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COVID-19 AND EMERGING MARKETS:
A SIR MODEL, DEMAND SHOCKS AND CAPITAL FLOWS

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ABSTRACT

We quantify the macroeconomic effects of COVID-19 for a small open economy. We use a two country framework combined with a sectoral-SIR model to estimate the effects of collapses in foreign demand and supply. The small open economy suffers from domestic demand and supply shocks due to its own pandemic. In addition, there are external shocks coming from rest of the world (country two). Aggregate exports of the small open economy go down when foreign demand goes down, and aggregate imports suffer from lockdowns in the rest of the world. We calibrate the model to Turkey. Our results show that the optimal policy, which yields the lowest output loss and saves the maximum number of lives, for the small open economy, is an early and globally coordinated full lockdown of 39 days.

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"Best safety lies in fear."
– William Shakespeare

1 Introduction

The COVID-19 pandemic had the potential to trigger the biggest emerging market (EM) crises of modern times. At the onset of the pandemic, EMs observed a collapse in domestic and external demand, capital outflows, and depreciating currencies. At the same time, their production capacity suffered from the lockdowns in the rest of the world. The worst case scenario had not materialized given the extensive world-wide fiscal stimulus, however, emerging markets still got off track and experienced not only more deaths but also lower outputs than advanced economies, compared to the path they were on before the pandemic.

Our goal is to measure the real output losses of a typical small open economy that is subject to both domestic and external COVID-19 related shocks. We assume a world with no vaccinations to zoom-in on the trade-off between lockdowns to minimize deaths vs no-lockdowns to minimize output losses. Although many countries are not subject to this trade-off anymore, there are still few countries under this situation, most notably China.

Our model is a two country version of Baqaee and Farhi (2022). The model allows for a rich set of sectoral shocks, aggregate shocks and nominal wage rigidity.[1] We consider two lockdown scenarios. In a full lockdown, all non-essential industries are shut down, with an immediate decline in output. Only essential industries are open and the on-site workers in the non-essential industries continue working. In the case of partial lockdowns, certain restrictions are imposed on daily life to incorporate social distancing rules but businesses remain open.

There is sectoral heterogeneity both in the supply and demand shocks for the domestic economy. On the supply side, heterogeneity depends on the ability to work from home and the physical proximity needed for the job. This is combined with the external shock for sectoral imports if the

[1] We have another paper, Çakmaklı et al. (2021), which is a multi country- multi sector global model focusing only on sectoral shocks, refraining from any nominal rigidity and aggregate shock. In addition, production structures in two papers are very different. The current paper does not combine country varieties into sectoral bundles as it does not focus on global supply chain disruptions, as done in Çakmaklı et al. (2021). The focus of the current paper is on the effects of external shocks for a small open economy.

foreign country imposes a lockdown. Demand shocks are also heterogeneous across sectors given the strength of foreign demand for a sector's output and the fluctuations in domestic demand based on infections in that sector.

In the case of a globally coordinated full lockdown, both countries suffer from supply and demand shocks in a synchronized manner. In the case of an uncoordinated full lockdown, we assume that the small open economy implements a full lockdown while the foreign country implements a partial lockdown. Our results show that, a small open economy can minimize output losses, while saving maximum lives, only when she coordinates the full lockdown with the rest of the world. The output losses are always lower under a full lockdown than a partial lockdown in the small open economy as under partial lockdown labor supply shocks are more negative given the larger number of infections. However, under full lockdown, output losses come close to the ones under partial lockdown when foreign country suffers from the pandemic and does not impose a lockdown. This is due to the decline in foreign demand and hence small open economy's exports, hurting the couuntry more.

Our paper is one of the few open economy papers that studies the macroeconomic effects of the pandemic.[2] Considering an open economy framework is beneficial to incorporate the role of global coordination, or lack thereof, in determining the effectiveness of lockdown measures. Contrary to the popular belief that no lockdown policies would minimize economic costs, we show that such policies are actually costlier than an effective full lockdown given the interaction between domestic and external shocks. If the lockdown is globally coordinated, the costs of a full lockdown are minimized by containing the pandemic at the global scale. Consistent with our findings, the countries that imposed early and strict lockdowns in a coordinated way, such as Australia, and New Zealand experienced earlier economic normalization in 2020 compared to the rest of the world.[3] In general, countries that implemented full and effective lockdowns at an early stage saved more lives and minimized the economic costs at the same time, a result that our model generates.

The time frame that we focus in our paper is the first year of the pandemic before the introduction of the vaccines and in the absence of any economic stimulus. Thus, the only means that the

[2] Antràs et al. (2020) analyze the interplay between globalization and pandemic via trade-induced personal interactions.

[3] https://www.imf.org/external/datamapper/NGDP_RPCH@WEO/OEMDC/ADVEC/WEOWORLD

countries can reduce the number of infections is through stringency measures. The economic costs and the benefits from coordination increase significantly when we incorporate the cost of lives that we extrapolate from Cutler and Summers (2020). We show that cost of lives add 0.2 percent to economic costs in the case of full and coordinated lockdown. The additional costs exceed 100 percent of the GDP in the case of partial or no lockdowns. These findings highlight the economic importance of globally coordinated full lockdowns. Our results illustrate that there is no trade off between saving lives vs. saving the economy. Globally coordinated full lockdowns not only minimize the number of deaths but they also minimize economic costs by normalizing the economy in the most effective way. Our approach is relevant under the threat of multiple waves after reopening. If the economy opens up prematurely, the increase in the number of infections would stall demand again, even if the businesses remain open. The consequent economic costs may lead to lasting economic damage by extending the duration of the recession. Indeed, if the lockdown ends prematurely, we show that the duration of a lockdown that is needed to contain the virus increases to more than one year.[4]

Several closed economy papers employing epidemiological models similar to us, though without the sectoral heterogeneity,[5] including Acemoğlu et al. (2021), Alvarez et al. (2021), Farboodi et al. (2021), and Eichenbaum et al. (2021) reach comparable conclusions. Engler et al. (2020) also build on Eichenbaum et al. (2021) to study the mitigating effect of trade in the presence of pandemic using a two country and a single sector model. Accordingly, imposing full lockdowns or stricter measures at the *early* stages of the pandemic lower economic costs by normalizing aggregate demand sooner. We argue that, for an open economy, the superiority of a coordinated full lockdown over a partial lockdown is even bigger. This is because demand will be lower in the absence of a full lockdown abroad. The intuition is similar to the work of Guerrieri et al. (2022), where supply shocks can turn into larger aggregate demand shocks given nominal rigidities. We have the open economy version of this, where foreign demand shock is more negative for the small open economy if the foreign country also suffers from supply shocks. The less the virus is contained (no lockdown) the bigger the negative supply shock is in the foreign country, as more people are sick and cannot go to work,

[4]See https://www.thelancet.com/journals/lanpub/article/PIIS2468-2667(20)30073-6/fulltext, that argues that re-opening too soon before the R number is below 1 might trigger another peak. The case of Singapore is an example with re-curring lockdowns: https://www.theguardian.com/world/2020/apr/21/singapore-coronavirus-outbreak-surges-with-3000-new-cases-in-three-days

[5]Osotimehin and Popov (2020) is an exception who study how economic and health risks cascade into other sectors.

showing up as a negative demand shock in the small open economy.

Since we did our analysis in the counterfactual world of no policy stimulus, in the last part of our paper, we evaluate the role of international financial linkages. Are capital flows act as amplifiers or smoothers? As losses to the small open economy go up due to trade linkages, we hypothesize that sectors with stronger international connections suffer more from the pandemic due to a significant decline in external demand for that sector. We show that capital flows act as a smoothing mechanism: sectors with large output losses suffer from weak foreign demand and lower exports but at the same time higher capital inflows.

We organize the remainder of the paper as follows: Section 2 describes the model. Section 3 presents our quantitative results. Section 4 concludes.

2 The Model

In this section, we exploit a model that illustrates how COVID-19 affects the economy.[6] We illustrate that despite the increasing costs due to business closures, a full and coordinated lockdown contains the virus in the fastest way. As we compare the recovery paths with and without the lockdown, we observe that a full lockdown lasts for approximately 40 days while partial lockdown cannot contain the virus within a year. Because the duration of the lockdown increases substantially, the economic costs of a partial lockdown are significantly higher than full lockdown. The mortality numbers present a stark contrast across alternative scenarios as well. Full lockdown, which has the lowest economic costs also stands out as the best option that minimizes the number of deaths. Only 0.002 percent of the population dies in a well implemented full lockdown whereas the numbers range between 0.32 to 0.96 percent in the case of partial lockdown.

2.1 The SIR Model for Pandemic

We use the workhorse model of the pandemic, the Susceptible-Infected-Recovered (SIR) model, which has been heavily used in epidemiology (see Allen (2017) for a primer). According to this

[6] See Table A.1 for the notation and parameter values we use.

model, the population (denoted by N) can be split into three disjoint groups, namely the Susceptible (S_t), Infected (I_t) and Recovered (R_t) individuals at any time t. The individuals in the susceptible group can contract the disease from the individuals in the infected group. Those who develop immunity to the disease (either by going through the disease or by vaccination) constitute the recovered group. At any given time, the number of susceptible individuals decreases and the number of people in the recovered group increases. The severity of the pandemic is related to the size of the infected group. We quantify the progression of the pandemic using certain assumptions. An interaction between a susceptible and an infected individual can occur with a probability proportional to $S_t \times I_t / N$, where N serves as the normalization constant. The disease would be transmitted with a ratio of β during this interaction. On the other hand, among the infected individuals, a ratio γ recovers from the disease.[7] Combining these ideas into a mathematical formulation, we arrive at the following equations that govern the law of motion of the pandemic at any given time:

$$
\begin{aligned}
\Delta S_t &= -\beta S_{t-1} \frac{I_{t-1}}{N} \\
\Delta R_t &= \gamma I_{t-1} \\
\Delta I_t &= \beta S_{t-1} \frac{I_{t-1}}{N} - \gamma I_{t-1} \qquad (1)
\end{aligned}
$$

Since $S_t + I_t + R_t + N$, the summation of the differences, i.e., $\Delta S_t + \Delta R_t + \Delta I_t = 0$, is always zero.

Conventional SIR models treat interactions between the individuals as homogeneous. In real life, however, interaction patterns exhibit a great degree of variation among different industries. For instance, a dentist needs to work in close proximity to others to perform her job whereas a computer programmer does not require physical proximity. Because each industry employs a variety of occupations, the physical proximity requirements of occupations would create sectoral heterogeneity in different work-spaces. In turn, this sectoral heterogeneity leads to different infection dynamics and trajectories. We assume that the industries that require a greater degree of physical proximity would be more prone to infections.[8]

[7] We do not model mortality here. Please see 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) for models with mortality.

[8] In a report analyzing the effects of the pandemic on its members, DISK labor union in Turkey claims that the infection rate increases three times among workers compared to rest of the society: http://disk.org.tr/2020/04/rate-of-covid-19-cases-among-workers-at-least-3-times-higher-than-average/

We incorporate the heterogeneity in infection dynamics stemming from sectoral composition into the SIR model. First, we distinguish between working and non-working populations, where the latter is denoted by N_{NW}. We assume that the economy consists of K sectors, which are indexed by $i = 1, \ldots, K$, each with L_i workers. During the pandemic, if a worker can do her job remotely, she does not need to show up to the work site. We classify these workers as "teleworkable." We calculate the teleworkable share of employment from Dingel and Neiman (2020)'s list of teleworkable occupations. The remaining workers need to be on-site to fulfill their tasks. The number of teleworkable employees in industry i is denoted by TW_i and on-site workers are denoted by N_i, such that:

$$L_i = TW_i + N_i. \tag{2}$$

In terms of disease susceptibility, teleworkable employees and non-working population can be lumped together because they are both assumed to be "at-home." We use $i = 0$ to represent the at-home group where the size of this group is:

$$N_0 = N_{NW} + \sum_{i=1}^{K} TW_i. \tag{3}$$

We assume that the at-home group is the least susceptible group and has an infection rate of β_0. Being at the job site increases the risk of contracting the disease and this increase is intimately related to the hetereogenity of physical proximity requirements of industries. Therefore, we define the infection rate within industry i to be:

$$\beta_i = \beta_0 \text{Prox}_i \qquad \text{for} \quad i = 1, \ldots, K \tag{4}$$

where Prox_i captures the proximity requirement of industry i. We calculate the physical proximity requirements for occupations using the O*NET dataset (see Section 3.1 for details). One caveat with this approach is that during the pandemic the physical proximity requirements of industries could be adjusted downwards (Eichenbaum et al., 2021). Here, we do not endogenize this decision in our model and consider the proximity measure as exogenous.

Because infection dynamics show sectoral heterogeneity, we track the on-site workers of industry

i's susceptible, infected and recovered groups separately, which are denoted by $S_{i,t}$, $I_{i,t}$ and $R_{i,t}$, respectively. At any given time, the sum of individuals in these groups give $S_{i,t} + I_{i,t} + R_{i,t} = N_i$, number of on-site workers in industry i. This specification also holds for the at-home group ($i = 0$). We assume that the individuals in the at-home group could contract the disease from all infected individuals:

$$\Delta S_{0,t} = -\beta_0 S_{0,t-1} \frac{I_{t-1}}{N} \tag{5}$$

where $I_t = \sum_{i=0}^{K} I_{i,t}$ is the number of infected people in the entire society.

An on-site worker in industry i, can either contract the disease from the general population like at-home individuals, or she can contract it from the work site. We assume that the infection rate on work site is β_i, defined in Equation 4. Hence, the size of the susceptible individuals for on-site workers in industry i evolves according to the following equation:

$$\Delta S_{i,t} = -\beta_i S_{i,t-1} \frac{I_{i,t-1}}{N_i} - \beta_0 S_{i,t-1} \frac{I_{t-1}}{N} \tag{6}$$

We assume that the recovery rate is the same for any type of infected individual:

$$\Delta R_{i,t} = \gamma I_{i,t-1} \tag{7}$$

The change in the number of infected individuals is related to the changes in the size of susceptible and recovered individuals in group i:

$$\Delta I_{i,t} = -\left(\Delta R_{i,t} + \Delta S_{i,t}\right) \tag{8}$$

We would like to use the most realistic parameters to capture the infection dynamics. To that end, we first gather information about the parameters in Equation 1 that dictate the simple SIR model from the literature. The γ parameter captures the mean recovery time. Here, we rely on a report by the World Health Organization (WHO),[9], which mentions a median recovery time of two weeks for mild cases. We use $\gamma = 1/14 \approx 0.07$ to obtain a mean recovery time of two weeks, acknowledging the fact that the mean recovery time could exceed the median recovery time. Nevertheless, we prefer

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

to err on the optimistic side. Another parameter that controls the disease progression is R_0, which is the average number of individuals infected by an already infected individual. In the simple SIR model, $R_0 = \beta/\gamma$. In the same WHO report, the range for R_0 is estimated to be between 2 and 2.5. Once again, we use the optimistic alternative and set $R_0 = 2$, which gives $\beta = 0.14$. These values agree with the parameters estimated by Stock (2020) and Pindyck (2020) who primarily focus on calibration of the SIR model for tracking the evolution of the COVID-19 pandemic under different scenarios. The readers should be reminded at this early stage that our choice of more optimistic parameter values might imply a shorter duration for the pandemic and underestimate the total economic costs, should the pandemic follow a more pessimistic path.

