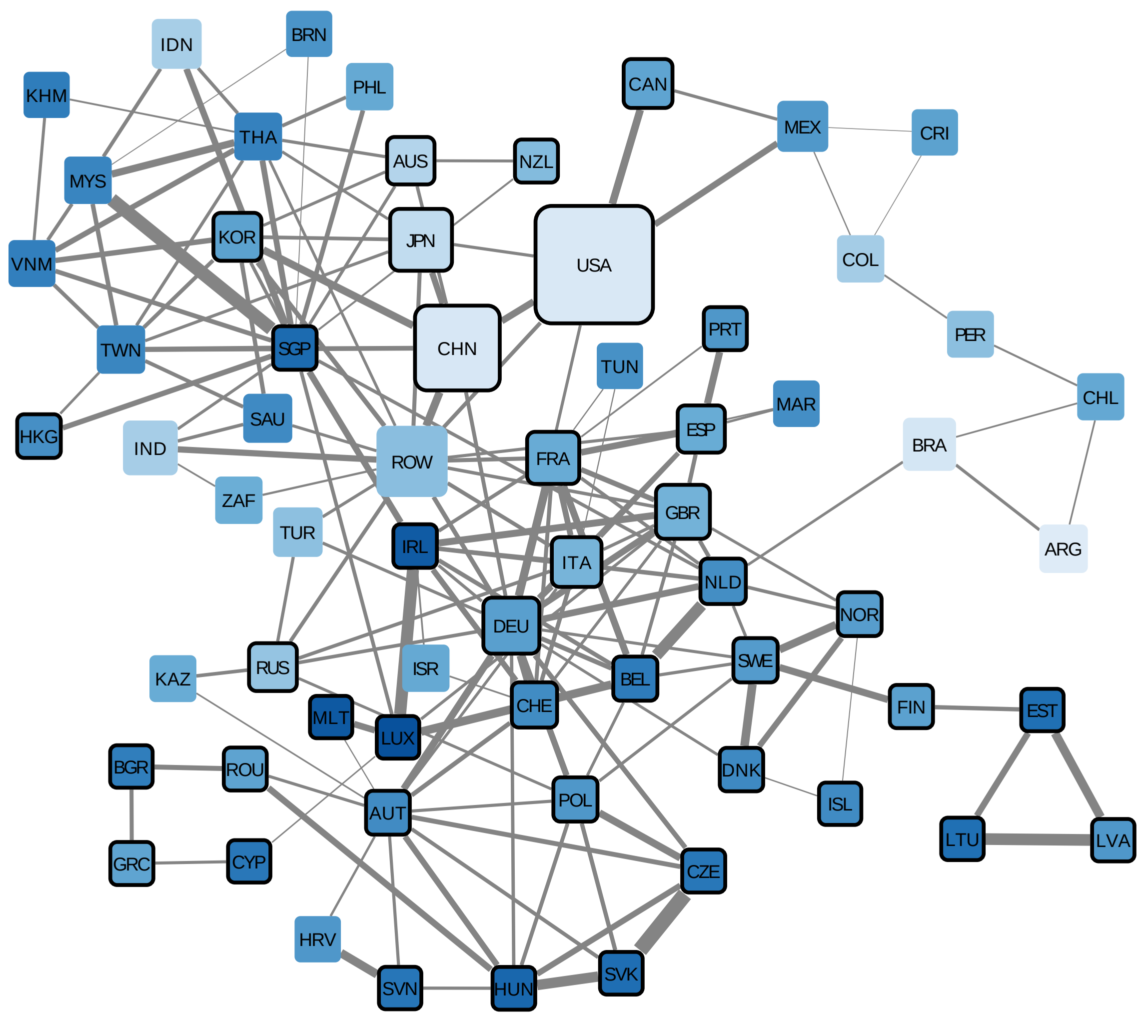
[3]See Gourinchas et al. (2020) who uses heterogenetiy in sectoral shocks to identify business failures.

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.

We estimate COVID losses for 65 countries and 35 sectors. 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. 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. 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.

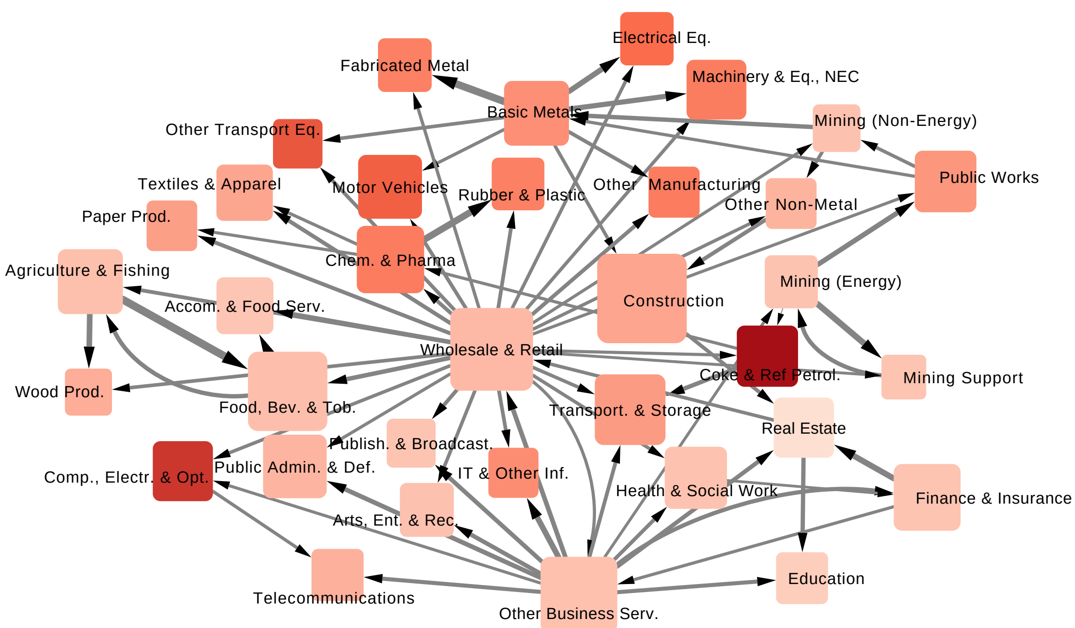
These international linkages are comprised of sectoral links. Industries use inputs from a variety of other industries. These inputs can be supplied either domestically or internationally. In Figure 2 we show a glimpse of the global inter-industry production network. In this network, each node represents 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. Looking at the figure, one can argue 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. The lines between the nodes show the supply relationships, where the thicker lines represent stronger relations. The directed 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 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 thickness of the line represents the ratio of total trade to total GDPs of the countries. In total, there are 65 nodes and 168 lines shown on the network. The trade values, openness calculations, and the GDP values are all based on OECD (2020) Tables.

Figure 2: Inter-industry Trade Linkages



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

Our approach is data-driven. We do not allow firms to optimize and change their positions in global value chains in response to changes in prices, wages, or shocks to labor because we focus on the very short-run. As argued by Shih (2020); Carvalho et al. (forthcoming), the time needed to re-build these networks is longer than the average duration of price stickiness. Our analysis is meant to capture the first-round effects of an unequal vaccine distribution throughout 2021. In this sense, our approach can be viewed as a special case of the sticky price closed economy network model of Baqaee and Farhi (2020a,b). We assume strong complementarities between intermediate inputs and do not allow labor adjustments within or across sectors. Such re-allocations are clearly important in the medium run and will likely reduce the estimated costs presented in this paper. Nevertheless, we opt for a data-centric approach because we want to focus on the immediate economic costs. We estimate the economic costs borne by the advanced economies in the absence of equitible distribution of vacccination in the rest of the world. Such costs arise due to the existing global trade and production networks. Thus, we use the inter-country inter-industry linkages in the data at the start of the COVID shock and calculate the costs in a baseline scenario where the vaccines are available in AEs but not in EMDEs, relative to a counterfactual of global vaccinations. Our approach amplifies the role of the production network since shortages of labor and intermediate inputs will have an immediate economic effect on the production.

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. These numbers are far larger than the 27.2 billion USD cost of manufacturing and distributing vaccines globally.[4] The trade related costs that we have calculated are an order of magnitude larger than those estimated by other studies that are in the range of 119 to 466 billion.[5] 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

[4] See Access to COVID-19 Tools (ACT) Accelerator Partnership.

[5] 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

trade by considering the loss in export revenue in main AEs from low-income countries (LICs) for few selected sectors. These studies lack epidemiological content and hence do not allow exports to evolve endogenously with the country-specific infection rates. As a result, our costs are larger.[6, 7]

We use OECD's multi-industry multi-national input-output tables with 65 countries and 35 industries. In order to show the key channels of our model, namely exports and imports, we consider three specifications. In the first specification, 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 second specification, we introduce the effects of interruptions in imported inputs at the country level in addition to weak external demand affecting exports. That is, we assume that total inputs are imported at the country level, regardless of where they came from, and distributed among the domestic sectors.[8] Continuing with our example from specification 1, suppose country B lowers its production due to sick workers, lockdowns, or due to interruptions to its own imports of intermediate goods from yet another unvaccinated country C. In turn, this will reduce total imports to country A coming both from countries B and C, relative to the counterfactual that both of these countries are also vaccinated.

In the third specification, we employ fully integrated inter-country inter-industry input-output matrices. Under this specification, inputs from different country-sectors cannot be distributed across the sectors of country A. Hence, it delivers the highest economic costs for 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 another vaccinated country such as D. Then, when imports from B goes down, construction industry cannot borrow steel from the manu-

[6]We should highlight that the costs that we calculate are not the overall costs of the pandemic in 2021 but the costs that stem from unequal global vaccine distribution in 2021. IMF projects a cumulative global cost of 11 trillion USD during 2020-2021 period due to the pandemic (See https://blogs.imf.org/2020/10/13/a-long-uneven-and-uncertain-ascent/.)

[7]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.

[8]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. We construct these input-output tables for each of the 65 countries separately.

facturing industry.

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 endogeneous lockdowns in EMDEs, different from the first scenario. The lockdown decisions depend on the ICU bed capacities of countries. This is motivated by the observation that COVID-19 overwhelmed health systems through sharp increases in ICU bed occupancies (Mendoza et al. (2020)). In the third scenario, we allow for a gradual distribution of the vaccines in both AEs and EMDEs, keeping the endogenous lockdowns. In this more realistic scenario, we still assume that only 50 percent of the population in EMDEs are vaccinated at the end of 2021. In contrast, there is universal vaccination in AEs, completed early in 2021.

In the first scenario, we find that the global aggregate GDP losses range from 2.9 to 4.3 trillion USD, depending on the three specifications based on the configuration of export and import shocks that we have 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 (specification 1), the costs that stem from the import channels (specifications 2 and 3) 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 vaccination is completed within four months in the AEs, whereas the full distribution of vaccines is still not completed by the end of 2021 in EMDEs. The losses are mitigated for all three specifications 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 2019 GDPs, depending on different scenarios.

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 model. In Section 4, we describe vaccine development and availability. Our quantitative findings are summarized in Section 5. 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 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. However, none of these papers model both supply and demand dynamics simultaneously.

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. Hence, our main contribution to the literature is to develop and open economy model with both sectoral demand and supply shocks that are endogenous to the infection rates. 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).[9] [10]

3 Conceptual Framework

We model a reduced form partial equilibrium multi-sector multi-country model. Our modeling choices are driven by the data as we calibrate our model to 65 country-35 sector international trade and production network. We incorporate both supply and demand shocks to the model through the epidemiological part. An important deviation of our work from the literature is the fact that we assume static global value chains, where producers and suppliers do not optimize as a response to the pandemic shock. We opt for this approach because we want to calculate the first-round effects of the shocks. These shocks are propagated through the existing global value chains as we observe them in the data as of 2020.[11] On the demand side, the empirical evidence illustrates that the consumers altered their consumption behavior in a sector-specific manner due to the the "fear factor" (Goolsbee and Syverson, 2020; Chetty et al., 2020). To capture this behavior, we model a reduced form consumption function and calibrate it to real-time spending data.

Ability to work from home, physical proximity requirements and lockdowns are all domestic factors that pin down the sectoral supply shock in a closed economy epidemiological model.[12] The

[9] 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).

[10] The only other study that we are aware of which considers both demand and supply shocks at the sectoral level is by del Rio-Chanona et al. (2020).

[11] For full optimization, see Baqaee and Farhi (2020a,b) and Bonadio et al. (2020), where the latter considers the response of the network to the supply shock and the former has a flexible model that can incorporate the responses to both supply and demand shocks.

[12] Most infection dynamics models, including Acemoglu et al. (2020), Alvarez et al. (2020), Farboodi et al. (2020), and

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 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.

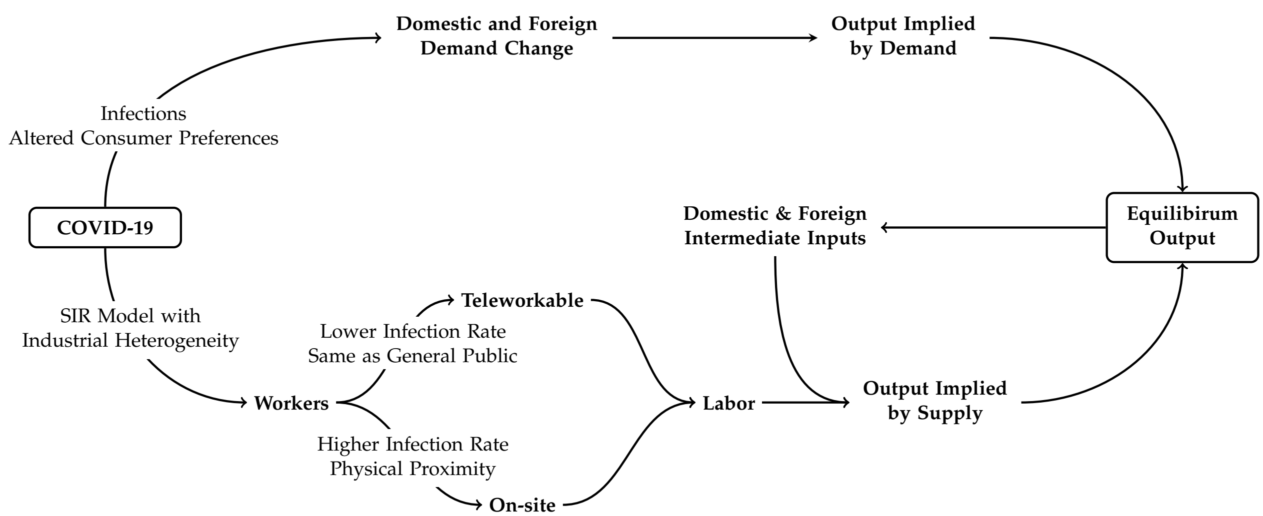
iv Imports of final goods: The goods and services produced and sold by EMDEs to AEs would decline as well.

3.1 The Economic Framework

Figure 3 summarizes our theoretical 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

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.

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 in to two parts: labor and intermediate inputs. The labor shock of an industry depends on its teleworkable share and its physical proximity requirements for the workers. The intermediate inputs vary during the pandemic as the output of these industries decline. When endogenous lockdowns are implemented, only the essential industries remain open (see Table B.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 and the demand channel by mitigating the number of infected individuals, which in turn change the consumption profiles.

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. We describe this in the next section in detail when we introduce the SIR model. 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 vaccines in our country as well as in other countries. Moreover, the output of an industry becomes intermediate inputs for other industries, albeit with a delay.

The economics profession unanimously agrees that the prerequisite for economic recovery is the elimination of the virus so that demand normalizes.[13] As shown in the upper part of the figure, infection rate affects both domestic and foreign demand, feeding into the equilibrium output in a given sector in our country. 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.