For our multi-sector SIR model, we match the weighted average of each individual group i – i.e., β_i– to the β of entire population. Here, weights are the shares of the sectoral population in total population. For an on-site worker of industry $i = 1, .., K$, the normalized rate of infection is $(\beta_0 + \beta_i)$.[10] For an at-home individual, the infection rate is only β_0. The relationship between β_i's and β_0 is given in Equation (4). Therefore:

$$\beta_0 \frac{N_0}{N} + \sum_{i=1}^{K} (\beta_0 + \beta_i) \frac{N_i}{N} = \beta_0 + \beta_0 \sum_{i=1}^{K} \text{Prox}_i \frac{N_i}{N} = \beta \tag{9}$$

We can write β_0 as a function of population β, industry size, and the industry proximity levels as:

$$\beta_0 = \beta \left(1 + \sum_{i=1}^{K} \frac{\text{Prox}_i N_i}{N} \right)^{-1} \tag{10}$$

with $\beta = 0.14$ is estimated from the WHO report.

2.2 Economic Environment

We use a small open economy version of the model by Baqaee and Farhi (2022). As in their case, we use a non-linear optimizer to solve the model. The non-linear solver helps us with downward wage-rigidity and aggregate demand shocks. Below, first, we describe the notation that we use in

[10] According to the report cited in Footnote 8, the infection rate is estimated to be 3 times higher for on-site workers compared to the non-working population. Here, we take a more optimistic stance and select the infection rate to be 2 times higher on average .

the economic model. Table A.1 of the Appendix provides the summary of the notation and the parameter values.

Countries, Sectors and Factors. There are N sectors in each country and we denote the set of industries with $\mathcal{N}$. Industries corresponding to Turkey are denoted with $\mathcal{N}_T$ and to RoW with $\mathcal{N}_R$. We index country-sector pairs with i, j or k. In case we would like to refer a specific sector i in a country, we use Ti or Ri. The set for all factors is $\mathcal{F}$, and the factors of Turkey (RoW) are represented by $\mathcal{F}_T$ ($\mathcal{F}_R$). We use f or g to refer to index factors when we do not need to specify countries. We split the Covid period into 365 days and index each day with t.

Output, Prices, Inputs, Final Consumption and Labor. The output of industry i is denoted with y_i and its price with p_i. Each industry uses labor and inputs from other industries. The amount of intermediate input used by country-sector i from country-sector $j \in \mathcal{N}$ is shown with x_{ij}. We denote the output of industry i consumed as final good in country $m \in \{T, R\}$ with c_i^m. We denote the level of factor f with L_f and its wage with w_f. We assume that the labor is the only factor of production and it is sector specific. When we refer to labor specific to the labor employed in country-sector i, we interchangeably use the index for the sector to use the labor as well as L_i and its wage as w_i.

Time indices. When we show daily values of these quantities or prices, we add the time index t. For example, the output of industry i on day t is denoted by $y_{i,t}$. When we do not use the time indices, we refer to the steady-state values of these variables pre-Covid. For example, y_i corresponds to the output of industry i at the steady state.

2.3 Production

During the pandemic period, the level of production decreases because the infected individuals cannot work until they recover from the disease. For each industry i, we have two groups of workers, teleworkable, whose size is TW_i and on-site, with size N_i. The number of infected individuals among on-site workers is $I_{i,t}$. Teleworkers are considered to be as a part of at-home group, whose size is N_0

with active infections of $I_{0,t}$. Hence, the total number of available workers at time t will be:

$$L_i \underbrace{\frac{(N_i - I_{i,t}) + TW_i\,(1 - I_{0,t}/N_0)}{L_i}}_{\equiv \mathcal{L}_{i,t}} = L_i\,\mathcal{L}_{i,t} \tag{11}$$

We normalize the labor in each industry to be $L_i = 1$. We assume that the production follows the following (normalized) nested CES structure:

$$y_{i,t} = \left[\gamma_i \mathcal{L}_{i,t}^{\frac{\phi-1}{\phi}} + (1-\gamma_i) \left(\sum_{j \in \mathcal{N}} \Omega_{ij} x_{ij,t}^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}\frac{\phi-1}{\phi}} \right]^{\frac{\phi}{\phi-1}}, \tag{12}$$

where

- γ_i is the value-added share at the steady state with:

$$\gamma_i \equiv \frac{w_i L_i}{p_i y_i},$$

- the second term in the parentheses is the intermediate input bundle with the corresponding price index $p^M_{i,t}$,
- ϕ is the elasticity of substitution between labor and the intermediate input bundle,
- θ is the elasticity of substitution between intermediate inputs,
- and Ω_{ij} is the input share at the steady state with:

$$\Omega_{ij} \equiv \frac{1}{1-\gamma_i} \frac{p_j x_{ij}}{p_i y_i}.$$

Note that the inputs can be both domestic and foreign.

2.4 Consumption

During the pandemic, the daily routines and priorities change drastically to avoid the risk of getting infected. This voluntary social distancing, or put differently, the "fear" of getting infected, leads to substantial changes in consumer preferences. This is true both for domestic and foreign demand. The demand channel allows us to incorporate the role of global coordination by focusing on how lockdown decisions in a country's trade partners affect the demand for its exports.

The changes in preferences evolve as the pandemic progresses. We assume that the demand transitions from the "normal" to a worst case scenario during the brunt of the pandemic. Specifically, we consider two demand profiles, representing the normal times and the turbulent times. To calibrate these profiles, we track the consumption data from the national accounts and the credit card spending data. While the first dataset is of low frequency and published with a delay, the latter is available at the weekly frequency. Therefore, it provides us with useful information on the changes in demand structure over the course of pandemic. We complement the credit card data with sector specific information in industry reports and expert opinions if the spending in a sector is not often done with credit cards.[11] We specify a smooth function that transition gradually between these two demand profiles depending on the number of infections. After determining demand, we use the input-output framework and map the final good consumption, both domestic and foreign, back to output in each industry.

Consumers optimize their consumption pattern in two periods. The first period corresponds to the Covid and the second period corresponds to the post-Covid epochs. All households in each country $m \in \{T, R\}$ optimize the consumption to optimize the intertemporal utility with a unit intertemporal elasticity of substitution:

$$C_m^{1-\beta^m} \tilde{C}_m^{\beta^m}, \tag{13}$$

where β captures the time preference of the consumers. We denote the Covid-era consumption with C_m and the post-Covid consumption with $\tilde{C}_m$. The corresponding price indices for the consumption are p_m and $\tilde{p}_m$, respectively. We assume that we are at the zero-lower bound in interest. Hence, the intertemporal budget constraint for the households can be written as:

$$p_m C_m + \tilde{p}_m \tilde{C}_m = I + \tilde{I}, \tag{14}$$

where I and $\tilde{I}$ denote the current and future household income, respectively. All the consumers

[11] We present these demand changes and related data resources in Table A.4 of the Appendix.

are Ricardian and smooth out their consumption over two periods. Therefor, the consumption will follow:

$$p_m C_m = \frac{1-\beta^m}{\beta^m} \tilde{p}_m \tilde{C}_m. \tag{15}$$

Hence, the consumers' choice of β^m determines the transfers from future to the current. We take $\tilde{p}_m = 1$ and the world production, $\mathrm{GDP}_W = 1$, as the numeraire. Assuming pre-Covid domestic production of GDP_m, we set $\tilde{C}_m = \mathrm{GDP}_m/\mathrm{GDP}_W$. Hence, $\sum_m \tilde{C}_m = 1$. In the Covid era, the consumption is split into 365 days, with each day's consumption denoted by $C_{m,t}$ such that $C_m = \sum_t C_{m,t}$.

Within each period, the consumers have Cobb-Douglas preferences over all domestic and foreign sectors. In particular, we focus in the Covid period. We split this period into 365 days. For a representative consumer in country $m \in \{T, R\}$, the utility function follows:

$$C_{m,t} = \prod_{i \in \mathcal{N}} (c^m_{i,t})^{\alpha^m_i \alpha^m_{i,t}}, \tag{16}$$

such that $\alpha^m_{i,t} \geq 0$ satisfy $\sum_i \alpha^m_i \alpha^m_{i,t} = 1$. If there are no infections in the country m, the baseline expenditure shares are assumed to be α^m_i, which can be calculated from the observed pre-Covid expenditure shares.

During Covid-19 pandemic, the consumption weights change depending on the infection level in country m. We denote the infection level in country m at time t with $I_{m,t}$. When infection numbers are small, we assume that the shares do not move. In particular, we take $\alpha^m_{i,t} = 1$ for a small number of infections, i.e., $I_{m,t} \leq 0.1\bar{I}_m$, where $\bar{I}_m$ is a scaling parameter for infections. In the Turkish context, we set $\bar{I}_T$ to 50,000 to capture a relevant range for the number of infections (see below for our simulations). Likewise, for the rest of the world, we set $\bar{I}_R = \bar{I}_T \mathrm{pop}_R/\mathrm{pop}_T$, where pop_R (pop_T) is the population of the RoW (Turkey). This limit implies that the utility function returns to normal times if the number of infections remain below 5,000 (in the Turkish case).

For large $I_{m,t}$, the limit level is defined as $\lim_{I_{m,t} \to \infty} \alpha^m_{i,t} \equiv \bar{\alpha}_i$, with $\bar{\alpha}_i$ are calculated from the apex of the pandemic. For the specific sectors, such as the airline industry, the demand might completely stall due to travel restrictions. For these sectors, $\bar{\alpha}_i = 0$. On the contrary, the demand might remain intact for the other sectors, such as the food industry. In this case $\bar{\alpha}_i = 1$. To sum up, $\bar{\alpha}_i$ is sector specific and it reflects the lower bound for the change in demand for an industry's final good at the peak of the pandemic. We pinpoint these sector specific lower bounds using credit card data for the Turkish industries at the peak of the first wave of the pandemic in March 2020. We provide details on this data set in the next section. When we compare the Turkish data with the other countries, we note that these lower bounds are very similar, as the first wave of the pandemic hit the countries almost contemporaneously. Without loss of generality and to simplify our analysis, we assume that changes in demand patterns that we observe in Turkey can be generalized to the rest of the world. Accordingly, we use the lower bounds used for Turkey for the other countries.[12]

Because we assume that the demand evolves gradually with the active number of infections in the society, we need to specify a functional form reflecting this smooth transition between $\bar{\alpha}_i$ and 1, representing the two limiting cases. We use an inverse hyperbolic functional form to achieve this property as:

$$\alpha_{i,t} = \begin{cases} 1 & \text{if} \quad I_{m,t} \leq 0.1\bar{I}_m \\ \bar{\alpha}_i \frac{1+(I_{m,t}/\bar{I}_m - 0.1)}{\bar{\alpha}_i + (I_{m,t}/\bar{I}_m - 0.1)} & \text{if} \quad I_{m,t} > 0.1\bar{I}_m. \end{cases} \tag{17}$$

Here $\bar{I}_m$ plays the role of normalizing the numbers. We select this number to be proportional to the population of the country. The advantage of using this functional form is that it allows the marginal impact of the number of infections to change inversely with the number of infections. As a result of the tuning parameters $\bar{I}_m$ and α_i which can change the limits and the slope of the function, we can specify sector specific fear factors that we estimate from the data. We rescale $\alpha_{i,t}$'s such that $\sum_i \alpha_i^m \alpha_{i,t}^m = 1$.

[12]For example, when we compare credit card spending in Turkey to the US and focus on two representative sectors such as "Accommodation" and "Gasoline Stations", we observe that the changes follow a strikingly similar pattern. For example, credit card spending in the accommodation sector declines by 40.1% in Turkey and 43.6% in the US for the week of March 25. In the gasoline industry, credit card spending declines by 81.1% in Turkey and 85.6% in the US. The credit card data follows a rather similar pattern in the following weeks as well, supporting our simplification to use Turkish credit card data as a proxy for global changes in demand during the pandemic.

2.5 Equilibrium

In equilibrium, wages and prices adjust such that all goods clear as intermediate inputs or final consumption:

$$y_i = \sum_j x_{ij} + \sum_m c_i^m, \tag{18}$$

and all available factors are employed.

2.6 Solution

First, we create the following matrices from the parameters we use for the consumption and production functions such that:

- $\boldsymbol{A}$: consumption weights with $A_{mi} \equiv \alpha_i^m$.
- $\boldsymbol{\Gamma}$: a diagonal matrix whose diagonal elements are value-added share in each industry such that $\Gamma_{ii} = \gamma_i$.
- $\boldsymbol{\Omega}^{\mathcal{N}}$: input shares whose elements are Ω_{ij}.
- $\boldsymbol{\beta}$: A diagonal matrix whose diagonal elements capture the preference between future and current consumption for each country such that $\beta_{mm} = \beta^m$.
- $\boldsymbol{I}$: the identity matrix.

We will stack all these matrices in a way such that each row corresponds to simple CES aggregates of the entries it corresponds to. The order of rows / columns follow:

- $1 \ldots M$: Consumption of each country (M is the number of countries).
- $M+1 \ldots M+MS$: Sectors (MS is the number of country-sector pairs).
- $M+MS+1 \ldots M+2MS$: Intermediate input bundles.
- $M+2MS+1 \ldots M+3MS$: Sector specific labor.
- $M+3MS+1 \ldots 2M+3MS$: Ricardian consumer for each country optimizing current and future consumption.

- $2M + 3MS + 1 \dots 3 < +3MS$: Future consumption for each country.

Overall input-output matrix that captures supply, demand and future consumption simultaneously is, therefore:

$$\Omega = \left[\begin{array}{c|c|c|c|c|c} 0_{(M\times M)} & \boldsymbol{A}_{(M\times MS)} & 0_{(M\times MS)} & 0_{(M\times MS)} & 0_{(M\times MS)} & 0_{(M\times M)} \\ \hline 0_{(MS\times C)} & 0 & \boldsymbol{I}-\boldsymbol{\Gamma} & \boldsymbol{\Gamma} & 0 & 0 \\ \hline 0_{(MS\times C)} & \boldsymbol{\Omega}^{\mathcal{N}} & 0 & 0 & 0 & 0 \\ \hline 0_{(MS\times C)} & 0 & 0 & 0 & 0 & 0 \\ \hline \boldsymbol{\beta}_{(M\times M)} & 0 & 0 & 0 & 0 & \boldsymbol{I}-\boldsymbol{\beta} \\ \hline 0_{(M\times M)} & 0 & 0 & 0 & 0 & 0 \end{array}\right] \tag{19}$$

Let's define the Leontief inverse for the goods as:

$$\Psi^{\mathcal{N}} \equiv \left[I - (\boldsymbol{I}-\boldsymbol{\Gamma})\Omega^{\mathcal{N}}\right]^{-1}.$$

The corresponding Leontief inverse matrix for the extended Ω matrix, $\Psi \equiv (I - \boldsymbol{\Omega})^{-1}$, is given by:

$$\Psi = \left[\begin{array}{c|c|c|c|c|c} I & A\,\Psi^{\mathcal{N}} & A\,\Psi^{\mathcal{N}}\,(I-\Gamma) & A\,\Psi^{\mathcal{N}}\,\Gamma & 0 & 0 \\ \hline 0 & \Psi^{\mathcal{N}} & \Psi^{\mathcal{N}}\,(I-\Gamma) & \Psi^{\mathcal{N}}\,\Gamma & 0 & 0 \\ \hline 0 & \Omega^{\mathcal{N}}\,\Psi^{\mathcal{N}} & I+\Omega^{\mathcal{N}}\,\Psi^{\mathcal{N}}\,(I-\Gamma) & \Omega^{\mathcal{N}}\,\Psi^{\mathcal{N}}\,\Gamma & 0 & 0 \\ \hline 0 & 0 & 0 & I & 0 & 0 \\ \hline \beta & \beta\,A\,\Psi^{\mathcal{N}} & \beta\,A\,\Psi^{\mathcal{N}}\,(I-\Gamma) & \beta\,A\,\Psi^{\mathcal{N}}\,\Gamma & I & I-\beta \\ \hline 0 & 0 & 0 & 0 & 0 & I \end{array}\right] \tag{20}$$

The corresponding CES elasticities for each row is:

$$\sigma = \left[\begin{array}{c|c|c|c|c|c} 1_{(1\times C)} & \phi_{(1\times CN)} & \theta_{(1\times CN)} & 0_{(1\times CN)} & 1_{(1\times C)} & 0_{(1\times C)} \end{array}\right]' \tag{21}$$

where elasticity of 1 corresponds to Cobb-Douglas and rows with 0 correspond to factors and future consumption. With this elasticity structure, for each row k with elasticity $\sigma_k \neq 0$ or 1, we have the following price equation:

$$p_k = \left[\sum_j \Omega_{kj} p_j^{1-\sigma_k}\right]^{\frac{1}{1-\sigma_k}}.$$

For the rows with Cobb-Douglas price index (i.e., $\sigma_k = 1$), we have:

$$\log p_k = \sum_j \Omega_{kj} \log p_j.$$

Recall that output of an industry or usage of factors satisfy:

$$p_k y_k = \sum_j p_k x_{kj} + \sum_m p_k c_k^m.$$

For any CES function with elasticity σ_j, we can write the share of input as:

$$\frac{p_k x_{kj}}{p_j y_j} = \Omega_{jk} \left(\frac{p_k}{p_j}\right)^{1-\sigma_j}.$$

With the integrated input-output matrix and underlying CES structure, we can write this as:

$$p_k y_k = \sum_j \Omega_{jk} p_k^{1-\sigma_j} p_j^{\sigma_j - 1} p_j y_j.$$

Dividing both sides with the world expenditure E, and defining the Domar weight we get:

$$\lambda_k \equiv \frac{p_k y_k}{E} = \sum_j \lambda_j \Omega_{jk} p_k^{1-\sigma_j} p_j^{\sigma_j - 1}.$$

Here, let's highlight the role of future consumption and the Ricardian consumer. For country m, let Rm denote the row corresponding to the Ricardian consumer optimizing between the current and future consumption and $*m$ denotes the future consumption. Then:

$$\lambda_m = \lambda_{Rm} \Omega_{Rm,m} \quad \text{and} \quad \lambda_{*m} = \lambda_{Rm} \Omega_{Rm,*m}.$$

Hence

$$\lambda_m = \frac{\Omega_{Rm,0m}}{\Omega_{Rm,*m}} \lambda_{*m} = \frac{\beta^m}{1-\beta^m} \lambda_{*m}.$$

We assume that the future consumption levels are the same as pre-shock levels and the prices are also normalized. Hence, in the future, the country's share in the world income is assumed to be the same as the pre-Covid share:

$$\lambda_{*m} = \frac{\mathrm{GDP}_m}{\mathrm{GDP}_W} \quad \text{and} \quad p_{*c} = 1.$$

For the Ricardian consumers, her income is the total income today and the future such that:

$$\lambda_{Rm} = \sum_{j \in \mathcal{F}_m} \lambda_j + \lambda_{*m},$$

where $\mathcal{F}_m$ defines the set of factors belonging to country m.

Initially all prices are set to 1 and all Domar weights set to their corresponding values using ICIO tables. We calibrate the model initially with these values. During Covid, the shocks alter $\boldsymbol{A}$ matrix and labor levels. Hence, the prices and Domar weights re-adjust to satisfy above equations. We solve the system using a commercially available non-liner solver. After obtaining the price levels, and Domar weights, we can easily calculate the real GDP changes. Formally, we use Törnqvist price index to compare the real GDP in the pandemic to the pre-pandemic values.

Elasticities. In our analysis, we have two elasticities to set: ϕ, which governs the substitution between the labor and the intermediate input bundle and θ, which adjusts the substitution between various intermediate inputs. Following the literature (See for example Baqaee and Farhi, 2022; Atalay, 2017; Boehm et al., 2019), we set $\phi = 0.6$ and $\theta = 0.2$.

3 Quantitative Analysis

3.1 Data

In our analysis, we use pre-pandemic OECD ICIO Tables. OECD employs an aggregation of 2-digit ISIC Rev. 4 codes to 36 sectors as industrial classification. We follow this practice in our analysis, and use this classification labeled as OECD ISIC Codes. The list of industries can be found in Table A.3.

Our infection dynamics are governed by the share of teleworkable workers and physical proximity measures at the industrial level. These measures are readily available at the occupational level and we utilize occupational structure of industries to calculate industrial measures. Recently, Dingel and Neiman (2020) identify a set of occupations where remote working is feasible. We use this set for calculating the share of teleworkable workers in each industry.

Because the remaining workers keep working on-site, they can get infected at varying degrees depending on the working conditions. Physical proximity in the workplace is one of the main factors contributing to the contagiousness of the virus. In order to compute physical proximity conditions at the sectoral level, we exploit the self-reported Physical Proximity values, which is provided in the the Work Context section of the O*NET database.[13] For physical proximity, O*NET data is gathered through surveys, which asks workers their occupations and whether their occupation requires physical proximity by selecting one of these 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 take category 3 as a benchmark since 'sitting in a shared office" is similar to sharing a house, which pins down our β_0. We divide the category values with 3 as our proximity measure of an individual. In a sense, we double the infection probability of a person sharing an office compared to an at-home individual.

We take the weighted average of individual responses to create a single occupation proximity value. A proximity value higher than 1 for a given occupation indicates a denser physical proximity compared to a shared office. To convert occupation level teleworkability and proximity values to

[13] https://www.onetcenter.org/database.html. Accessed on April 1, 2020. Dingel and Neiman (2020) also use several measures from O*NET to identify which occupations are teleworkable.

industry-level, we use the information on occupational composition of industries from the the Occupational Employment Statistics (OES) by the U.S. Bureau of Labor Statistics (BLS). OES uses NAICS classification at four digit level and we map these into OECD ISIC codes using the concordance table provided by the U.S. Census Table between NAICS codes and ISIC Rev. 4 industry classification. We report OECD ISIC level teloworkable share and proximity values in Table A.3 of the Appendix.

We use the employment data from the Turkish Social Security (SGK) Agency. SGK follows four-digit NACE Revision 2 codes to classify industries. In order to aggregate employment data to 36 OECD ISIC codes, we make use of the Eurostat correspondence table between NACE Revision 2 and ISIC Revision 4 Industry Codes. SGK lacks the data on the number of employees working in the "Public Administration Sector," so we fill this information using the relevant data provided by the President's office of Turkey.

We rely on publicly available credit card spending data from the CBRT to compute the industry specific changes in the demand structure in the non-tradable sectors. We provide the mapping between CBRT industry codes and OECD ISIC industries in Table A.6. For the tradable sectors where credit card is not the common means of payment, we use a combination of reports from the sectoral associations, Turkish Statistical Institute's monthly revenue indices, experiences from the similar sectors of other countries, and historical records of these specific sectors and the manufacturing sector as a whole. This information is provided in Table A.4 of the Appendix, together with detailed information on the sources of data the list of OECD ISIC industries. The implied aggregate demand shock corresponds to 23% when we consider the sectors with credit card spending data. The implied aggregate demand shock is 16% when we consider all sectors. Thus, our results are not sensitive to the coverage of those sectors with credit card data alone.

Under full lockdown, only a few industries are active. We use the decree issued by the Turkish Ministry of Interior on April 10, 2020 to identify the industries that remain active during lockdowns. Turkish full lockdowns are typically on weekends and holidays and, thus, the list does not include some critical sectors. We supplement the list with the food sector as well as household and sanitary goods sectors. The list of those sectors that are active during the lockdowns is given in Table A.5 of the Appendix. The list is provided with 2 to 4 digit ISIC REV 4 classifications. To transform what proportion of each OECD ISIC industry is active during the lockdowns, we use the detailed employment data at 4 digit level. Finally, we estimate the share of public workers that continue working during the lockdown using the publicly available information, which is listed in Table A.7 of the Appendix.

3.2 Alternative Lockdown Scenarios

In this section, we illustrate the consequences of alternative lockdown scenarios within our framework. In these scenarios, we impose changes on β_0 (i.e., the infection rate of the non-working population) and possibly on β_i for (i.e., the infection rate of the working population in industry i) and simulate the course of the pandemic. The decline in β reflects the effectiveness of a particular lockdown scenario which depends on country characteristics such as demographic dynamics, whether or nor there is a more authoritarian culture with less resistant public, the influence of the scientific committees in shaping political decisions, or the ability of a trustworthy and independent media in affecting public sentiment. The effectiveness of the lockdown also depends on the recovery rate that depends on the quality of healthcare services as well as ICU capacity.

We assume that the pandemic is successfully contained if the number of total infections declines to 5000 after observing the peak.[14] These calibrations allow us to calculate the economic costs of alternative lockdown scenarios.

We first assume that there is an epidemic in Turkey while the rest of the world is pandemic-free. In this world, Turkey is the only country that implements stringency measures to control the contagion of the virus. We assume that the sectors have heterogeneous infection rates based on proximity and there are shocks to both labor supply and demand. We then compare these results to an alternative world where the entire world suffers from the pandemic. Comparing the economic costs in these alternative worlds allow us to to elicit the importance of foreign linkages associated with the economic costs at home.

Table 1 shows the results where there is an epidemic in Turkey. In a partial lockdown, social

[14] We note that the 5000 threshold that is assigned for the containment of the pandemic differs from the notion of Critical Community Size (CCS) (Bartlett, 1960) CCS is the threshold for the number of susceptible individuals to die out by itself. Instead, the 5000 threshold that we set in the model represents the number of infectious individuals who can be feasibly tested, traced, and eventually quarantined so that the pandemic can be contained successfully. We assume that for each infected individual, we need to test ten additional people on average. Thus, if there are 5000 patients, tracing the infection requires about 50,000 tests, which is close to the current testing capacity in Turkey.

distancing rules are implemented while businesses remain open. This implies that under partial lockdown β_0 is diminished compared to the case where no action is taken, but β_i for $i = 1, \ldots, K$ remain unchanged. We consider two cases of partial lockdown where the infection rate, β_0 is reduced by the proportion of 0.5 and 0.10 compared to the reference setting. The table reports hypothetical partial lockdowns that are implemented for 240 days, starting early on the 10$^{\text{th}}$ day and remains active until the 250$^{\text{th}}$ day. The third column illustrates a full lockdown. If the full lockdown is put into practice when the number of infections is around 80,000, a fully effective procedure lowers the reproduction rate to zero ($R_0 = 0$), and contains the pandemic within 39 days.[15]

Table 1: Economic Costs under only SOE being affected by the Pandemic: $\beta_0 \neq \beta_i$

Scenario:	**Partial Lockdown** 10^{th}-250^{th}, $0.1 \times \beta_0$	**Partial Lockdown** 10^{th}-250^{th}, $0.5 \times \beta_0$	**Full Lockdown** 93^{rd}-132^{nd}, $\beta_0 = 0$
	(1)	(2)	(3)
Economic Loss (%Δ VA)	3.08	2.94	2.25

NOTES: Table 1 reports the economic costs of the pandemic under different scenarios with the following specifics: Turkey imposes a partial lockdown between the 10^{th} and 250^{st} days and the pandemic evolves with a relatively high infection rate i.e., $0.5 \times \beta_0$ (column 1); a relatively low infection rate i.e., $0.1 \times \beta_0$ (column 2). Turkey imposes a fully effective lockdown between the 93^{rd} and 132^{nd} days of the pandemic with a zero infection rate (column 3). In each scenario, economic cost is measured as the percentage change in overall economic activity proxied by the value added for the Turkish economy during pandemic relative to its pre-pandemic level.

Table 1 illustrates that the economic costs are the lowest in the case of full lockdown restrictions (column 3) where the GDP declines by 2.25 percent. Comparing column 1 against column 2, we note that a lower initial β does not necessarily yield a lower economic cost because overall economic cost depends on how the infections progress after the restrictions are removed, as described in the next section. The economic costs are minimized in the case of full lockdown (column 3) which contains the pandemic in the most effective way.

Next, we assume that there is a pandemic in the rest of the world and hence global lockdowns are necessary. We assume that lockdowns are coordinated, which implies that all countries adopt the same stringency measures simultaneously. Table 2 shows the corresponding results. Comparing the economic costs in this table against Table 1, we observe that partial lockdown scenarios yield rather similar results regardless of whether the virus is spread globally or not. In the case of full lockdown, we note that overall economic costs increase by 0.25 percent (from 2.25 percent in Table 1

[15]We pick 80,000 because this was approximately the level of infections when Turkey imposed lockdowns.

to 2.48 percent in Table 2) when the rest of the world has to deal with the pandemic and impose their own full lockdowns. This additional cost illustrates the role of foreign demand in Turkey when our trade partners are exposed to the pandemic and lower their imports from Turkey.

Table 2: ECONOMIC COSTS WHEN BOTH COUNTRIES ARE AFFECTED BY THE PANDEMIC: $\beta_0 \neq \beta_i$

Scenario:	**Partial Lockdown** 10^{th}-250^{th}, $0.1 \times \beta_0$	**Partial Lockdown** 10^{th}-250^{th}, $0.5 \times \beta_0$	**Full Lockdown** 93^{rd}-132^{nd}, $\beta_0 = 0$
	(1)	(2)	(3)
Economic Loss (%Δ VA)	3.05	2.95	2.48

NOTES: Table 2 reports the economic costs of the pandemic under different scenarios with the following specifics: Turkey imposes a partial lockdown between the 10^{th} and 250^{st} days and the pandemic evolves with a relatively high infection rate i.e., $0.5 \times \beta_0$ (column 1); a relatively low infection rate i.e., $0.1 \times \beta_0$ (column 2). Turkey imposes a fully effective lockdown between the 93^{rd} and 132^{nd} days of the pandemic with a zero infection rate and the rest of the world coordinates with her (column 3). In each scenario, economic cost is measured as the percentage change in overall economic activity proxied by the value added for the Turkish economy during pandemic relative to its pre-pandemic level.

3.2.1 Infection Dynamics in Alternative Lockdowns

In the previous section, we reported the summary results under alternative lockdown scenarios. In this section, we provide further information on the evolution of the number of infected patients in each lockdown scenario. This allows us to better comprehend how infection dynamics affect economic costs.