3.2 The Epidemiological SIR Model

We use the main workhorse framework in many epidemiological studies, namely the Susceptible-Infected-Recovered (SIR) model.[14] 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 individ-

[13] See IMF World Economic Outlook, April 2020. Also contributions in Baldwin and di Mauro (2020). Former Federal Reserve Chairman Bernanke noted in March 2020 that "Nothing will work if health issues aren't resolved," sending a clear message to governments. See the transcript of Bernanke's interview on March 25 is available at this link: https://www.cnbc.com/2020/03/25/cnbc-transcript-former-fed-chairman-ben-bernanke-speaks-with-cnbcs-andrew-ross-sorkin-on-squawk-box-today.html

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

ual 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.[15] To track any changes in the number of individuals in the above-mentioned three groups, the following set of difference equations is used:

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

$$\Delta R_t = \gamma I_{t-1} \tag{2}$$

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

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:

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

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

For the disease propagation, we lump the non-working population and the employees in the tele-workable 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.[16] 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.

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:

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

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

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 $(\beta_0 + \beta_i)$. [17] For a non-working individual, this parameter is only β_0. Using Equation (6), we impose:

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

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

$$\Delta \mathcal{I}_t \quad = \quad F \mathcal{I}_{t-1} - \nu \mathcal{I}_{t-1} \tag{13}$$

where $\mathcal{I}_t = (I_{0,t}, I_{1,t}, \ldots, I_{i,t}, \ldots, I_{K,t})'$ together with

[17] 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.

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

Using these system matrices, R_0 can be computed using the largest eigenvalue of the matrix $F^{-1}\nu$.

Given the initial size of the groups based on employment numbers, the eigenvalue would approximately correspond to the normalization present in Equation 12.

3.3 Production Side

As shown in the lower half of Figure 3, the pandemic affects production through labor supply and inputs. First, the labor supply is decreased from the 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. 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). In general, we can write the unit output requirement in industry i in country c in terms of its inputs as:

$$y_{c,i} = \left\{ l_{c,i}, z_{c,i}^{i_1}, \dots, z_{c,i}^{i_{n_i}} \right\} \tag{14}$$

where $l_{c,i}$ denotes the unit labor requirement of industry i in country c and $z^{i_j}_{c,i}$ denotes the amount of intermediate inputs that should be used in industry i from industry i_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 and assume that firms take the COVID-19 shock as temporary and hence do not adjust their production and position in the global value chain. As a result, we use the Leontief production function to combine labor and intermediate inputs.

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

$$Y_{c,i} = \min \left\{ \frac{L_{c,i}}{l_{c,i}}, \frac{Z^{i_1}_{c,i}}{z^{i_1}_{c,i}}, \ldots, \frac{Z^{i_{n_i}}_{c,i}}{z^{i_{n_i}}_{c,i}} \right\} \tag{15}$$

where $L_{c,i}$ captures the amount of labor allocated by country c to industry i and $Z^{i_j}_{c,i}$ denotes the amount of output of industry i_j used in industry i of country c. The i_j could capture an industry from another country as well a domestic industry. In our car company example, one of i_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.

During the pandemic, the inputs are affected differently. On the labor side, we have two groups of workers, at-home and on-site. These workers have different infection dynamics as shown in the previous section. The total number of available workers at time t is:

$$\tilde{L}_{c,i,t} = (N_{c,i} - I_{c,i,t}) + TW_i \left(1 - \frac{I_{c,0,t}}{N_{c,0}}\right) \tag{16}$$

where $N_{c,i}$ is the number of on-site workers in industry i in country c, $I_{c,i,t}$ is the number of infected workers among on-site workers, and TW_i is the number of at-home workers (i.e., those who can work remotely) in industry i. The ratio $I_{c,0,t}/N_{c,0}$ 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.[18]

When there are no international supply shocks, changes in the local labor supply are the only factors that lower aggregate supply during to the pandemic. When there are supply shocks to imported inputs, the output in country c in industry i would decline by a multiplicative factor $\tilde{d}_{c,i}$. This multiplicative factor is implicitly a function of the global pandemic. Following the supply shock, the output level changes to:

$$\tilde{Y}_{c,i} = \tilde{d}_{c,i} Y_{c,i}. \tag{17}$$

We assume that the intermediate inputs from this industry will also decline with same ratio.

The shocks propagate through input-output linkages. In our model, we assume that the production is being done daily. We assume that the propagation of a foreign 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 produced two weeks prior to the production of a 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.

In order to determine the level of final output imposed by the supply constraints during the pandemic, we combine the changes in the domestic labor force with the changes in the availability of imported intermediate inputs. Hence, the output in industry i in country c coming from the domestic and international supply channel during the pandemic is equal to:

$$\tilde{Y}^{S}_{c,i} = Y_{c,i} \min \left\{ \frac{\tilde{L}_{c,i}}{L_{c,i}}, \frac{\tilde{Z}^{i_1}_{c,i}}{Z^{i_1}_{c,i}}, \ldots, \frac{\tilde{Z}^{i_{n_i}}_{c,i}}{Z^{i_{n_i}}_{c,i}} \right\}. \tag{18}$$

where $\tilde{Z}^{i_j}_{c,i}$ is the level of industry i_j during the pandemic. Using the car company example 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

[18]To declutter the notation, we will skip the time index below.

supplies for this car company was also affected by the pandemic and could only produce 300 tires fourteen days ago for the car company to use in today's production. 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 is the available tires for production.

Utilizing this framework, we introduce different specifications involving the availability of intermediate inputs in our simulations below. In equilibrium, we take the minimum level of the output implied by supply vs. the output implied by demand to find the level of output for the economy during the pandemic.

3.4 The Demand Side

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.[19] The progression

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

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). 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 on input-output analysis (see, for example Acemoglu et al. (2012), among others), we assume that the representative agent has a Cobb-Douglass utility function:

$$U(e_1, \ldots, e_n) = \prod_{i=1}^{n} e_i^{\alpha_i}, \tag{19}$$

with e_i denoting the level of expenditure in industry i, and α_i representing the share of industry i in total expenditure with $\sum_{i=1}^{n} \alpha_i = 1$ and $0 < \alpha_i < 1$ for all $i = 1, \ldots, n$. The utility function in Equation 19 incorporates a budget restriction which implies that the total income (w) equals total expenditure, i.e., $w = \sum_{i=1}^{n} e_i$. 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, $\delta_i(I)$, that is directly linked to the number of active infections. This shows the expenditure in industry i when the infection level is I, relative to the expenditure during normal times (See Çakmaklı et al. (2020) for details). During the pandemic, the expenditure shares as a function infections can be written as:

$$\tilde{e}_i = \delta_i(I) e_i$$

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 $\delta_i(I)$. For small I (i.e., $I \leq 0.1\bar{I}$), $\delta_i(I) = 1$. 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, $\lim_{I \to \infty} \delta_i(I) \equiv \bar{\delta}_i$. If the demand for an industry i completely collapses during the pandemic (e.g., the airline industry), then $\bar{\delta}_i = 0$. If there is no change in demand during the pandemic (e.g., food industry), then, $\bar{\delta}_i = 1$. We assume that $\bar{\delta}_i$ 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, $\delta_i(I)$, smoothly fluctuates between 1 when nobody is infected and $\bar{\delta}_i$ when a very large number individuals get infected using the functional form as:

$$\delta_i(I) = \begin{cases} 1 & \text{if} \quad I \leq 0.1\bar{I} \\ \bar{\delta}_i \frac{1+(I/\bar{I}-0.1)}{\bar{\delta}_i+(I/\bar{I}-0.1)} & \text{if} \quad I > 0.1\bar{I} \end{cases} \tag{20}$$

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 (20), we err on the conservative side by assuming a faster recovery.

In our simulations, we let the pandemic take its course separately in each country 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 δ values. Let's illustrate the final demand of country c in industry i with $F_{c,i}$. Accordingly, the new level of final demand in industry i in country c during the pandemic becomes:

$$\tilde{F}_{c,i}(I) = F_{c,i}\delta_i(I_c) \tag{21}$$

where $\tilde{F}_{c,i}(I)$ represents the revised demand during the pandemic when the number of infections is I_c in country c.