Figure 2 compares the no lockdown scenario against partial lockdowns. Figure 1a shows partial lockdowns that end prematurely at the end of 240 days. As shown, none of the partial lockdown scenarios are successful in containing the pandemic. When the lockdown is removed on day 250, the number of infections in all both partial lockdown scenarios are in the same ballpark. Once the lockdown is removed, however, the virus follows a different course in each scenario. For the scenario in which the infections follow a milder course during the lockdown period (black line) the number of new cases increase rapidly, leading to peak levels within 50 days after the lockdown. Meanwhile the high infection and no lockdown scenarios show a steady decline (the blue and red lines). This is because less people get infected during partial lockdown (and get immunity) under the low infection rate scenario, shown by the area under the black line. Hence, by the time the lockdown is removed, the number of susceptible people are significantly higher under the low infection rate scenario, increasing the effective R_0 $(= \beta/\gamma)$. Thus, in the absence of an efficient drug or vaccination, a partial lockdown may need to continue indefinitely, until the number of cases decline to 5000.

In terms of the economic implications, the increase in the number of infections through a second wave due to a premature reopening prevents the economy from a jump start. Even though the supply side remains unrestricted, demand remains supressed due to the increase in the number of infections, dragging the economic growth. These implications are supported by a recent study Andersen et al. (2020) that compares Denmark which had a full lockdown, with Sweden, with partial and voluntary lockdown. Aggregate spending dropped 29 per cent in Denmark and 25 per cent in Sweden. These numbers suggest that merely opening the economy does not imply that demand will be normalized until the outbreak is contained. Thus, a partial lockdown policy might not yield the lowest economic costs as implied by our model.

Figure 1b shows the calibration results if partial lockdown lasts for a full year. As in Figure 1a, we assume that the industries are operating as usual and thus β_i's (for $i = 1, \ldots, K$) remain unaffected. If no action is taken against the COVID-19 pandemic, which is shown with the blue line, the pandemic advances at a rate implied by the benchmark reproduction rate of $R_0 = 2$. This implies that the pandemic reaches its peak around the 160$^{\text{th}}$ day with a total toll of around 14 million infections. Following this state of "herd immunity", the number of infections starts to decline. After approximately 300 days, the virus is taken under control. Under the no lockdown scenario, 1.13 percent of the population dies if we assume a 1.5 percent mortality rate. The GDP declines 3.32% in this case. We should remind the readers that the economic costs that are expressed in terms of GDP should not be misinterpreted as annual growth forecasts. We merely express the cost of the lockdown in terms of the GDP. Compared to Figure 1a, we observe that the main advantage of an extended partial lockdown is that it flattens the curve by spreading the number of infections over time and allowing for a larger recovery rate.

Figure 1: PARTIAL LOCKDOWN SCENARIOS

(a) Duration: 240 Days (b) Duration: Full Year

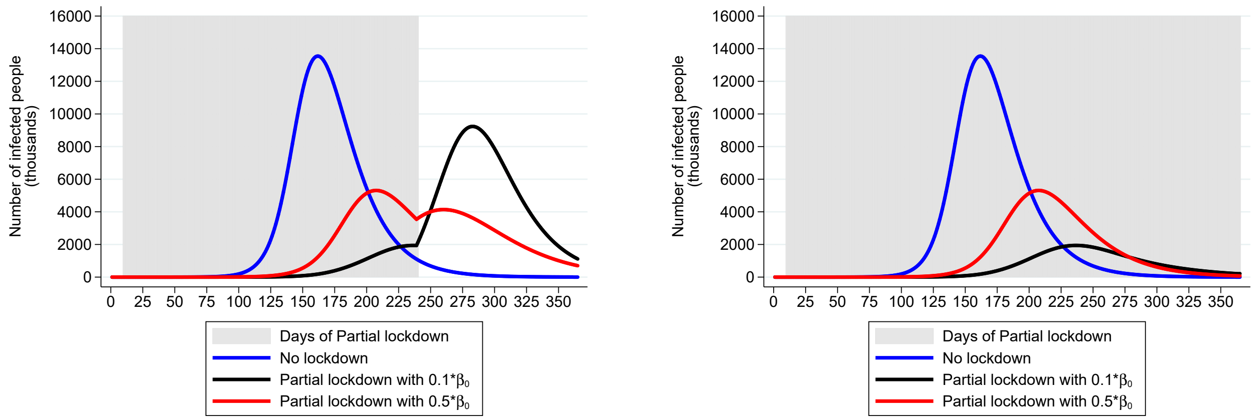


Figure 3 shows the infection dynamics under the full lockdown scenarios. Figure 2a illustrates the implications of our model under full lockdown. If the lockdown is put into practice when the number of infections is around 80,000, a fully effective procedure lowers the reproduction rate to zero ($R_0 = 0$), which is shown by the blue line, and contains the pandemic within 39 days (the gray shaded area).[16] The consequent decline in GDP is about 2.48 percent. If the lockdown is not very effective and the infection continues to spread with some minimal reproduction number ($R_0 = 0.02$), then the duration of the lockdown increases by 15 days (yellow shaded area) to 54 days and the GDP declines by 2.93 percent.

The costs of delaying full lockdown are shown in Figure 2b. The benchmark scenario that is illustrated in Figure 2a is shown with the blue line. If the lockdown is delayed by only one day, the number of infections increases by more than 10,000. In the model, we assume that the number of infections increases faster than the official statistics, which report only the tested patients. Under these circumstances, a 39-day lockdown is no longer sufficient to control the pandemic. Thus, in exchange for a one-day delay, the lockdown needs to be extended by two more days (the red line), which increases the costs of the lockdown. If there is a two-day delay (the green line), this time the duration of the lockdown increases to 43 days. If the lockdown is delayed by one week (the black line), the number of infections and hence the consequent decline in GDP will be the highest. After

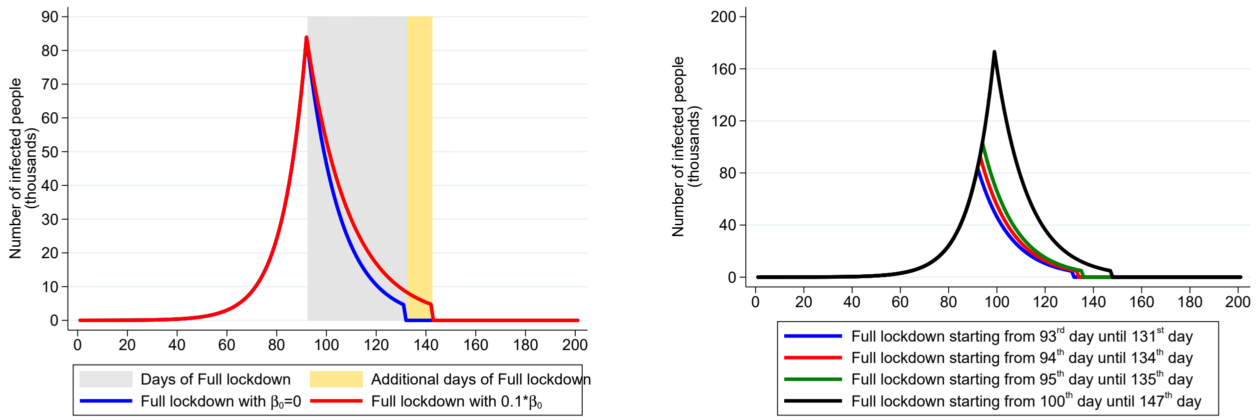
[16] We pick 80,000 because this was approximately the level of infections when Turkey imposed lockdowns.

100 days, the virus starts to spread again and hence prematurely ending the lockdown is rather ineffective.

Figure 2: FULL LOCKDOWN SCENARIOS

(a) Scenarios

(b) Costs of Delay in Implementing Full Lockdown



3.2.2 Global Coordination

The results that are reported so far assume full global coordination. If there is imperfect coordination, the effectiveness of the lockdown measures would change because the pandemic cannot be contained due to cross-border contamination. Table 3 reports the economic costs that are calculated for alternative scenarios of coordination and uncoordination. The first column shows the results where Turkey implements full lockdown while the rest of the world implements partial lockdown. The second column shows the results where the rest of the world implements full lockdown along with Turkey. We observe that the economic costs decrease as the extent of global coordination increases because the pandemic can be contained more effectively.

Table 3: THE ROLE OF COORDINATION, $\beta_0 \neq \beta_i$

Scenario:	**No Coordination** 93^{rd}-132^{nd}, $\beta_0 = 0$, $\rho = 0$	**Full Coordination** 93^{rd}-132^{nd}, $\beta_0 = 0$, $\rho = 1$
	(1)	(2)
Economic Loss (%Δ VA)	2.53	2.31

NOTES: Table 3 reports the economic costs of the pandemic under different full lockdown scenarios with details as follows: Turkey imposes a fully effective lockdown between the 93^{rd} and 132^{nd} days with a zero infection rate, but the rest of the world does not coordinate with her i.e., the probability of coordination (ρ) equals 0 (column 1). Turkey imposes a fully effective lockdown between the 93^{rd} and 132^{nd} days of the pandemic with a zero infection rate and the rest of the world fully coordinates with her (column 2). This scenario corresponds to our benchmark full lockdown scenario, column (4) in Table 2. In each scenario, economic cost is measured as the percentage change in overall economic activity proxied by value added for Turkish economy during pandemic relative to its pre-pandemic level.

3.2.3 Cost of Lives

Our benchmark analysis above excludes the heavy burden that would arise from the lost lives due to infections. Our next step is to investigate the additional costs that would be incurred when the cost of lives are incorporated into analysis. In order to come up with an estimate for the lives lost due to infections, we adapt the conservative value of 7 million USD per life, as exploited in Cutler and Summers (2020). We weigh this value by the ratio of Turkish GDP per capita as a fraction of US GDP per capita.

The first row of Table 4 shows the number of deaths in each lockdown scenario. As shown, the number of deaths is negatively correlated with the strictness of the lockdown restrictions. In the case of no lockdowns, close to a million people lose their lives, which is more than 1 percent of the population (row 2). As we multiply this number with 7 million USD per life, we reach close to 900 billion USD (row 3), which is close to 118 percent of the GDP (row 4). As we move to lockdown policies, we observe that even the partial lockdown policies are able to reduce the death numbers by up to 200,000 people, and reduce the output loss from 117 percent of the GDP in 2019 to up to 91 percent of the GDP in 2019 . The benefits of lockdowns are even more noticeable in the case of full lockdown (column 4). We observe that 0.001 percent of the population dies under an effective full lockdown, compared to 1 percent of the population under no lockdown and about 0.8 percent of the population under partial lockdown scenarios that last for 250 days.The number of deaths decline below 2000 people, reducing the additional costs to less than a quarter percent of 2019 GDP.

Table 4: COSTS OF LIVES UNDER DIFFERENT SCENARIOS: $\beta_0 \neq \beta_i$

Scenario:	No Lockdown $\beta_0 = 0.14$	Partial Lockdown 10^{th}-250^{th}, $0.5 \times \beta_0$	Partial Lockdown 10^{th}-250^{th}, $0.1 \times \beta_0$	Full Lockdown 93^{rd}-132^{nd}, $\beta_0 = 0$
	(1)	(2)	(3)	(4)
(1) No. Deaths	911,681	707,392	813,070	1,630
(2) No. Deaths/Pop	1.13%	0.88%	1.02%	0.00%
(3) U.S. Dollars (mil.)	894,254	693,870	797,528	1,599
(4) % of 2019 GDP	117,51%	91,18%	104,80%	0,21%

NOTES: Table 4 reports the costs of lives under different scenarios with details as follows: Turkey does not take any action against the Covid-19 pandemic and the pandemic evolves with the highest infection rate i.e., $\beta_0 = 0.14$ (column 1). Turkey imposes a partial lockdown between the 10^{th} and 250^{st} days and the pandemic evolves with a relatively high infection rate i.e., $0.5 \times \beta_0$ (column 2); a relatively low infection rate i.e., $0.1 \times \beta_0$ (column 3). Turkey imposes a fully effective lockdown between the 93^{rd} and 132^{nd} days of the pandemic with a zero infection rate and the rest of the world coordinates with her (column 4). In each scenario, economic cost is measured as the percentage change in overall economic activity proxied by value added for Turkish economy during pandemic relative to its pre-pandemic level.

3.2.4 Importance of Sectoral Heterogeneity

The benchmark results that we have illustrated so far assume sectoral heterogeneity. As a robustness check, we explore how our findings would change if all sectors have identical proximity in terms of virus exposure. Table 5 shows the economic costs that are calculated under alternative lockdown scenarios, assuming that all sectors are exposed to the virus equally, Specifically, we set the industry specific infection rate β_i to be equal to at-home infection rate β_0.

Compared to our benchmark results under sectoral heterogeneity, we observe that the economic costs decrease in the no lockdown scenario from 3.32 percent to 3.18 percent. A closer look at infection dynamics illustrates that this finding is due to the fact that the overall infection rate is lower in the case of homogeneous sectors. Specifically, Figure 3a compares the number of infections for the no lockdown scenario under the assumption of homogeneous (the red line) and heterogeneous (the blue line) sectors. It illustrates that it takes 173 days to reach over 135,000 infections under homogeneous sectors. In contrast, it only took 162 days to reach over 135,000 infections in the case of heterogeneous sectors. Thus, the pandemic spreads more slowly in the case of homogeneous sectors, reducing economic costs.

Table 5: Economic Costs of the Pandemic with no Sectoral Disease Heterogeneity: $\beta_i = \beta_0$

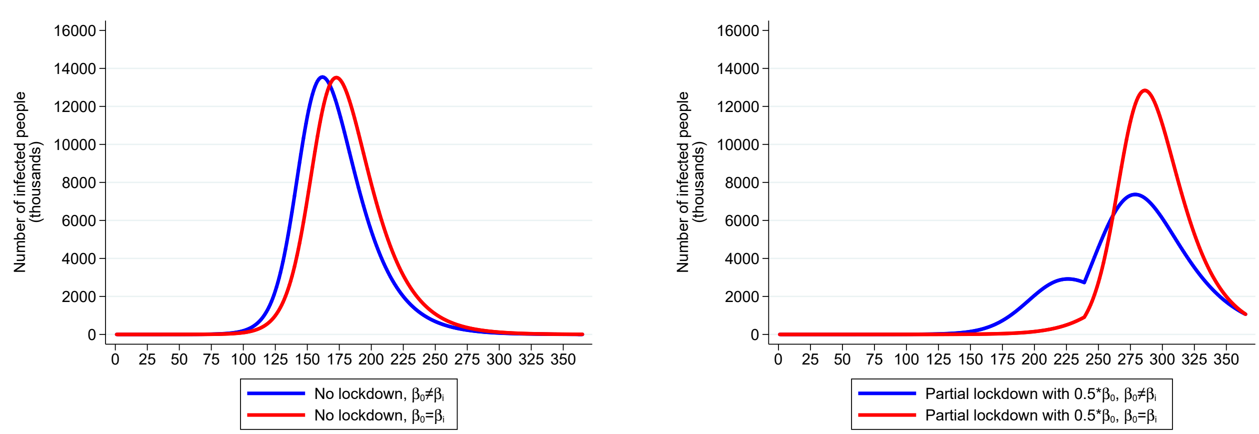
Scenario:	**No Lockdown** $\beta_0 = 0.14$	**Partial Lockdown** 10^{th}-250^{th}, $0.1 \times \beta_0$	**Partial Lockdown** 10^{th}-250^{th}, $0.5 \times \beta_0$	**Full Lockdown** 93^{rd}-132^{nd}, $\beta_0 = 0$
	(1)	(2)	(3)	(4)
Economic Loss (%Δ VA)	3.18	3.04	3.14	2.31

Notes: Table 5 reports the economic costs of the pandemic under different scenarios with details as follows: Turkey does not take any action against the Covid-19 pandemic and the pandemic evolves with the highest infection rate i.e., $\beta_0 = 0.14$ (column 1). Turkey imposes a partial lockdown between the 10^{th} and 250^{st} days and the pandemic evolves with a relatively high infection rate i.e., $0.5 \times \beta_0$ (column 2); a relatively low infection rate i.e., $0.1 \times \beta_0$ (column 2). Turkey imposes a full lockdown between the 93^{rd} and 142^{nd} days of the pandemic with a relatively low infection rate i.e., $0.1 \times \beta_0$ (column 3). Turkey imposes a fully effective lockdown between the 93^{rd} and 132^{nd} days of the pandemic with a zero infection rate and the rest of the world coordinates with her (column 4). In each scenario, economic cost is measured as the percentage change in overall economic activity proxied by value added for Turkish economy during pandemic relative to its pre-pandemic level.

When we impose lockdown restrictions (columns 2 to 4 in Table 5, we observe a different picture. This time the economic costs increase in partial lockdown scenarios. This finding suggests that the weights of the closed sectors change with homogeneous proximity assumption such that the overall infection rate increases. For illustrative purposes Figure 3b compares the number of infections for a partial lockdown scenario under the assumption of heterogenous (the blue line) versus homegenous (the red line) sectors where the lockdown is removed on day 240. As suspected, we observe that the overall infection rate increases significantly for the homogenous sectors scenario once the stringency measures are removed. In turn, the higher infection rate results in higher economic costs.

Figure 3: The Impact of Sectoral Heterogeneity

(a) No Lockdown (b) Partial Lockdown

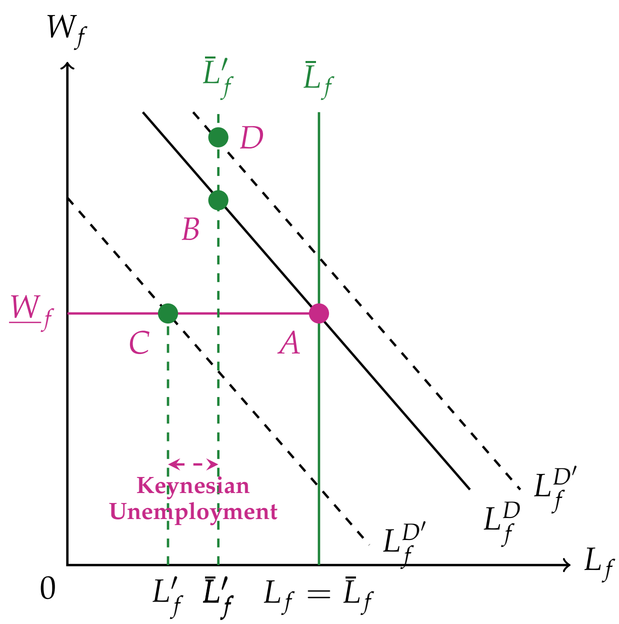


In the Appendix, we report the cost of lives estimates that are calculated under the assumption of homogeneous infections in each sector. Table A.8 shows the results. Overall, we observe that the cost of lives are higher compared to heterogenous sectors framework. Figure A.1 in the Appendix shows the evolution of the pandemic under the assumption of homogenous sectoral infections.

3.3 Downward Wage Rigidity

After introducing the case without wage rigidity, this section undertakes our main analysis with wage rigidity to illustrate the importance of aggreate demand vs aggreate supply shocks.

Figure 4: Effects of Wage-Rigidity on Employment



We assume wages cannot go below a lower limit due to reasons such as minimum wages or a decline in the workers' willingness to work below a certain threshold. These factors create a downward wage rigidity. Figure 4 shows the sketch of the analysis with downward wage rigidity. The solid black line (labeled L_f^D) is the labor demand and the solid green line shows the labor supply ($\bar{L}_f$) pre-Covid. The equilibrium labor is at point A with $L_f = \bar{L}_f$ and wage at W_f. During Covid, potential labor supply will decrease to $\bar{L}'_f \leq \bar{L}_f$ due to sickness or lockdowns. On the other hand, the labor demand also shifts with Covid. If there is no wage-rigidity, the equilibrium labor would be equal to the potential labor. But with downward wage-rigidity, there might be a slack in employment due to higher wage than that would have been implied by the equilibrium. The downward wage rigidity is not binding for the upper labor demand curve with $\bar{L}'_f = L'_f$. However, it is binding for the lower curve. In that case, $\bar{L}'_f > L'_f$ with $\bar{L}'_f - L'_f$ defined as the Keynesian unemployment by several papers in the literature. These sectors are demand constrained because the demand is not strong enough to pull the wages to higher levels. With the Keynesian unemployment, the real output decreases below the potential of the economy.

To counteract Keynesian unemployment, we introduce aggregate demand shocks. Our model is flexible to include aggregate demand shocks through a transfer from future consumption to current consumption—a discount factor shock. Without the wage rigidity, aggregate demand shock would only create inflation. With wage rigidity, aggregate demand shock increases the employment in the demand constrained sectors.

Table 6 reports the economic costs that are calculated under the assumption of wage rigidity. We maintain our baseline assumption of sectoral heterogeneity. If the epidemic only exists in Turkey, the economic costs increase from 2.25 (recall column 3 in Table 1) to 2.4 (Table 6, column 1). If there is a pandemic and no coordination, the economic costs increase from 2.53 percent (Table 3, column 1) to 3.32 percent (column 2, Table 6). If there is full coordination, economic costs increase from 2.31 percent (Table 3, column 2) to 2.47 percent (Table 6, column 3). These findings are consistent with the intuition that wage rigidity generates Keynesian unemployment, which increases overall economic shocks. In columns 4 and 5 we add positive aggregate demand shocks. A priori, one would expect the increase in aggregate demand to reduce the Keynesian unemployment and hence lower economic costs. Indeed, we observe a decline in economic costs as we compare column 2 to column 4 (no coordination), or column 3 to column 5 (coordination).

Table 6: ECONOMIC COSTS OF THE PANDEMIC WITH DOWNWARD WAGE RIGIDITY UNDER FULL LOCKDOWN SCENARIOS: $\beta_0 \neq \beta_i$

Scenario:	**Full Lockdown**, 93^{rd}-132^{nd}, $\beta_0 = 0$				
	Only Turkey Epidemic	**No Coordination** $\rho = 0$	**Full Coordination** $\rho = 0$	**No Coordination** $\rho = 0$	**Full Coordination** $\rho = 0$
	(1)	(2)	(3)	(4)	(5)
Economic Loss (%Δ VA)	2.4	3.32	2.47	3.11	2.37
Pandemic	No	Yes	Yes	Yes	Yes
AD Shock	No	No	No	Yes	Yes

NOTES: Table 6 reports the economic costs of the pandemic under different full lockdown scenario that Turkey imposes fully effectively between the 93^{rd} and 132^{nd} days of the pandemic with a zero infection. The specifics of these scenarios are as follows: There is an epidemic disease in Turkey, but the rest of the world (ROW) does not suffer from this disease (column (1)). There is a pandemic in the world, but the ROW does not coordinate with Turkey i.e., the probability of coordination (ρ) equals 0 (columns (2) and (4)). There is a pandemic in the world, and the ROW coordinates with Turkey i.e., the probability of coordination (ρ) equals 1 (columns (3) and (5)). In columns (4)–(5), we run the same scenarios presented in columns (2)–(3) adding aggregate demand shock to our model. In each scenario, economic cost is measured as the percentage change in overall economic activity proxied by the value added for the Turkish economy during pandemic relative to its pre-pandemic level.

3.4 Sectoral Heterogeneity

In this section we provide further evidence on the rich sectoral heterogeneity in our results and show how this matches well with what happened during the pandemic.

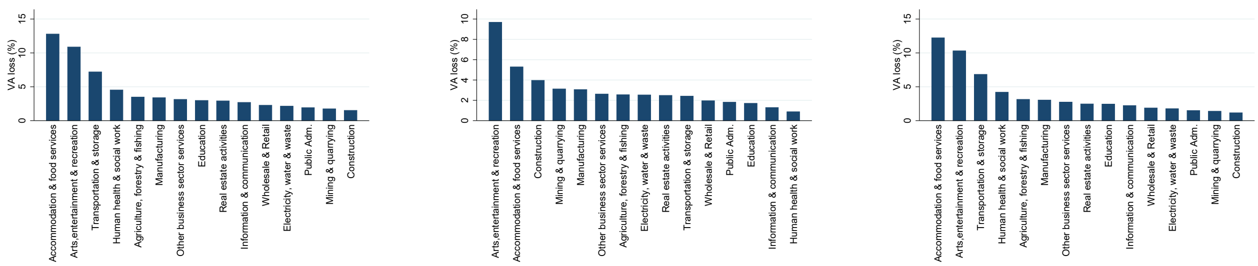
Figure 5 shows how hard each sector is hit from the pandemic under alternative lockdown scenarios. Consistent with our earlier findings, we observe that the full lockdown has the lowest economic costs compared to the alternatives. In terms of sectoral heterogeneity, we note that teleworkable or essential sectors are less severely affected because they continue functioning for all lockdown scenarios (such as education, IT, public administration). Meanwhile, non-essential sectors or those that require on-site work are more severely affected (such as accommodation and food services, arts, entertainment, and recreation, construction).

Figure 5: Sectoral Heterogeneity in terms of Economic Cost of Covid-19 Shock

(a) **Scenario 1:** No Lockdown, $\beta_0 = 0.14$

(b) **Scenario 2:** Full Lockdown, 93^{rd}-132^{nd}, $\beta_0 = 0$

(c) **Scenario 3:** Partial Lockdown, 10^{th}-250^{th}, $0.5 \times \beta_0$



NOTES: This figure shows how the economic cost of Covid-19 shock differs across sectors in a particular lockdown scenario. The panels show three alternative scenarios: (a) No action is taken against the COVID-19 pandemic; (b) Turkey imposes a partial lockdown between the 10^{th} and 250^{st} days and the pandemic evolves with a relatively high infection rate i.e., $0.5 \times \beta_0$; (c) Turkey imposes a fully effective lockdown between the 93^{rd} and 132^{nd} days of the pandemic with a zero infection rate. For each scenario, we measure the sector-level economic cost as the percentage change in overall economic activity (proxied by value added) for a given sector during pandemic relative to its pre-pandemic level. Economic costs are aggregated from the 2-digit OECD ISIC codes to the 1-digit NACE code using 2-digit sector value added values that we obtain from the OECD ICIO Tables. NACE 1-digit sectors are A, B C, D&E, F, G, H, I, J, L, M&N, P, Q, R&S. In each panel, the sectors are ranked in a descending order according to the magnitude of economic cost under the corresponding scenario.

After documenting the heterogeneous economic costs of the pandemic for different sectors, we investigate whether these costs are accrued from demand or supply pressures. Figure 6 counts the days in which output implied by the demand channel or supply channel prevails to bring about the equilibrium output in a given industry.

To interpret the findings present in this figure, we consider three benchmark scenarios: Panel (a) compares the no lockdown scenario against full lockdown (Panel (b)), and partial lockdown with high infection rate (Panel (c)). Panel (a) suggests that under the no lockdown scenario, the demand channel, shown by the red bars, drives output in most of the services sectors until the virus is fully contained. The supply channel, presented by the blue bars, prevails in manufacturing sectors. Among the 15 industry groups, "Accommodation and food services," "Arts, entertainment, recreation and other service activities," and "Transportation & storage" are those that result in the highest economic costs of 12.8%, 10.9%, and 7.2% of the value added generated in those sectors, respectively. These results are shaped by the infection numbers as they drive both sectoral supply and demand shocks. While the evolution of the infections are not directly observable from these figures, they are reported in Figures 1 and 2. When the infection numbers are low (either early or late in the pandemic), the demand is normal. Hence, all the results will be driven by the supply. When infection numbers are high (which corresponds to the middle of the pandemic), demand shock dominates in the services sectors. In other sectors such as manufacturing, either supply or demand can dominate.

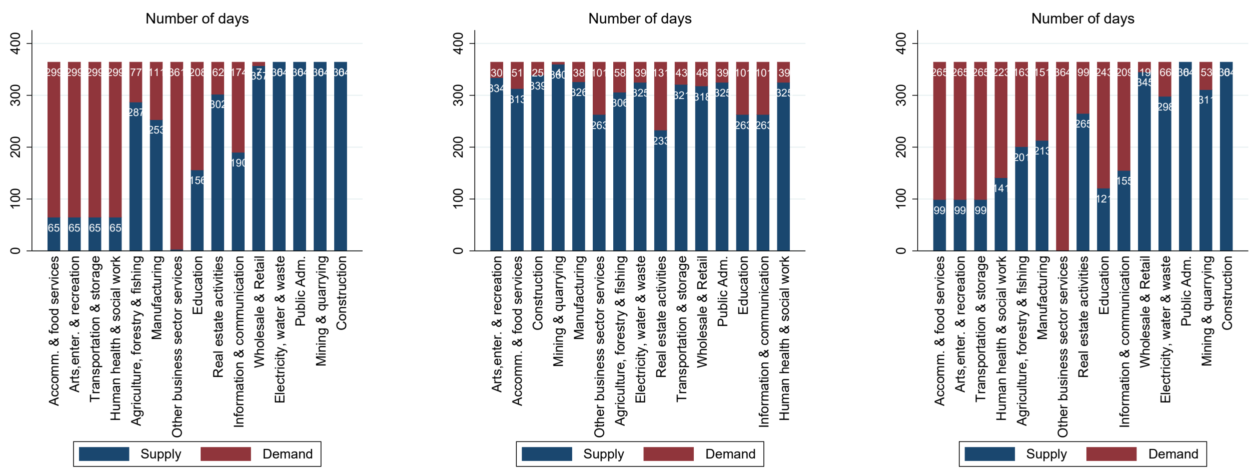
Furthermore, another aspect of sectoral heterogeneity is clearly seen under no lockdown scenario such that the demand channel prevails longer in those sectors. This is because households are more likely to cut back on their expenditure on the goods produced by those non-essential sectors following the Covid-19 shock .