In order to account for the total demand of each sector, we need to consider not only domestic but also foreign demand. We utilize OECD Inter-Country Input-Output (ICIO) Tables,[20] 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 combina-

[20] https://www.oecd.org/sti/ind/inter-country-input-output-tables.htm

tion. 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:

$$Y = \mathbf{A}Y + F \tag{22}$$

Here, Y denotes the output vector and F denotes the final demand vector whose entries are $Y_{c,i}$ and $F_{c,i}$ respectively.[21] Therefore, we can solve for the output to satisfy the final demand as:

$$Y = (\mathbf{I} - \mathbf{A})^{-1}F \tag{23}$$

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

$$Y_c = \sum_{i=1}^{n} Y_{c,i} \tag{24}$$

Using the demand change from Equation 21 during the infection, the demand channel changes the output as:

$$Y_t^D = (\mathbf{I} - \mathbf{A})^{-1}\tilde{F}(I_t). \tag{25}$$

where Y_t^D represents the output and $\tilde{F}(I_t)$ represents the vector of demand at time t as a function of the number of infections, I_t. Therefore, the output also changes with the dynamics of the pandemic.

3.5 Equilibrium

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

$$Y_t^{EQ} = \min(Y_t^S, Y_t^D) \tag{26}$$

where min represents element by element minimum function for two vectors, namely Y_t^S and Y_t^D.

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

The value-added of the output in industry i in country c is calculated from the shares of value added in each industry during normal times as:

$$VA^{EQ}_{c,i,t} = Y^{EQ}_{c,i,t} \frac{VA_{c,i}}{Y_{c,i}} \tag{27}$$

Therefore, GDP of the country c at time t can be obtained through:

$$GDP^{EQ}_{c,t} = \sum_{i=1}^{n} VA^{EQ}_{c,i,t} \tag{28}$$

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 B.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

The countries in our sample have distinct experiences regarding the course of the pandemic. Considering 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 [22], the median recovery time for the mild cases is reported to be 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 is closely related to the measures taken by the countries to contain the pandemic. The infection rate might

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

vary across countries and across time, depending on the timing of such measures. Accordingly, for the calibration of β, we make use of publicly available datasets.[23] For each country, we estimate a generic SIR model described in (1)-(3) using official data on the pandemic. We employ the methodology proposed in Cakmakli and Simsek (2020) to capture the changes in the rate of infection over time for the countries in our sample. Briefly, this involves estimating a SIR model with time-varying parameters in a statistically coherent way to accommodate various non-pharmaceutical interventions. These factors include lockdowns or other changes such as the virus's mutations and advancements in the treatment of the disease. 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 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 B.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 B.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 Changes

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

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

US credit card data reflects that the changes in demand patterns are rather similar between EMDEs and AEs.[24] 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 B.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 20 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 during 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.

[24]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.

4.4 Supply Shock Specifications

Recall from Equation 18 that the supply is affected from the inputs during the pandemic with the following relationship:

$$\tilde{Y}^S_{c,i} = Y_{c,i} \min \left\{ \frac{\tilde{L}_{c,i}}{L_{c,i}}, \frac{\tilde{Z}^{i_1}_{c,i}}{Z^{i_1}_{c,i}}, \ldots, \frac{\tilde{Z}^{i_{n_i}}_{c,i}}{Z^{i_{n_i}}_{c,i}} \right\}.$$

where "~" sign denotes the levels of the inputs and the output during the course of pandemic. During the pandemic, we assume that the output of country c in industry i changes to:

$$\tilde{Y}_{c,i} = \tilde{d}_{c,i} Y_{c,i}$$

where $\tilde{d}$ captures the proportional decline in the production of that industry. We refrain from the time index but we solve for this equation daily. When we incorporate the intermediate inputs into our calculations, we assume that these inputs are produced fourteen days earlier, in order to accommodate the transportation time.

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:

$$\tilde{Y}_{c,i} S = Y_{c,i} \frac{\tilde{L}_{c,i}}{L_{c,i}}. \tag{29}$$

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 i_j present in country c is allocated to industry i. We can write the fixed proportion term as:

$$r_{c,i}^{i_j} \equiv \frac{\sum_x Y_{x,i_j}^{c,i}}{\sum_x \sum_i Y_{x,i_j}^{c,i}} \tag{30}$$

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

$$Z_{c,i}^{i_j} = r_{c,i}^{i_j} \sum_x \sum_i Y_{x,i_j}^{c,i} \tag{31}$$

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

$$\tilde{Z}_{c,i}^{i_j} = r_{c,i}^{i_j} \sum_x \sum_i \tilde{d}_{x,i_j} Y_{x,i_j}^{c,i}. \tag{32}$$

Hence, the output implied in the second specification becomes:

$$\tilde{Y}_m^{i,S} = Y_m^i \min \left\{ \frac{\tilde{L}_m^i}{L_m^i}, \frac{\sum_x \sum_i \tilde{d}_{x,i_1} Y_{x,i_1}^{c,i}}{\sum_x \sum_i Y_{x,i_1}^{c,i}}, \ldots, \frac{\sum_x \sum_i \tilde{d}_{x,i_{n_i}} Y_{x,i_{n_i}}^{c,i}}{\sum_x \sum_i Y_{x,i_{n_i}}^{c,i}} \right\}. \tag{33}$$

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 i_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:

$$Z_{c,i}^{i_j} = \sum_x Y_{x,i_j}^{c,i}. \tag{34}$$

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

$$\tilde{Z}_{c,i}^{i_j} = \sum_x \tilde{d}_{x,i_j} Y_{x,i_j}^{c,i} \tag{35}$$

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

$$\tilde{Y}_{c,i}^{S} = Y_{c,i} \min \left\{ \frac{\tilde{L}_{c,i}}{L_{c,i}}, \frac{\sum_x \tilde{d}_{x,i_1} Y_{x,i_1}^{c,i}}{\sum_x Y_{x,i_1}^{c,i}}, \ldots, \frac{\sum_x \tilde{d}_{x,i_{n_i}} Y_{x,i_{n_i}}^{c,i}}{\sum_x Y_{x,i_{n_i}}^{c,i}} \right\}. \tag{36}$$

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 Effects	Intermediate Input Effects	Inputs
1	Yes	No	Only Labor
2	Yes	Yes	Country Level I-O
3	Yes	Yes	Intercountry / Interindustry 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

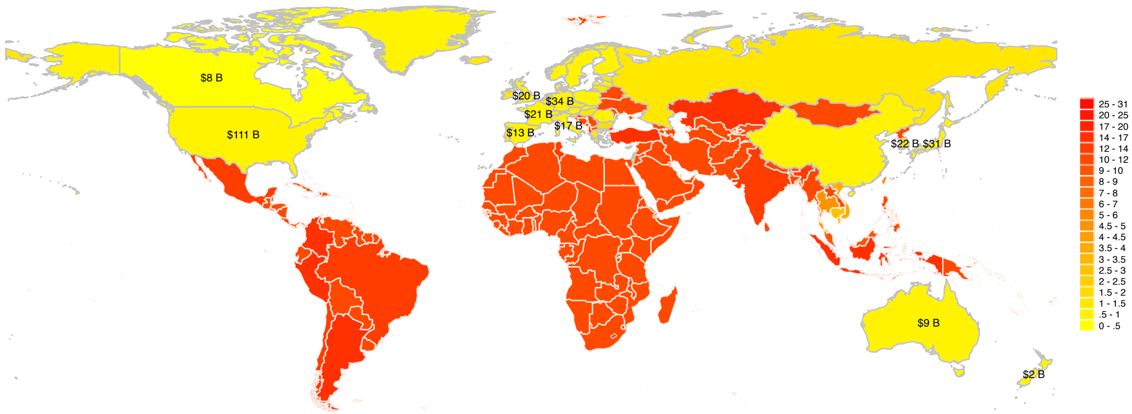
5.1 Scenario 1: Vaccination only in AEs, No Lockdowns in EMDEs

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.

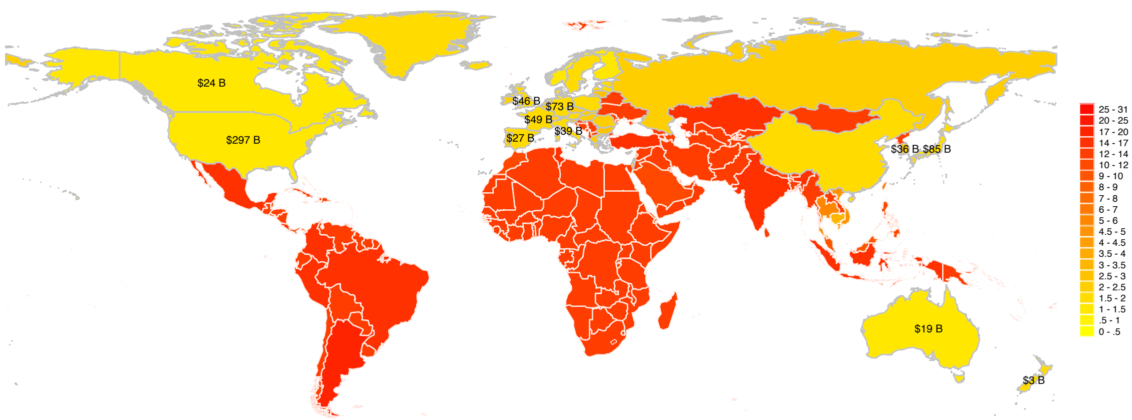
Figure 4 relays several critical messages. First, the severe domestic effects of the pandemic can be immediately noticed for the EMDEs which correspond to darker shades of red on the map. The overall negative drag is far more pronounced in all three specifications compared to AEs. In Morocco and Malaysia, 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 (%)

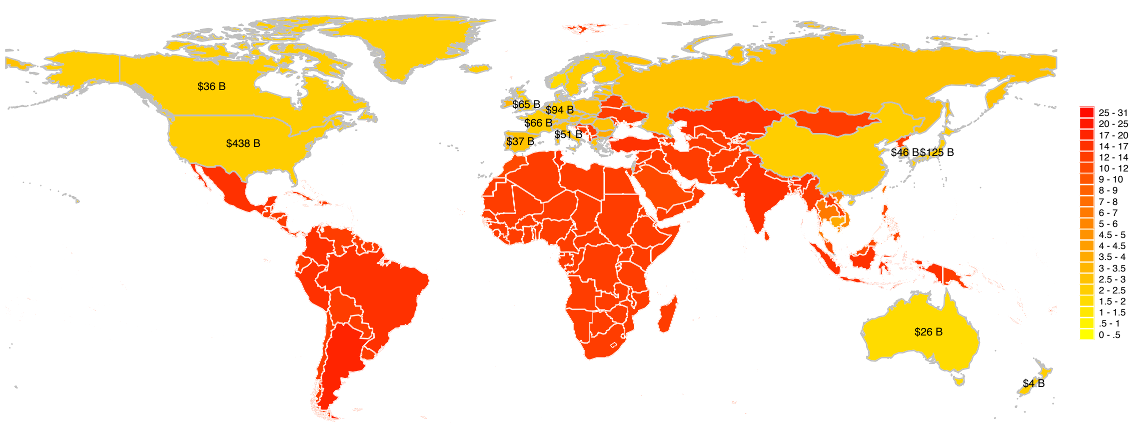
(a) Specification 1 – Only Demand



(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 4.87% and the GDP of AEs declines by 2.72%.

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

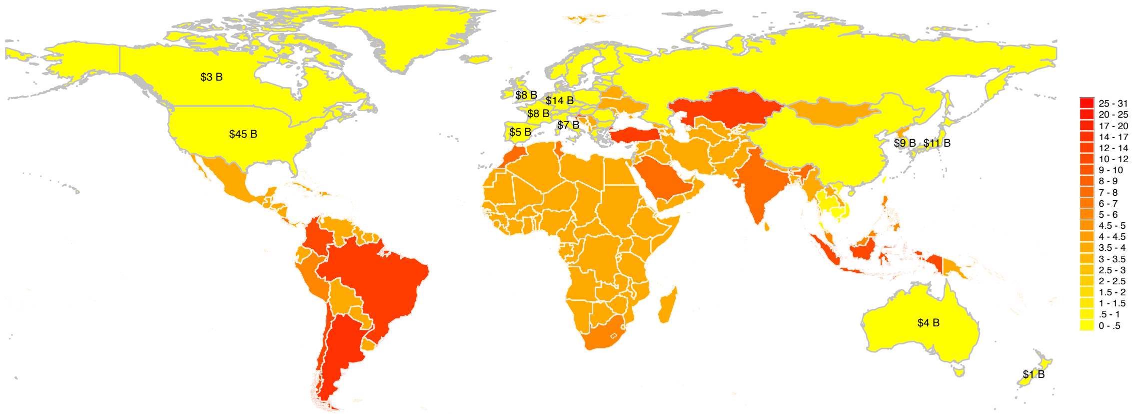
The second scenario is similar to the first scenario with the exception of endogenous lockdowns in EMDEs. In this scenario, the countries impose multiple lockdowns when the number of COVID-19 patients that require intensive case units (ICUs) exceed the number of ICUs that are reserved for COVID-19 patients. 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 B.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. [25]

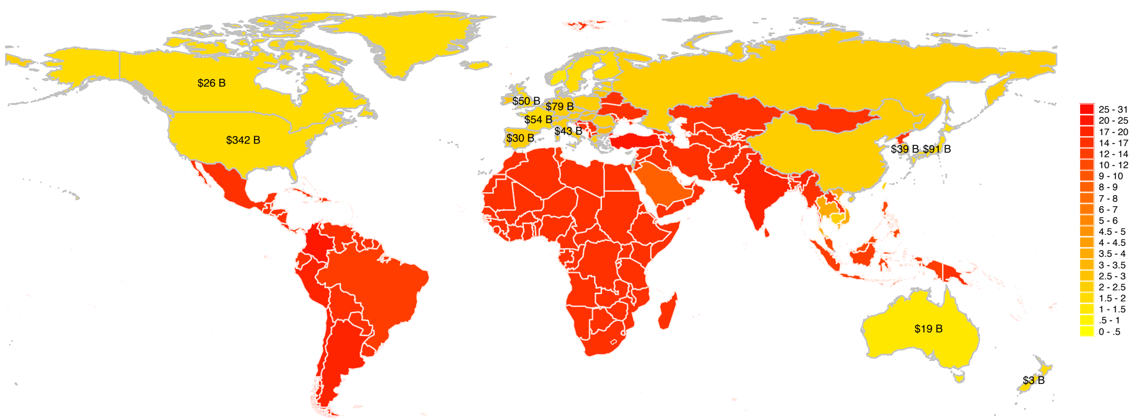
[25] Table 3 uses a conservative setting where we filter out small industries from our calculations as explained at the end of section 4.4. As a robustness check, if we bring these small industries back into our calculations –i.e., consider input industries even if their share is lower than 2.85%– the 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 (%)

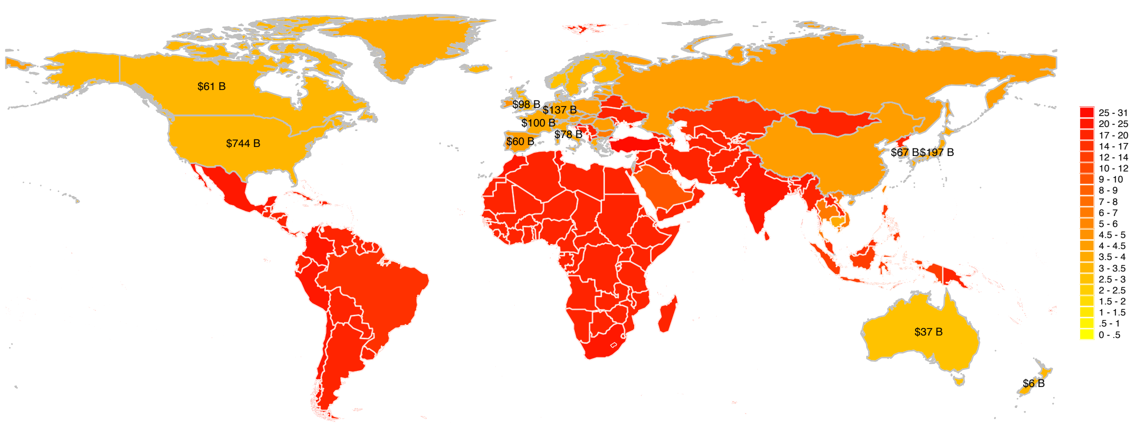
(a) Specification 1 – Only Demand



(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 a few selected countries.