Figure 6: Supply and Demand Pressures under Benchmark Lockdown Scenarios

(a) **Scenario 1:** No Lockdown, $\beta_0 = 0.14$

(b) **Scenario 2:** Full Lockdown, 93^{rd}-132^{nd}, $\beta_0 = 0$

(c) **Scenario 3:** Partial Lockdown, 10^{th}-250^{th}, $0.5 \times \beta_0$



NOTES: In this figure, each bar shows the number days in which the supply channel (shown by the blue bars) or the demand channel (shown by the red bars) prevails to bring the economy into equilibrium in a given industry. The panels show three alternative scenarios: (a) No action is taken against the COVID-19 pandemic; (b) Turkey imposes a partial lockdown between the 10^{th} and 250^{st} days and the pandemic evolves with a relatively high infection rate i.e., $0.5 \times \beta_0$; (c) Turkey imposes a fully effective lockdown between the 93^{rd} and 132^{nd} days of the pandemic with a zero infection rate. For each scenario, we measure the sector-level economic cost as the percentage change in overall economic activity (proxied by value added) for a given sector during pandemic relative to its pre-pandemic level. Economic costs are aggregated from the 2-digit OECD ISIC codes to the 1-digit NACE code using 2-digit sector value added values that we obtain from the OECD ICIO Tables. NACE 1-digit sectors are A, B C, D&E, F, G, H, I, J, L, M&N, P, Q, R&S. In each panel, the sectors are ranked in a descending order according to the magnitude of economic cost under the corresponding scenario.

Under full lockdown scenario, the supply channel drives output due to the closure of all non-essential industries, whereas the demand channel prevails approximately 30 days before the restrictions are implemented (Panel (b)). Among the 15 industry groups, “Arts, entertainment, recreation and other service activities,” “Accommodation and food services,” and “Construction” are those that result in the highest economic costs of 9.7%, 5.3%, and 3.9% of the valued added generated in those sectors, respectively. Different from the no lockdown scenario, sectoral heterogeneity is not highly pronounced in terms of supply and demand pressures under this scenario. To be specific, after the restrictions are implemented the supply channel dominates for all the sectors excluding "Human health & social work," and "Public administration."

Panel (c) shows that under partial lockdown that is put into practice between 10^{th}-250^{th} days of the pandemic and evolves with a high infection rate ($0.5 \times \beta_0$), the supply channel dominates in manufacturing sectors similar to no lockdown scenario in Panel (a). In both Panels (a) and (c), the number of infections remain higher than the full lockdown case. Consequently, the demand shocks cannot be eliminated particularly in services sectors. To the extent that the stringency measures lower the number of infections via partial lockdowns, however, we observe that the impact of demand shocks diminishes. This is visible when we compare the number of days that supply shocks exceed demand shocks in Panel (a) vs. Panel (c). Among the 15 industry groups, "Accommodation and food services," "Arts, entertainment, recreation and other service activities," and "Transportation & storage" are those that result in highest economic costs of 12.2%, 10.3%, and 6.8% of the value added generated in those sectors, respectively. We note that sectoral heterogeneity in terms of supply and demand pressures is very similar to the no lockdown scenario.

3.5 The Role of External Finance

If the sectors that have closer trade linkages to the rest of the world suffer more from uncoordinated lockdowns, then a natural question is whether external finance can help the fiscal needs of these sectors.

To investigate this question, we consider a regression specification at the sector-level. Specifically, we regress the economic cost in each sector onto sectoral trade and sectoral capital flows under different lockdown scenarios to highlight the role of external linkages in driving these costs. Recall from panel (c) in Figure 6 that in the case of a global partial lockdown, demand channel drives output particularly in services sectors, leading to demand-driven economic costs of the pandemic. In contrast, panel (b) illustrates that supply channel is dominant in the case of a globally coordinated full lockdown, reducing the role of external as well as domestic demand. Consequently, in the regression results below, we expect to find the role of external linkages to increase as the lockdown measures become less strict in the trade partners of home country in an environment of uncoordinated lockdowns.

We use data from international I-O matrix to measure sectoral trade. For sectoral capital flows, we use a sectoral weighted average of country-pair capital flows, where sector shares come from sectoral trade.[17,18] And then we run the following regression for sector i:

$$\Delta Y_i = \beta_0 + \beta_1 \text{Trade}_i + \beta_2 \text{Capital Flows}_i + \varepsilon_i \tag{22}$$

where ΔY_i stands for the economic cost of the Covid-19 shock for sector i for $i = 1, \ldots, K$, that we estimate under different lockdown scenarios. We measure the sector-level economic cost as the percentage change in overall economic activity (proxied by value added (VA_i), where value added equals total production minus intermediate inputs i.e., VA_i=Y_i-INT_i.) for a given sector during pandemic relative to its pre-pandemic level.

The regression results are highly consistent with our expectations. The first two columns show the case of full coordination while the last two columns show the case of no coordination, all estimated under the assumption that Turkey implements an effective full lockdown. In an uncoordinated lockdown, the rest of the world adopts partial lockdown while Turkey implements full lockdown. The positive and highly significant coefficient estimates in Table 7 confirm the importance of international linkages on sectoral Covid-19 losses. The results suggest that sectors with stronger trade links suffer from larger Covid-19 related losses due to a significant decline in external demand (row 1). They further suggest that sectors with larger losses receives more capital inflows, hence they borrow externally to smooth out the losses. (row 2). We control sectoral FX debt (measured as the ratio of foreign currency debt in total debt as of 2016) (row 3). This control variable is not

[17] We calculate the sector-level proxy as follows: $\text{Capital Flows}_i = \sum_{c=1}^{n} (((\text{Exports}_{c,i} - \text{Imports}_{c,i})/\text{Output}_i) \times \text{Capital Flows}_c)/n$ where $\text{Exports}_{c,i}$, $\text{Imports}_{c,i}$ and Output_i refer to final goods and intermediate goods made in sector i to be sold in the corresponding country c, final goods and intermediate goods that are bought from the corresponding country c to be used in sector i, and total output produced in sector i, respectively.

[18] The related data on capital flows is obtained from BIS and it is publicly available at https://stats.bis.org/statx/srs/table/A6.2?c=TR&p=20194&m=. Capital flows data of Turkey from 26 countries refers to data on Turkish banking sector external liabilities vis-a-vis those countries for 2019-Q4. We normalize flows by GDP as of 2019.

Table 7: SECTOR-LEVEL REGRESSIONS

Dep. Var: Economic Loss (%Δ VA)	Full Coordination, $\rho = 1$ (1)	(2)	No Coordination, $\rho = 0$ (3)	(4)
(1) Trade	1.5945*	1.6284*	4.0597**	4.1392**
	(0.888)	(0.880)	(1.918)	(1.952)
(2) Capital Flows	4.1454**	4.2031**	8.9378*	9.0732*
	(1.912)	(1.904)	(4.519)	(4.558)
(3) FX		0.0106		0.0249
		(0.015)		(0.028)
R^2	0.03	0.042	0.073	0.093

NOTES: Table 7 reports the results of estimation of Equation (22) for two alternative scenarios. Turkey imposes a fully effective lockdown between the 93^{rd} and 132^{nd} days of the pandemic with a zero infection rate and the rest of the world fully coordinates with her (columns 1 and 3). Turkey imposes a fully effective lockdown between the 93^{rd} and 132^{nd} days with a zero infection rate, but the rest of the world does not coordinate with her i.e., the probability of coordination (ρ) equals 0 (columns 2 and 4). We report the results for additional scenarios where the countries that implement partial lockdowns consider stimulus packages or not. Dependent variable is defined as sector-level economic cost of the COVID-19 shock that is measured as the percentage change in overall economic activity proxied by value added for a given sector during pandemic relative to its pre-pandemic level. Heteroskedastic-consistent standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

significant.

When we compare full coordination results against no coordination, we observe that the coefficient estimates associated with both Trade and Capital Flows increase in value, suggesting an increase in overall costs when the stringency measures are relaxed in our trade partners. Columns (3) and (4) illustrate that the coefficient estimates associated with trade linkages more than double compared to the coordination scenario. This is due to the deterioration in external demand as a result of weak lockdown measures abroad. Even if Turkey implements full lockdown at home, sectoral economic costs will be adversely affected stemming from the decline in demand for Turkish exports despite the containment of the pandemic in Turkey.

3.6 Comparing the Model's Predictions to Real-Life Experiences

When we take a look at the experiences of the countries over the course of the pandemic, we note that there are several paths adopted by different countries:

(i) **Full lockdown:** China, New Zealand, and Denmark provide good examples for an effective full lockdown. Our analysis indicates that this is the policy that minimizes economic costs by containing the pandemic in the most effective way.

(ii) **No lockdown:** Very few countries considered no lockdown since the beginning of the pandemic. No lockdown approach might yield lower economic costs but the death toll is significantly higher. The economic costs are mostly dependent on the changes in demand.

(iii) **Partial lockdown followed by full lockdown:** Many countries followed this route including Italy, France, Germany, Spain, Iran, Russia among others. Several of these counties recently announced that they will gradually lift restrictions. The duration of full lockdown is longer than it could have been, had it been implemented earlier. In Italy, for example, a full lockdown went into effect on March 10, and the restrictions are announced to be removed by May 4, after approximately two months under full lockdown.

(iv) **Enhanced Partial lockdown:** Turkey started with immediate partial lockdown measures which were enhanced over the course of the pandemic. Schools were closed on March 16 and the businesses were encouraged to work remotely where possible. On March 21, a curfew was imposed for people above the age of 65 and those with chronic diseases. The curfew was extended to those younger than 20 on April 5, effectively putting close to 40% of the population under full lockdown. Furthermore, a full lockdown was implemented on weekends and national holidays starting on April 9 in 31 largest cities which constitute approximately 87% of the population.[19] After about 45 days since the beginning of enhanced partial lockdown measures, R_0 is reduced below 1 and the number of new patients is lower than the number of recovered patients as of the last week of April.

(v) **Full or Partial lockdown followed by pre-mature openings** As the pandemic extended into its second year, many countries loosened the lockdown restrictions prematurely and had to re-introduce them as the number of infections increased, generating second and the third waves consistent with our analysis of pre-mature openings.

Figure 7 illustrates the course of the pandemic for a selected group of countries including Italy,

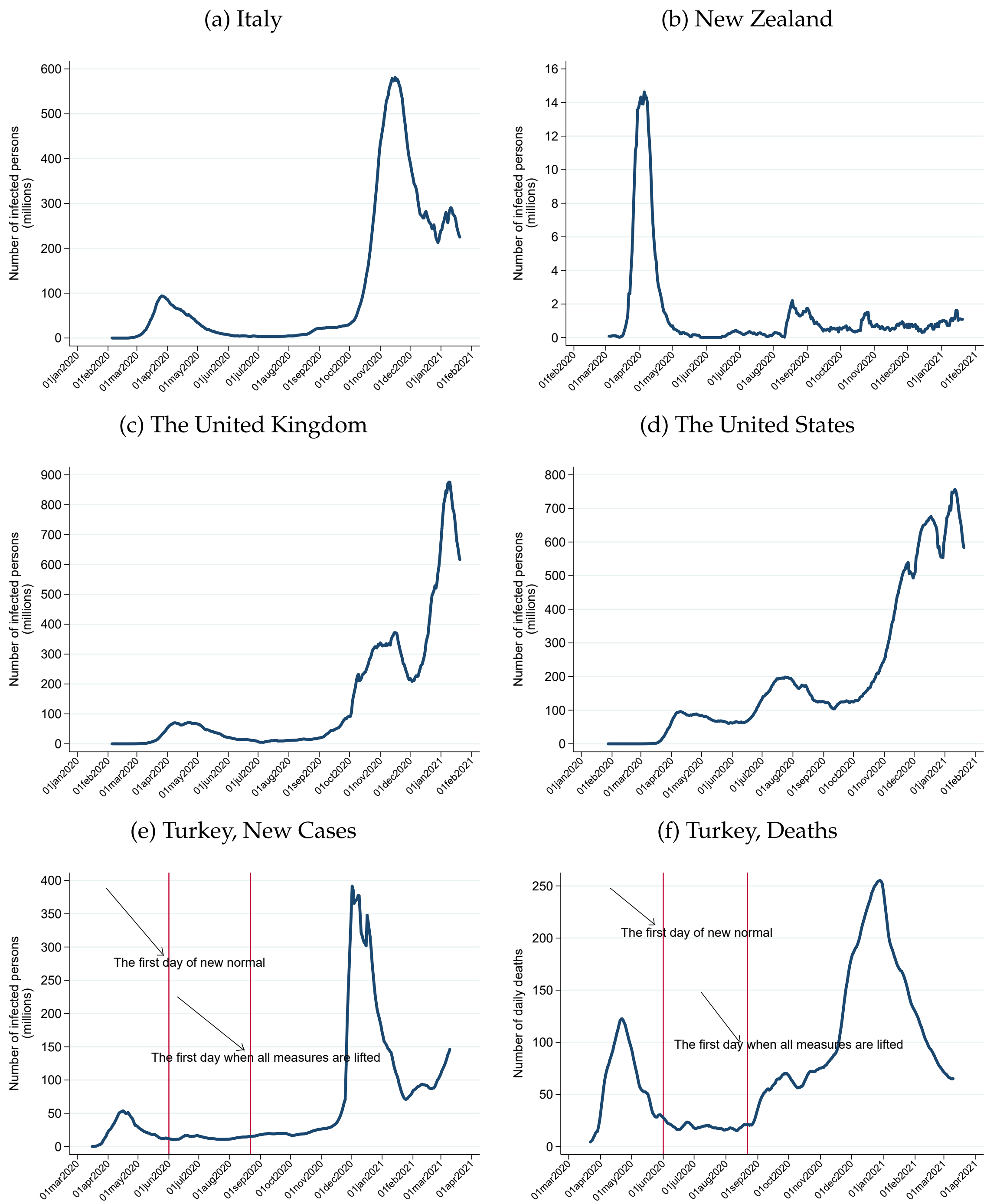
[19] These cities include the 30 metropolitan municipalities and Zonguldak, which constitute close to 79% of the population. On top of these, the age-based restrictions are intact in the rest of Turkey, which increases the number close to 87%.

New Zealand, the United Kingdom, the United States, and Turkey. Except for New Zealand, most of the other countries opened up their economies prematurely and experienced multiple waves. New Zealand, on the other hand, was able to implement an effective full lockdown early on and contained the outbreak afterwards. This figure matches very well with the figures from our model in terms of the effects of different lockdowns. New Zealand mimics our illustration of an effective lockdown in Figure 7 while the rest of the countries mimic partial lockdown with premature opening scenario illustrated in Figure 1a.

Where does this take us? Our analysis indicates that a full lockdown at the early stages of the crisis can bring the pandemic under control relatively quickly. There are countries who implemented this successfully but also countries such as India, who tried an early full lockdown but did not succeed. The individual performance of the country depends on several factors that affect the recovery and the infection rates. An evaluation of Turkey's performance, one year after the introduction of lockdown measures indicates that Turkey did reasonably well during the first wave. Potential reasons for the superior performance are the remarkable ICU capacity, young population, less care homes, as well as the generally compliant population where government decrees are not challenged.[20] As the pandemic extended, however, Turkey was among many other countries that removed the restrictions too soon and faced consequential waves in the number of infections. As the duration of lockdown increases, policy makers get anxious about opening up their economies. In this paper, we modelled demand as a function of the number of infections and combined this with actual spending decline during Covid-19, measured in the data with credit card purchases. Thus, our framework implies that demand would not normalize by the mere attempt of removing the restrictions, so long as the number of infections are sizable. What is worse is that the number of infections would increase again as businesses open.