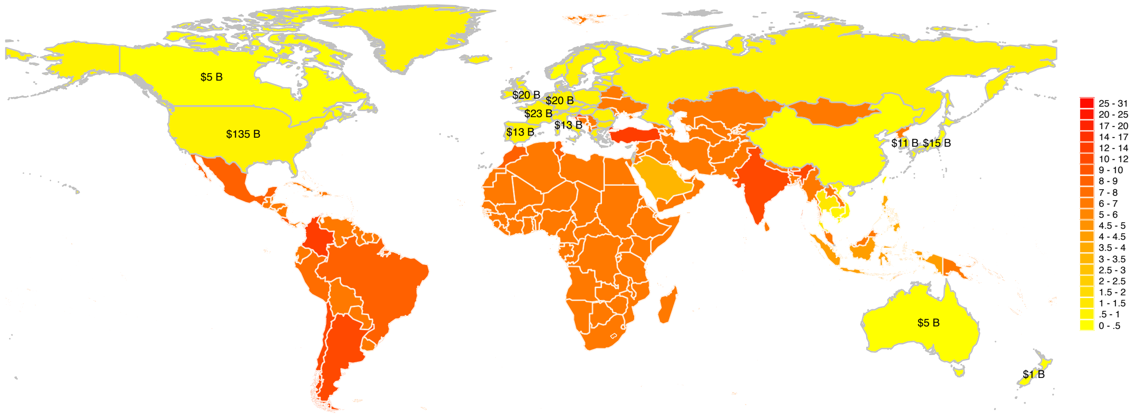
5.3 Scenario 3: Gradual Vaccination in EMDEs and in AEs, Endogenous Lockdowns in EMDEs and AEs

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 B.4.

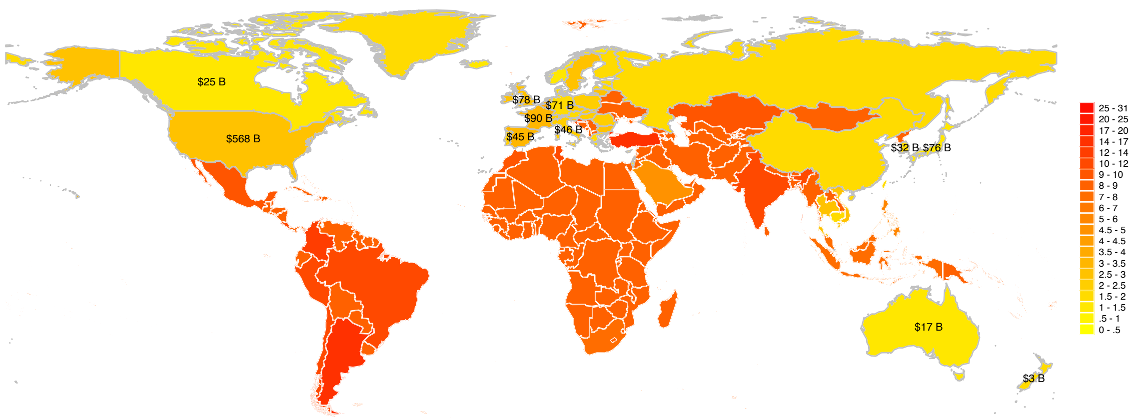
While the cost incurred by the advanced AEs is on average 2% for the second specification (Figure 6b), it increases to 3% on average under the third specification (Figure 6c). When we compare the total economic costs in Table 3, we observe that the costs increase for both AEs and EMDEs under the first 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 (%)

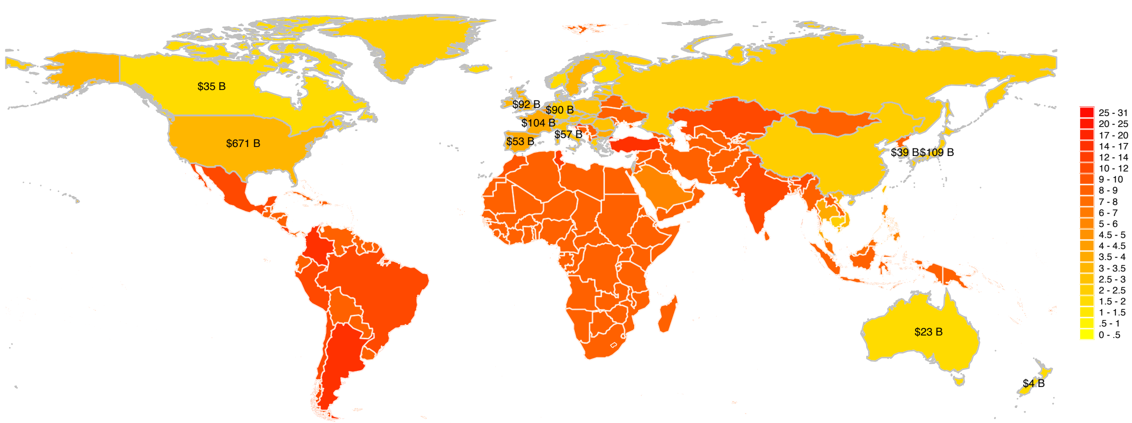
(a) Specification 1 – Only Demand



(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 a few selected countries.

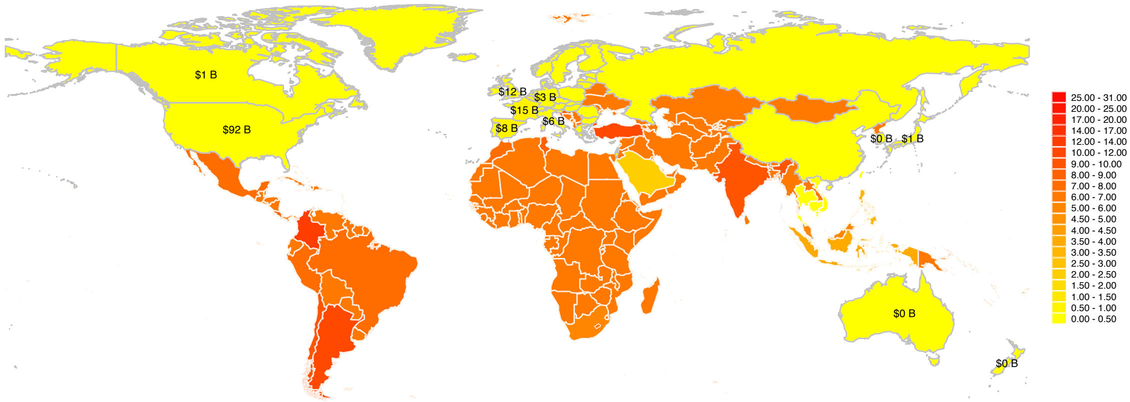
slow inoculation calendar such as the one depicted in scenario 3 is ”too little, too late.” Under this relatively more realistic scenario, the total cost for the world varies between 1.8 and 3.8 trillion USD depending on the availability of the intermediate goods. Strikingly, for the third specification, 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 27.2 billion USD cost reported by Access to COVID-19 Tools (ACT) Accelerator partnership to manufacture and distribute the vaccine globally.

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)



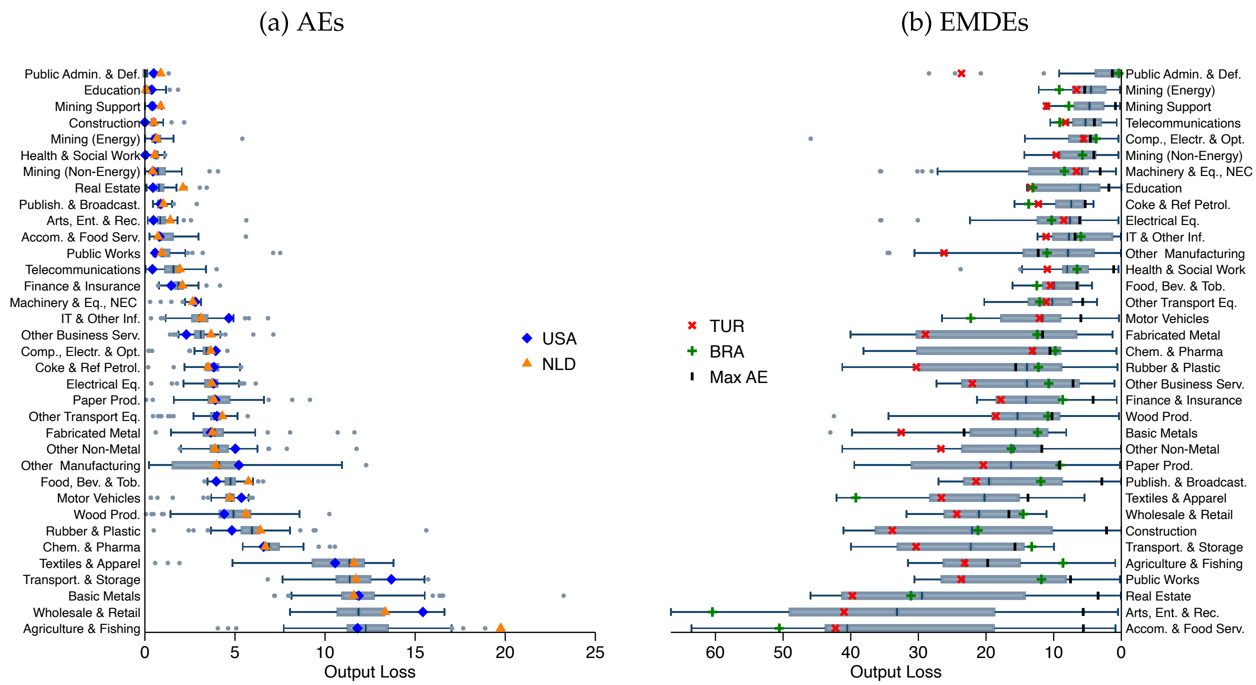
NOTES: This figure illustrates the domestic shocks under specification 3 of scenario 3. Here, we eliminated all the shocks associated with the pandemic except within a given country. We run our simulations for 65 countries separately. The shades of yellow correspond to relatively lower ratios and the 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 a few 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 of output loss in corresponding economies. 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 B.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, basic metals, or food, beverage, and tobacco industries. 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) 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.

6 Conclusion

Equitable global distribution of vaccines is primarily an ethical and humanitarian responsibility. Our analysis in this paper reveals that an equitable allocation of vaccines can produce significant economic benefits for the world economy as well. To estimate these gains, 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.

Our framework captures the short run. Hence, we do not allow for adjustments to labor or intermediate input usage in response to price changes or other sectoral re-allocations. In this framework, 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. Depending on the different underlying scenarios, this range corresponds to 0.3 to 3.7 percent of their 2019 GDPs.

To minimize these economic costs of the pandemic, a globally coordinated push for the production and the distribution of the COVID-19 vaccine is required. EMDEs have more at stake if the delivery of effective vaccines is delayed. Nevertheless, our analysis shows that AEs have strong economic incentives to eliminate the pandemic at their trade partners in order to achieve a faster recovery at home. 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 still substantial uncertainties ahead of us regarding the course of vaccine distribution. Hence our estimates are upper bounds. 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 the others. The economic losses of the pandemic can only be mitigated through a multilateral coordination ensuring the equitable access of vaccines, tests and therapeutics.

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APPENDIX

A Vaccine Development and Availability

The competition to produce a safe and effective COVID-19 vaccine heated up in the second half of 2020 with the unstoppable global march of the virus. Vaccine safety trials in humans started as early as March 2020, and thirteen of them reached the final stages of testing by year-end 2020. [26]

The development cycle of an effective vaccine from the lab to clinic requires years of intense research and testing until it finally reaches people's arms. In this section, we go over the development and accessibility of all the coronavirus vaccines that have reached publicly disclosed deals across the globe, along with a brief discussion of the vaccine testing process.

A.1 Vaccines Classified by Developmental Phases

A.1.1 Preclinical Phase

Scientists typically kick off the development of a new vaccine with a preclinical phase. During this phase, an experimental vaccine goes through a set of screenings and evaluations to determine which antigen should be used to trigger an immune response. Before tested on humans, it is first tested on cells and then on animals such as mice or monkeys to evaluate its safety and potential to prevent the disease. As of December 2020, the WHO confirmed 87 preclinical vaccines in active development. Among all, in September 2020, Saint-Herblain-based company Valneva announced that they signed a vaccine partnership with the UK government for its inactivated COVID-19 vaccine, VLA2001. Under the agreement, if vaccine development is successful, Valneva will provide the UK government with 60 million doses in the second half of 2021. UK Government then has options over 40 million doses in 2022 and a further 30 million to 90 million doses, in aggregate, across 2023 to 2025. UK government is also investing upfront in the scale up and development of the vaccine.

[26] For timely updates on the COVID-19 vaccination, see the following websites: https://www.bloomberg.com/graphics/covid-vaccine-tracker-global-distribution/ and https://www.nytimes.com/interactive/2020/science/coronavirus-vaccine-tracker.html

A.1.2 Phase 1

If the vaccine successfully stimulates the immune system, scientists proceed with the testing of the vaccine in human clinical trials in three phases. In Phase 1, the vaccine is given to a small number of volunteers to assess its safety, confirm that it triggers an immune response, and determine the accurate dosage. Generally during this phase vaccines are tested in young, healthy adult volunteers. As of December 2020, the WHO confirmed that there are 41 vaccines testing safety and dosage in active Phase 1. Among all, a protein-based vaccine developed by the University of Queensland confirmed its potential to protect hamsters from the virus. The university then launched Phase 1 trials in July 2020, supplementing the proteins with an adjuvant made by CSL to trigger the immune system. In September 2020, the vaccine developers signed an agreement with the Australian government to deliver 51 million doses if the trials deliver positive results. They expected their first supply of the vaccines to be ready in mid-2021.

A.1.3 Phase 2

In Phase 2, the vaccine is given to hundreds of volunteers to further assess its safety and ability to invoke an immune response. This phase consists of multiple trials in which various age groups and different formulations of the vaccine are investigated. Besides the inoculated group, a placebo group is included to determine whether the changes in the vaccinated group are due to the vaccine, or whether they took place as a coincidence. As of December 2020, the WHO confirmed that there are 17 vaccines in expanded safety trials of Phase 2. Among all, Sanofi/GlaxoSmithKline (GSK), CureVac, and UBI Group are those that negotiated several deals to supply the vaccine.

Paris-based company Sanofi and Brentford-based company GSK announced that they collaboratively launched Phase 1 and 2 clinical trials in September. During the preclinical phase, Sanofi developed a protein-based vaccine, supplementing the viral proteins with adjuvants made by GSK to trigger the immune system. Before kicking off their clinical trials, Sanofi negotiated several major deals to supply the vaccine, including agreements with the United States, European Union, and Canada to provide 100 million doses, 300 million doses, and up to 72 million doses, respectively. Sanofi also reached an agreement with COVAX– an international collaboration to deliver the vaccine equitably across the world and led by the World Health Organization, Global Vaccine Alliance Gavi, and the Coalition for Epidemic Preparedness–to provide 200 million doses. They have plans to extend their supply of the vaccine to one billion doses in 2021.

After observing a promising response in the immune systems of their vaccinated volunteers in a Phase 1 clinical trial, Tubingen-based company CureVac launched the next Phase 2 trial in September 2020 to further assess the safety and ability to generate an immune response of its mRNA based-genetic vaccine. They expect to make the preliminary data of their Phase 3 study public in the first quarter of 2021.

In November 2020, CureVac negotiated a deal to provide the European Union with up to 225 million doses of their vaccine. They have plans to extend their supply of the vaccine to 300 million doses in 2021 and up to 600 million doses the following year.