[20] See https://blogs.lse.ac.uk/covid19/2020/06/04/how-has-turkey-done-in-its-fight-against-covid-19-the-jury-is-still-out/ for a detailed evaluation of Turkey's performance based on our framework

Figure 7: The Progression of Covid-19 Pandemic



NOTES: Panels (a)-(d) plot the number of daily active cases (7-day smoothed) in Italy, New Zealand, the United Kingdom and the United States, respectively. Panels (e)–(f) plot the number of daily infections and deaths in Turkey.

In the model, we did not explicitly incorporate expectations about infections and implicitly assumed that the two are highly correlated. Meanwhile, one can imagine a forward looking demand curve, which could be a function of infection expectations rather than the actual number of infections. In this case, leaders might be able to affect expectations about the number of infections and revive demand by removing the restrictions. To the extent that leaders can successfully convey a more optimistic outlook, the negative demand effect that we model in this paper may weaken and the economic costs of prematurely ending a lockdown might decline.

Another imminent issue is the potential follow up waves once the restrictions are removed. This is particularly a problem for those countries that adopted a full lockdown at the early stages of the crisis and controlled the pandemic in their own countries. If they open their borders, there is the risk of a second wave. If they do not open their borders, then they cannot fully normalize and suffer from an extended partial lockdown given the importance of the amplification effects on economic costs for open economies. The takeaway at this stage is that if a second wave of the COVID-19 virus hits, then an immediate and potentially *global* lockdown would work in the most effective way.

Our theoretical predictions are highly accurate for the Turkish economy where a relatively successful first wave was followed by an early opening and thus a sizable second and third waves. Figure 7e shows the actual number of infections while Figure 7f shows the actual number of death in Turkey. Because of a change in the definition infections in the middle of the pandemic in Turkey, the reporting of infections is subject to a break. Therefore, we find it more accurate to look at the number of death. As shown, following the removal of all contingency measures, we do observe a significant second wave.

4 Conclusion

With a lack of access to vaccines, the emerging markets and developing countries consider lockdowns to deal with each new wave of the pandemic. Our SIR model for an open economy can account for effects of multiple pandemic waves combined with domestic and foreign sectoral demand and supply shocks. We illustrate that even if these countries implement strict lockdowns to contain the pandemic, they would still bear additional costs coming from the external demand channel.

Our findings show the importance of globally coordinated lockdowns. We illustrate that globally uncoordinated lockdowns increase the economic costs of the pandemic by almost 0.2 percent of the GDP for a small open economy.

Our preamble is a quote from Hamlet: ”Best safety lies in fear”. We show that large economic costs do not come from lockdowns but rather from the collapse in domestic and foreign demand, that is the “fear factor.” Thus, the recovery with demand normalization is only possible once the disease is under control. We underline that there does not need to be a trade-off between saving lives versus livelihoods. An early and effective lockdown can save more lives and contain the pandemic sooner, especially if it is globally coordinated. This way, it eliminates the fear factor and allows the economies to recover through demand normalization. We end the paper with yet another quote from Shakespeare, but this time from Macbeth. If countries have to implement lockdowns, “'twere well / It were done quickly.”

References

Acemoğlu, Daron, Victor Chernozhukov, Iván Werning, and Michael D Whinston, “Optimal targeted lockdowns in a multigroup SIR model,” *American Economic Review: Insights*, 2021, *3* (4), 487–502.

Allen, Linda JS, “A primer on stochastic epidemic models: Formulation, numerical simulation, and analysis,” *Infectious Disease Modelling*, 2017, *2* (2), 128–142.

Alvarez, Fernando, David Argente, and Francesco Lippi, “A simple planning problem for COVID-19 lock-down, testing, and tracing,” *American Economic Review: Insights*, 2021, *3* (3), 367–82.

Andersen, Asger Lau, Emil Toft Hansen, Niels Johannesen, and Adam Sheridan, “Pandemic, Shutdown and Consumer Spending: Lessons from Scandinavian Policy Responses to COVID-19,” 2020. arXiv preprint arXiv:2005.04630.

Antràs, Pol, Stephen J Redding, and Esteban Rossi-Hansberg, “Globalization and Pandemics,” Working Paper 27840, National Bureau of Economic Research 2020.

Atalay, Enghin, “How important are sectoral shocks?,” *American Economic Journal: Macroeconomics*, 2017, *9* (4), 254–80.

Atkeson, Andrew, “How Deadly is COVID-19? Understanding the Difficulties with Estimation of its Fatality Rate,” Working Paper 26965, National Bureau of Economic Research 2020.

Baqaee, David and Emmanuel Farhi, “Supply and demand in disaggregated keynesian economies with an application to the COVID-19-19 crisis,” *American Economic Review*, 2022, *112* (5), 1397–1436.

Bartlett, M. S., "The Critical Community Size for Measles in the United States," *Journal of the Royal Statistical Society: Series A (General)*, 1960, *123* (1), 37–44.

Bendavid, Eran and Jay Bhattacharya, "Is Coronavirus as Deadly as They Say?," *Wall Street Journal*, 2020, *24.*

Boehm, Christoph E, Aaron Flaaen, and Nitya Pandalai-Nayar, "Input linkages and the transmission of shocks: Firm-level evidence from the 2011 Tōhoku earthquake," *Review of Economics and Statistics*, 2019, *101* (1), 60–75.

Çakmaklı, Cem, Selva Demiralp, Şebnem Kalemli-Özcan, Sevcan Yeşiltaş, and Muhammed Ali Yıldırım, "The Economic Case for Global Vaccinations: An Epidemiological Model with International Production Networks," Working Paper 27191, National Bureau of Economic Research 2021.

Cutler, David M and Lawrence H Summers, "The COVID-19 pandemic and the $16 trillion virus," *JAMA*, 2020, *324* (15), 1495–1496.

Dewatripont, Mathias, Michel Goldman, Eric Muraille, and Jean-Philippe Platteau, "Rapidly identifying workers who are immune to COVID-19 and virus-free is a priority for restarting the economy," Working Paper, VOX CEPR Policy Portal 2020.

Dingel, Jonathan I and Brent Neiman, "How many jobs can be done at home?," *Journal of Public Economics*, 2020, *189*, 104235.

Eichenbaum, Martin S, Sergio Rebelo, and Mathias Trabandt, "The macroeconomics of epidemics," *The Review of Financial Studies*, 2021, *34* (11), 5149–5187.

Engler, Philipp, Nathalie Pouokam, Diego Rodriguez Guzman, and Irina Yakadina, "The Great Lockdown: International Risk Sharing Through Trade and Policy Coordination," IMF Working Papers 242, International Monetary Fund 2020.

Farboodi, Maryam, Gregor Jarosch, and Robert Shimer, "Internal and external effects of social distancing in a pandemic," *Journal of Economic Theory*, 2021, *196*, 105293.

Fauci, AS, HC Lane, and RR Redfield, "COVID-19-Navigating the Uncharted.," *The New England Journal of Medicine*, 2020, *382* (13), 1268–1269.

Guerrieri, Veronica, Guido Lorenzoni, Ludwig Straub, and Iván Werning, "Macroeconomic Implications of COVID-19: Can Negative Supply Shocks Cause Demand Shortages?," *American Economic Review*, 2022, *112* (5), 1437–74.

Li, Ruiyun, Sen Pei, Bin Chen, Yimeng Song, Tao Zhang, Wan Yang, and Jeffrey Shaman, "Substantial undocumented infection facilitates the rapid dissemination of novel coronavirus (SARS-CoV-2)," *Science*, 2020, *368* (6490), 489–493.

Linton, Natalie M, Tetsuro Kobayashi, Yichi Yang, Katsuma Hayashi, Andrei R Akhmetzhanov, Sung mok Jung, Baoyin Yuan, Ryo Kinoshita, and Hiroshi Nishiura, "Incubation period and other epidemiological characteristics of 2019 novel coronavirus infections with right truncation: a statistical analysis of publicly available case data," *Journal of Clinical Medicine*, 2020, *9* (2), 538.

Osotimehin, Sophie and Latchezar Popov, "Sectoral Impact of COVID-19: Cascading Risks," Institute Working Paper 31, Federal Reserve Bank of Minneapolis 2020.

Pindyck, Robert S, "COVID-19 and the welfare effects of reducing contagion," Working Paper 27121, National Bureau of Economic Research 2020.

Stock, James H, "Data gaps and the policy response to the novel coronavirus," Working Paper 26902, National Bureau of Economic Research 2020.

Vogel, Gretchen, "New blood tests for antibodies could show true scale of coronavirus pandemic," *Science*, March 19 2020.

A APPENDIX

List of Figures and Tables:

Table A.1: NOTATION AND PARAMETERS

Variable	Explanation	Value / Range
L_i	Number of workers in i	
TW_i	Number of teleworkable workers in i	
N_i	Number of on-site workers in i	
N_{NW}	Number of non-working population	
K	Number of sectors	35
β_0	Infection rate in general population	
β_i	Infection rate within sector i	
Prox_i	Average proximity in i	1–5
γ	Recovery rate from Covid	1/14
R_0	Reproduction number of Covid	2
pop_m	Population of country m	
$\mathcal{N}$	Set of country-sector pairs; indexed by i, j or k	
$\{T, R\}$	Set of countries; indexed by m	
$\mathcal{F}$	Set of factors; indexed by f	
$\mathcal{F}_m$	Set of factors in county m	
$y_{i,t}$	Output of sector i at time t	
$p_{i,t}$	Price of the good produced by i at time t	
$L_{i,t}$	Ratio of active workers in i at time t	
$x_{ij,t}$	Inputs used from j by sector i at time t	
γ_i	Value-added share in i (from ICIO)	
Ω_{ij}	The input share of j in i (from ICIO)	
ϕ	The elasticity of substitution between labor and the intermediate input bundle	0.6
θ	The elasticity of substitution between intermediate inputs	0.2
C_m	Consumption bundle in country m	
$\tilde{C}_m$	Future consumption bundle in country m	
p_m	Consumption price index in country m	
$\tilde{p}_m$	Future consumption price index in country m	
β^m	Preference between current and future consumption	
$c^m_{i,t}$	Final consumption of i in country m	
α^m_i	Pre-Covid consumption share of i in m (from ICIO)	
$\alpha^m_{i,t}$	Change in the consumption share of i in m at time t	
$\bar{I}_m$	Normalization factor for infections	$\text{pop}_m/20,000$
GDP_m	GDP of country m	
GDP_W	GDP of the world m	
M	Number of countries	2
MS	Number of country-sector pairs	70
$\boldsymbol{A}$	$M \times MS$ matrix of consumption weights (from ICIO)	
$\boldsymbol{\Gamma}$	$MS \times MS$ diagonal matrix of value-added shares (from ICIO)	
$\boldsymbol{\Omega}^{\mathcal{N}}$	$MS \times MS$ matrix of input shares (from ICIO)	
$\boldsymbol{\beta}$	$M \times M$ diagonal matrix of the preference between future and current consumption for each country	
$\boldsymbol{I}$	The identity matrix	
$\Psi^{\mathcal{N}}$	Leontief inverse for the goods	
Ω	Overall input-output matrix that captures supply, demand and future consumption	
Ψ	Leontief inverse of Ω	
λ_k	Domar weight of k, where k is a row of Ω	
	Lockdown threshold	$\text{pop}_m/1000$
CCS	Crticial Community Size	$\text{pop}_m/20000$

Table A.2: FISCAL RESPONSES TO THE COVID-19 SHOCK IN THE G20 COUNTRIES

Country	% GDP	Explanation
Argentina	3	Adopted measures (totaling about 3.0 percent of GDP, 1.2 percent in the budget and 1.8 percent off-budget, based on authorities' estimates)
Australia	10.8	Total expenditure and revenue measures of A$194 billion (9.9 percent of GDP). The Commonwealth government has committed to spend almost an extra A$5 billion (0.3 percent of GDP). State and Territory governments also announced fiscal stimulus packages, together amounting to A$11.5 billion (0.6 percent of GDP)
Brazil	6.5	The authorities announced a series of fiscal measures adding up to 6.5 percent of GDP. Public banks are expanding credit lines for businesses and households, with a focus on supporting working capital (credit lines add up to over 3 percent of GDP), and the government will back a 0.5 percent of GDP credit line to cover payroll costs.
Canada	8.4	Key tax and spending measures (8.4 percent of GDP, $193 billion CAD).
China	3.8	An estimated RMB 2.6 trillion (or 2.5 percent of GDP) of fiscal measures or financing plans have been announced. The overall fiscal expansion is expected to be significantly higher, reflecting the effect of already announced additional measures such as an increase in the ceiling for special local government bonds of 1.3 percent of GDP.
France	19	The authorities have announced an increase in the fiscal envelope devoted to addressing the crisis to €110 billion (nearly 5 percent of GDP, including liquidity measures), from an initial €45 billion included in an amending budget law introduced in March. A new draft amending budget law has been introduced on April 16. This adds to an existing package of bank loan guarantees and credit reinsurance schemes of €315 billion (close to 14 percent of GDP).
Germany	31.6	The federal government adopted a supplementary budget of €156 billion (4.9 percent of GDP). The government is expanding the volume and access to public loan guarantees for firms of different sizes and credit insurers increasing the total volume by at least €757 billion (23 percent of GDP). In addition to the federal government's fiscal package, many state governments (Länder) have announced own measures to support their economies, amounting to €48 billion in direct support and €73bn in state-level loan guarantees (Authors: Another 3.7% of GDP).
India	1.1	Finance Minister Sitharaman on March 26 announced a stimulus package valued at approximately 0.8 percent of GDP. These measures are in addition to a previous commitment by Prime Minister Modi that an additional 150 billion rupees (about 0.1 percent of GDP). Numerous state governments have also announced measures thus far amount to approximately 0.2 percent of India's GDP.
Indonesia	2.8	In addition to the first two fiscal packages amounting to IDR 33.2 trillion (0.2 percent of GDP), the government announced a major stimulus package of IDR 405 trillion (2.6 percent of GDP) on March 31, 2020.
Italy	26.4	On March 17, the government adopted a €25 billion (1.4 percent of GDP) 'Cura Italia' emergency package. On April 6, the Liquidity Decree allowed for additional state guarantees of up to €400 billion (25 percent of GDP).
Japan	21.1	On April 7 (partly revised on April 20), the Government of Japan adopted the Emergency Economic Package Against COVID-19 of ¥117.1 trillion (21.1 percent of GDP)
Mexico	0.7	to request additional resources from Congress, that could reach up to 180 billion pesos (0.7 percent of 2019 GDP). AND The week of April 19 the President further announced an austerity program for public expenditures including wage reductions and a hiring in order to free up 2.5 percent of GDP to finance additional health expenditures and priority investment.
Republic of Korea	10	Direct measures amount to 0.8 percent of GDP (approximately KRW 16 trillion. On March 24, President Moon announced a financial stabilization plan of KRW 100 trillion (5.3 percent of GDP). This was augmented by a further KRW 35 trillion (1.8 percent of GDP) on April 22 through additional measures. On April 22, President Moon announced a key industry stabilization fund would be established for KRW 40 trillion (2.1 percent of GDP)
Russian Federation	2.1	The total cost of the fiscal package is currently estimated at 2.1 percent of GDP.
Saudi Arabia	5	A SAR 70 billion ($18.7 billion or 2.8 percent of GDP) private sector support package was announced on March 20. they will reduce spending in non-priority areas of the 2020 budget by SAR 50 billion (2.0 percent of GDP) to accommodate some of these new initiatives within the budget envelope. on April 3, the government authorized the use of the unemployment insurance fund (SANED) to provide support for wage benefits, within certain limits, to private sector companies who retain their Saudi staff (SAR 9 billion, 0.4 percent of GDP). On April 15, additional measures to mitigate the impact on the private sector were announced, including temporary electricity subsidies to commercial, industrial, and agricultural sectors (SAR 0.9 billion) and resource support to the health sector was increased to SAR 47 billion.
South Africa	0.2	https://www.globalpolicywatch.com/2020/04/south-africas-economic-response-to-the-covid-19-pandemic/
Spain	11.7	Key measures (about 1.6 percent of GDP, €18 billion; depending on the usage and duration of the measures the amount could be higher). In addition, the government of Spain has extended up to €100 billion government guarantees for firms and self-employed. Other measures include additional funding for the Instituto de Credito Oficial (ICO) credit lines (€10 billion); introduction of a special credit line for the tourism sector through the ICO (€400 million);
Turkey	5	A TL100 billion package was announced. This consists of TL75 billion ($11.6 billion or 1.5 percent of GDP) in fiscal measures, as well as TL 25 billion ($3.8 billion or 0.5 percent of GDP) for the doubling the credit guarantee fund. Gradually, this package increased to be 5% of GDP.
United Kingdom	18.8	Policy measures adding £86 billion in 2020-21. Coronavirus business interruption loan scheme and the Covid Corporate Financing Facility: the business interruption loan scheme was announced as up to £330 billion of support for businesses. Source: https://obr.uk/coronavirus-reference-scenario/
United States of America	13.6	US$484 billion Paycheck Protection Program and Health Care Enhancement Act . An estimated US$2.3 trillion (around 11% of GDP) Coronavirus Aid, Relief and Economy Security Act ("CARES Act"). US$8.3 billion Coronavirus Preparedness and Response Supplemental Appropriations Act and US$192 billion Families First Coronavirus Response Act . They together provide around 1% of GDP.