Colorado-based company UBI Group launched its Phase 2 study to vaccinate hundreds of volunteers to evaluate the ability of its protein-based vaccine to stimulate their immune systems. UBI group negotiated a few deals with Covax and Other Jurisdictions to provide 200 million doses and 2 million doses, respectively.

A.1.4 Phase 3

In Phase 3, the vaccine is given to thousands of volunteers to see how many get infected, compared to those who received a placebo. This phase consists of multiple trials that help scientists to assess whether the vaccine is effective against the coronavirus. It further confirms its safety in a much larger group of people. As of December 2020, the WHO confirmed that there are 13 vaccines in large-scale efficacy tests. Among all, 9 companies have entered deals with several countries to supply their vaccine needs.

A.1.5 Authorization for use

In early November 2020, New York-based Pfizer and the German company BioNTech made their first evidence public that their mRNA-based genetic coronavirus vaccine was 95 percent effective, which was a milestone in the development of an effective coronavirus vaccine. Afterwards, the companies applied to the U.S. Food and Drug Administration (FDA) for an emergency use authorization. On December 2, the UK gave emergency authorization to their vaccine. Following the go-ahead given by the FDA, Pfizer and BioNTech is expected to manufacture over 1.3 billion doses of their vaccine worldwide by the end of 2021.

In a partnership with US National Institutes of Health, Boston-based company Moderna launched its Phase 3 study and announced that its mRNA-based genetic coronavirus vaccine's efficacy rate is estimated as 94.1 percent by late November 2020. Following Pfizer & BioNTech, Moderna made the second application to FDA to get approval. In the meantime, the company negotiated with several countries including Canada, Japan, and Qatar and EU members to supply the vaccine after approval. In August 2020, the US government awarded the company an additional $1.5 billion in exchange for 100 million doses if the vaccine proves safe and effective.

The British-Swedish company AstraZeneca and the University of Oxford created a coronavirus vaccine using the viral vector technology based on chimpanzee adenovirus. Based on their recent scientific trials, the efficacy rate is announced to be 70 percent. Meanwhile AstraZeneca signed a series of deals to supply their vaccine if its safety and efficacy is approved. The US government awarded the project $1.2 billion in support for 300 million doses. The company declared that they expect to manufacture two billion doses of their vaccine if approved.

The Gamaleya Research Institute, part of Russia's Ministry of Health, has created a coronavirus vaccine–renamed Sputnik V–that is developed by viral vector technology based on two adenoviruses Ad5 & Ad26. According to the preliminary results of Phase 3 trials announced in November 2020, the efficacy rate is estimated to be 91 percent. Russia negotiated a set of agreements to supply the vaccine to several countries including Brazil, India, Mexico, Venezuela, Uzbekistan, Egypt, and Nepal.

In addition to the above-mentioned biotech companies, Novavax, Johnson & Johnson, Sinovac Biotech, CanSino Biologics, Sinopharm, Medicago/GSK are those that have launched their Phase 3 trials to assess the efficacy and safety of their vaccines. Tables A.1–A.2 provide further details on the coronavirus vaccines, the companies that developed them as well as the supply of the vaccines to the countries with which they have negotiated.

Table A.1: TRACKING THE DETAILS OF CORONAVIRUS VACCINES

Vaccine	Technology	Stage	Efficacy	Dose/ patient	Price*/ dose	Long Term	Short Term
Moderna	mRNA based	Phase 3	95%	2	$10-50	-20 °C	2-8 °C (30 d)
Pfizer/BioNTech	mRNA based	Phase 3	95%	2	$20	-70 °C	2-8 °C (5 d)
AstraZeneca/Oxford	Viral vector (chimpanzee adenovirus)	Phase 2/3	70%	2	$3-4	2-8 °C	
Novavax	Protein based	Phase 3	TBA	2	$16	2-8 °C	
Johnson & Johnson	Viral vector (adenovirus Ad26)	Phase 3	TBA	1	$10	2-8 °C	
Sinovac Biotech	Inactivated Coronavirus	Phase 3	TBA	2	$60	2-8 °C (3 y)	
Gamaleya	Viral vector (adenoviruses Ad5 & Ad26)	Phase 3	91%	2	$13	-18 °C (6 m)	
CanSino Biologics	Viral vector (adenovirus Ad5)	Phase 3	TBA	1	TBA	2-8 °C	
Sinopharm	Inactivated Coronavirus	Phase 3	TBA	2	$72.5	2-8 °C	
Medicago/GSK	Protein-based	Phase 3	TBA	2	TBA	TBA	
CureVac	mRNA based	Phase 2/3		TBA	TBA	TBA	
UBI Group	Protein based	Phase 2		TBA	TBA	TBA	
Valneva	Inactivated Coronavirus	Preclinical		TBA	TBA	TBA	
U.of Queensland	Protein based	Phase 1		TBA	TBA	TBA	
Sanofi/GSK	Protein based	Phase 1/2		TBA	TBA	TBA	

NOTES: This table summarizes the details regarding the development and availability of the COVID-19 vaccine, focusing on the promising vaccines that have publicly disclosed deals with those countries listed in Table A.2. Data is from https://www.nytimes.com/interactive/2020/science/coronavirus-vaccine-tracker.html, https://www.bloomberg.com/graphics/covid-vaccine-tracker-global-distribution/ as well as the websites of respective Biotech companies as of December 5, 2020.
*Price of the coronavirus vaccine might differ based on negotiations between the respective country and the companies.

As of December 2020, several vaccines are awaiting approval by health authorities. The factories of the biotech companies located in the United States, Europe and Asia are expected to manufacture hundreds of millions of doses of coronavirus vaccine. Thus, the worldwide storage and shipping of the vaccines could pose some challenges. Therefore, once all vaccines get approval, a historical global effort will be strongly needed for the distribution of vaccines around the world.

Table A.2: CORONAVIRUS VACCINE ORDERS

Vaccine / Country	**Moderna**	**Pfizer/BioNTech**	**AstraZeneca/Oxford**	**Novavax**	**Johnson & Johnson**	**Sinovac Biotech**	**Gamaleya**	**CanSino Biologics**	**Sinopharm**	**Medicago/GSK**	**CureVac**	**UBI Group**	**Valneva**	**U. of Queensland**	**Sanofi/GSK**
India			100	100			200								
U.S.	100	100	300	110	100										100
EU	80	200		400	200						225				300
Canada	20	20	20	76	38					76					72
Japan	50	120	120												
U.K.	7	40	100	60	30								60		60
Brazil			100			46	100								
Indonesia			100			50		15	60						
Mexico		34	77				64	35							
China			200												
Russia							160								
Australia		10	34	40										51	
Pakistan									88						
Uzbekistan							70								
Egypt							50								
Nepal							50								
Latin America Bloc			160												
Turkey						50									
Middle East Bloc									75						
Covax			300									200			200
Other	5	45	63			20	4					2			

NOTES: This table summarizes the COVID-19 vaccine orders (in millions) given by countries. We use information available in various resources including https://www.nytimes.com/interactive/2020/science/coronavirus-vaccine-tracker.html, https://www.bloomberg.com/graphics/covid-vaccine-tracker-global-distribution/ as well as the websites of respective Biotech companies as of December 5, 2020. The Latin America bloc covers all countries in the region except Brazil. The European Union bloc represents the 27 countries of the European Union. The Covax agreement extends to most countries in the world, including many in Africa that wouldn't otherwise be covered. The countries included in "Other" without a population figure, such as Somalia and Syria, have been omitted. The Middle East bloc covers United Arab Emirates, Egypt, Bahrain and Jordan.

B Additional Figures and Tables

List of Figures and Tables:

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

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

NOTES: This table illustrates the structure of OECD Inter-Country Input-Output Table (ICIO), which represents the breakdown of output corresponding to 36 industries and 65 countries, giving us a matrix of 2340×2340 entries. In any industry-country combination, the output (Y) equals intermediate use (Z) plus final demand (F) of 36 industries in 65 countries. Industry list can be found in Table B.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 B.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 B.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 B.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 B.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 B.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 B.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.