NOTES: This table reports the COVID-19 relief packages (as percent of GDP) by the G20 countries along with the details of the fiscal packages. Source: IMF Policy Tracker unless otherwise noted. Access Date: April 29, 2020.

Table A.3: PROXIMITY INDEX AND TELEWORKABLE SHARE ACROSS INDUSTRIES

OECD ISIC Code	Definition	Proximity Index	Teleworkable Share
01T03	Agriculture, forestry and fishing	0.86	0.06
05T06	Mining and extraction of energy producing products	1.08	0.32
07T08	Mining and quarrying of non-energy producing products	1.06	0.14
09	Mining support service activities	1.21	0.20
10T12	Food products, beverages and tobacco	1.12	0.13
13T15	Textiles, wearing apparel, leather and related products	1.09	0.20
16	Wood and products of wood and cork	1.03	0.15
17T18	Paper products and printing	1.08	0.22
19	Coke and refined petroleum products	1.11	0.22
20T21	Chemicals and pharmaceutical products	1.06	0.25
22	Rubber and plastic products	1.10	0.18
23	Other non-metallic mineral products	1.08	0.18
24	Basic metals	1.09	0.14
25	Fabricated metal products	1.08	0.21
26	Computer, electronic and optical products	1.03	0.54
27	Electrical equipment	1.07	0.29
28	Machinery and equipment, nec	1.06	0.29
29	Motor vehicles, trailers and semi-trailers	1.09	0.19
30	Other transport equipment	1.06	0.31
31T33	Other manufacturing; repair and installation of machinery and equipment	1.07	0.32
35T39	Electricity, gas, water supply, sewerage, waste and remediation services	1.08	0.29
41T43	Construction	1.21	0.19
45T47	Wholesale and retail trade; repair of motor vehicles	1.13	0.37
49T53	Transportation and storage	1.18	0.21
55T56	Accomodation and food services	1.26	0.10
58T60	Publishing, audiovisual and broadcasting activities	1.11	0.69
61	Telecommunications	1.07	0.58
62T63	IT and other information services	1.01	0.88
64T66	Financial and insurance activities	1.02	0.79
68	Real estate activities	1.10	0.54
69T82	Other business sector services	1.09	0.46
84	Public admin. and defence; compulsory social security	1.16	0.39
85	Education	1.22	0.86
86T88	Human health and social work	1.28	0.35
90T96	Arts, entertainment, recreation and other service activities	1.18	0.34

NOTES: This table provides the physical proximity index along with the share of those who can work remotely for the industries. Both these measures are first obtained at the occupational level and we utilize occupational structure of industries to calculate industrial level measures. For computing this physical proximity conditions at sectoral level, we consult on the self-reported Physical Proximity values, which is provided in the the Work Context section of the O*NET database.[21] For physical proximity, O*NET data is gathered through surveys, which ask workers their occupations and whether their occupation requires physical proximity by selecting one of these 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 take category 3 as a benchmark and divide the category values with 3 as our proximity measure of an individual. We take the weighted average of individual responses to create a single occupation proximity value. For an occupation, a proximity value higher than 1 would indicate a denser physical proximity compared to a shared office. To convert occupation level teleworkability and proximity values to industry-level, we use the information on occupational composition of industries from the the Occupational Employment Statistics (OES) by the U.S. Bureau of Labor Statistics (BLS). OES uses NAICS classification at four digit level and we map these into OECD ISIC codes using the concordance table provided by the U.S. Census Table between NAICS codes and ISIC Rev. 4 industry classification. Industry level proximity values are calculated after removing the employees whose occupations are teleworkable. Dingel and Neiman (2020) identify a set of occupations where remote working is feasible. We use this set for calculating the share of teleworkable workers in each industry.

Table A.4: DEMAND CHANGES ACROSS INDUSTRIES

OECD ISIC	Definition	Change	Explanation
01T03	Agriculture, forestry and fishing	100%	Projections from CBRT credit card spending data.
05T06	Mining and extraction of energy producing products	100%	Projections from CBRT credit card spending data.
07T08	Mining and quarrying of non-energy producing products	100%	Projections from CBRT credit card spending data.
09	Mining support service activities	100%	Projections from CBRT credit card spending data.
10T12	Food products, beverages and tobacco	100%	Projections from CBRT credit card spending data.
13T15	Textiles, wearing apparel, leather and related products	50%	Projections from CBRT credit card spending data.
16	Wood and products of wood and cork	90%	Projections from CBRT credit card spending data.
17T18	Paper products and printing	90%	Projections from CBRT credit card spending data.
19	Coke and refined petroleum products	75%	Projections from CBRT credit card spending data.
20T21	Chemicals and pharmaceutical products	90%	Projections from CBRT credit card spending data.
22	Rubber and plastic products	90%	Projections from CBRT credit card spending data.
23	Other non-metallic mineral products	90%	Projections from CBRT credit card spending data.
24	Basic metals	90%	Historical data and sectoral reports, https://tr.steelorbis.com/celik-haberleri/guncel-haberler/abd-ham-celik-uretimi-haftalik-181-dustu-1141735.htm
25	Fabricated metal products	90%	Historical data and sectoral reports.
26	Computer, electronic and optical products	100%	Projections from CBRT credit card spending data.
27	Electrical equipment	90%	Projections from CBRT credit card spending data and sectoral reports, https://www.ibisworld.com/industry-insider/media/4637/covid-19-special-report.pdf
28	Machinery and equipment, nec	90%	Projections from CBRT credit card spending data.
29	Motor vehicles, trailers and semi-trailers	70%	Evidence from other countries and sectoral reports, https://edition.cnn.com/2020/04/01/business/car-sales-coronavirus/index.html https://econsultancy.com/how-coronavirus-is-impacting-sales-marketing-in-the-automotive-industry/
30	Other transport equipment	70%	Same as automobiles.
31T33	Other manufacturing; repair and installation of machinery and equipment	90%	Projections from CBRT credit card spending data.
35T39	Electricity, gas, water supply, sewerage, waste and remediation services	100%	No change.
41T43	Construction	75%	Historical data and sectoral reports, https://www.ft.com/content/3c27d23e-befe-4a53-be52-325adacdb929
45T47	Wholesale and retail trade; repair of motor vehicles	110%	Projections from CBRT credit card spending data.
49T53	Transportation and storage	80%	Evidence from other countries and sectoral reports, https://www.mckinsey.com/~/media/McKinsey/Business%20Functions/Risk/Our%20Insight/COVID%2019%20Implications%20for%20business/COVID%2019%20March%2030/COVID-19-Facts-and-Insights-April-3-v2.ashx
55T56	Accomodation and food services	25%	Projections from CBRT credit card spending data.
58T60	Publishing, audiovisual and broadcasting activities	85%	Projections from CBRT credit card spending data.
61	Telecommunications	100%	Projections from CBRT credit card spending data.
62T63	IT and other information services	100%	Evidence from other countries and sectoral reports, https://www.reuters.com/article/us-heatlh-coronavirus-technology/coronavirus-may-cut-global-corporate-tech-spending-4-1-in-2020-survey-idUSKBN21I38C https://www.fiercetelecom.com/telecom/coronavirus-flushes-it-spending-to-a-2-7-decline-idc
64T66	Financial and insurance activities	100%	Projections from CBRT credit card spending data.
68	Real estate activities	60%	Projections from CBRT credit card spending data.
69T82	Other business sector services	85%	Projections from CBRT credit card spending data.
84	Public admin. and defence; compulsory social security	100%	Median Package size 5%. Public spending is close to %20 of GDP.
85	Education	85%	In line with other business services.
86T88	Human health and social work	100%	Evidence from other countries and sectoral reports, https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/NationalHealthAccountsHistorical https://www.fairhealth.org/publications/briefs
90T96	Arts, entertainment, recreation and other service activities	25%	Evidence from other countries and sectoral reports, https://www.nytimes.com/interactive/2020/04/11/business/economy/coronavirus-us-economy-spending.html

NOTES: This table provides the demand changes at the sectoral level along with the explanations. We use publicly available data and the credit card spending data from the Central Bank of Republic of Turkey (CBRT) to calculate the estimated demand change during the pandemic in each industry, which is categorized based on OECD ISIC Codes.

Table A.5: LIST OF THE LOCKDOWN SECTORS

Panel A: Lockdown Sectors

NACE Rev. 2	Definition
01	Crop and animal production, hunting and related service activities
1071	Manufacture of bread; manufacture of fresh pastry goods and cakes
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
4646	Wholesale of pharmaceutical goods
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
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

Panel B: Additional Sectors

NACE Rev. 2	Definition
10	Manufacture of food products
1722	Manufacture of household and sanitary goods and of toilet requisites
463	Wholesale of food, beverages and tobacco
4711	Retail sale in non-specialised stores with food, beverages or tobacco predominating
472	Retail sale of food, beverages and tobacco in specialised stores
4781	Retail sale via stalls and markets of food, beverages and tobacco products

NOTES: This table provides the list of the lockdown sectors. We use the decree issued by the Turkish Ministry of Interior on April 10, 2020 to identify these industries. This lockdown was effective for only two days and cover those given in Panel A. We supplement the list with those available in Panel B.

Table A.6: CBRT Credit Card Spending Titles Corresponding to OECD ISIC Sectors

CBRT	Definition	OECD ISIC Code
1	Total	
2	Car Rental	69T82
3	Car Rental-Sales/Service/Parts	45T47
4	Petrol Stations	19
5	Various Food	10T12
6	Direct Marketing	45T47
7	Education/Stationary	45T47
8	Electric & Electronic Goods, Computers	26
9	Clothing and Accessory	13T15
10	Airlines	49T53
11	Service	58T60 & 68 & 69T82
12	Accomodation	55T56
13	Club/Association/ Social Services	55T56
14	Casino	55T56
15	Jewellery	45T47
16	Marketing and Shopping Centers	45T47
17	Furnishing and Decoration	31T33
18	Contractor Services	41T43
19	Health/Health Products/Cosmetics	20T21
20	Travel Agencies/Forwarding	69T82
21	Insurance	64T66
22	Telecommunication	61
23	Building Supplies, Hardware, Hard Goods	25
24	Food	55T56
25	Government/Tax Payments	84
26	Private Pensions	64T66
27	Others	
28	E-commerce Transactions	62T63
29	Mail or Phone Shopping	
30	Customs Payments	84

Notes: This table provides the concordance that we use to match the titles used in the CBRT's credit card spending data with the OECD ISIC Codes.

Table A.7: List of the Active Sectors in Public Administration during full lockdown

Type	Size	Source
Public (All)	2820095	http://www.sbb.gov.tr/kamu-istihdami/
Security	273000	https://tr.wikipedia.org/wiki/Emniyet_Genel_M%C3%BCd%C3%BCrl%C3%BC%C4%9F%C3%BC
Gendarmerie	150000	https://www.jandarma.gov.tr/jandarma-genel-komutanligi-2019-yili-faaliyet-raporu
Health	642184	https://www.saglik.gov.tr/TR,11588/istatistik-yilliklari.html
Share	37.77%	

Notes: This table provides the list of occupations in Public Administration that work during full lockdown, together with the number of people within those occupations. The data sources are provided as well. The share of the active sub-sectors in the entire sector is 37%.

Table A.8: COSTS OF LIVES UNDER DIFFERENT SCENARIOS: $\beta_i = \beta_0$, WITH LABOR SUPPLY SHOCK

Scenario:	**No Lockdown** $\beta_0 = 0.14$	**Partial Lockdown** 10^{th}-250^{th}, $0.5 \times \beta_0$	**Partial Lockdown** 10^{th}-250^{th}, $0.1 \times \beta_0$	**Full Lockdown** 93^{rd}-132^{nd}, $\beta_0 = 0$
	(1)	(2)	(3)	(4)
No Deaths	919,606	842,894	873,641	2,164
No Deaths/Pop	1.15%	1.05%	1.09%	0.00%
U.S. Dollars (mil.)	902,027	826,782	856,941	2,123
% of 2019 GDP	118.53%	108.64%	112.61%	0.28%

NOTES: Table A.8 reports the costs of lives under different scenarios with details as follows: Turkey does not take any action against the Covid-19 pandemic and the pandemic evolves with the highest infection rate i.e., $\beta_0 = 0.14$ (column 1). Turkey imposes a partial lockdown between the 10^{th} and 250^{st} days and the pandemic evolves with a relatively high infection rate i.e., $0.5 \times \beta_0$ (column 2); a relatively low infection rate i.e., $0.1 \times \beta_0$ (column 3). Turkey imposes a fully effective lockdown between the 93^{rd} and 132^{nd} days of the pandemic with a zero infection rate and the rest of the world coordinates with her (column 4). In each scenario, economic cost is measured as the percentage change in overall economic activity proxied by value added for Turkish economy during pandemic relative to its pre-pandemic level.

Figure A.1: ALTERNATIVE LOCKDOWN SCENARIOS WITH HOMOGENEOUS SECTORS: $\beta_i = \beta_0$