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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 in the absence of vaccinations. We use a framework that combines a multi-sector SIR model with data on international and inter-sectoral trade to estimate the effects of a joint collapse in domestic and foreign demand. We calibrate our framework to Turkey and estimate the COVID-19 related output losses for each sector. Domestic infection rates feed directly into sectoral demand shocks, where sectoral supply is affected both from sick workers and lockdowns. Sectoral demand shocks additionally capture foreign infection rates through foreign demand. We use real-time credit card purchases to pin down the magnitude of these domestic and foreign demand shocks. Our results show that the optimal policy, which yields the lowest economic cost and saves the maximum number of lives, can be achieved under an early and globally coordinated full lockdown of 39 days, amounting to a loss of 5.8 percent of GDP in the small open economy. To illustrate the importance of foreign demand, we compare the economic costs under globally coordinated vs. uncoordinated lockdown scenarios and incorporate the role of fiscal stimulus packages. Our findings illustrate that the economic drag in the rest of the world due to ineffective lockdown measures increases the economic toll in the small open economy by up to 2 percent of GDP. Meanwhile the stimulus packages abroad, by increasing foreign demand for small open economy's goods, reduce costs by 0.5 percentage points. We further show that the lack of a similar large fiscal package in the small open economy can be remedied by capital inflows into sectors with large losses.

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"Best safety lies in fear."
– William Shakespeare

1 Introduction

The COVID-19 pandemic has 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. Although the capital flows came back thanks to the ultra expansionary monetary policies of the major central banks, domestic and external demand are not fully back to pre-pandemic levels in emerging markets. With the extensive fiscal stimulus and the vaccine-led recovery in the advanced countries, notably the U.S., many argued that emerging markets can turn the corner as a result of the increase in demand for their goods from the advanced countries (OECD, 2021).

To understand the positive spillover effects of an increase in foreign demand, while emerging markets are still battling the pandemic, we first need to understand the macroeconomic effects of the original collapse in domestic and foreign demand as a result of the health shock. To do so, we utilize an epidemiological Susceptible-Infected-Recovered (SIR)- multi-sector-macro model to calculate the sector level output losses for a small open economy. We then evaluate the optimal lockdown policy to avoid these losses by calibrating our model to Turkey.[1]

The key properties of our framework are as follows. On the demand side, our model contains a domestic component and a foreign component for sectoral demand shocks. Both types of demand decline as the infections increase in the home country and foreign country, where the lowest demand is calibrated using real time sector-level credit card purchases. The supply shock is purely domestic, as a function of sick workers and lockdowns. In order to filter out the role of foreign demand, we compare the costs under a globally coordinated full lockdown against an uncoordinated full lockdown. In the case of a globally coordinated full lockdown, all countries suffer from supply and demand shocks in a synchronized manner. In the case of an uncoordinated full lockdown, we assume that Turkey implements a full lockdown while its trade partners implement either a full or

[1] See Cakmakli et al. (2020) for the earlier working paper version of our model, April (2020).

a partial lockdown. The increase in estimated costs in the case of an uncoordinated full lockdown reflects the additional decline in foreign demand due to the rise in the number of cases as a result of partial lockdown in these trading partners. The consequent decline in demand in these countries is reflected as a decline in the export revenue for Turkey. In a similar vein, adoption of stimulus packages in the rest of the world reduces the economic costs in Turkey due to improvement in demand for Turkish exports.

There will be sectoral heterogeneity both in the supply and demand shocks. For the supply side, heterogeneity will depend on the ability to work from home and physical proximity needed for the job. 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 consumer preferences that depend on infections. Our methodology is for the short run, where the output is demand determined with fixed prices.

Our approach has the advantage of being simple and easily mapped to real time data. The model is calibrated to Turkey by using Turkey's international linkages to 65 other countries through 35 sectors. We use international input-output (I-O) linkages to measure the foreign demand for each of the domestic sectors' output. We show that, almost 30 percent of the sectoral economic costs for Turkey stem from lower foreign demand in a coordinated full lockdown. Our work differs starkly from the COVID-19 literature that put the epidemiology at the center but focus mostly on closed economies.[2] Considering an open economy framework allows us 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 importance of domestic and external demand shocks. If the lockdown is globally coordinated, the costs of a full lockdown are further minimized by containing the pandemic at the global scale and preventing future waves. Our findings are consistent with the findings of Goolsbee and Syverson (2020) for the US, who shows that, using real time data, legal shutdown orders account for only a modest share of the decline of economic activity. Data on real GDP growth in 2020 further support our predictions.

[2]The two exceptions that highlight the open economy dimension are Arellano et al. (2020) who focus on sovereign default risk under COVID shock with a SIR and sovereign debt model; and Antràs et al. (2020), who analyze the interplay between globalization and pandemic via trade-induced personal interactions.

The countries that imposed early and strict lockdowns such as China, Australia, and New Zealand experienced earlier economic normalization 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.

Our model based estimate for the total cost of containing the pandemic immediately, with an early and strict lockdown is about 5.8 percent of the GDP (at an annualized rate). This implies that output declines by 17.5 percent during the quarter in which the lockdown is imposed, compared to the previous quarter. The optimal lockdown lasts 39 days. Demand normalizes after the lockdown, and the economy returns to normal during the rest of the year, smoothing out the shock. Under no lockdown, the cost of the pandemic increases from 5.8 to 11 percent of GDP annually. The reason for the increase is that, under no lockdown (or partial lockdown), even though businesses remain open, there are still interruptions in supply as people get infected, and demand declines due to voluntary social distancing measures. Demand particularly declines for those sectors where the possibility of getting infected is higher such as travel or restaurants. In general, sectors that are most severely affected from the pandemic are those that are either (i) closed due to lockdown measures, (ii) observe a collapse in demand due to close proximity requirements, or (iii) more exposed to international spillovers through trade linkages.

We consider several experiments to underline the role of global coordination and its implications on external demand. If the full lockdown is not globally coordinated and the rest of the world implements partial lockdown while Turkey implements full lockdown, then the costs that are borne by Turkey increase from 5.8 percent to 7.8 percent of GDP. If 50 percent of the countries in the world implement full lockdown together with Turkey, then the costs are estimated to be 6.9 percent of Turkish GDP. The key message from this exercise is that, even if a small open economy implements the most strict full lockdown and eliminates the pandemic at home, it will bear further costs through a decline in foreign demand if the rest of the world does not cooperate. When the pandemic prolongs in the outside world, then it will reduce the exports of the country that contains the virus within its borders.

Several closed economy papers employing epidemiological models similar to us, including Ace-

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

moglu et al. (2020), Alvarez et al. (2020), Farboodi et al. (2020), and Eichenbaum et al. (2020) reach comparable conclusions. 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, which amplifies the domestic demand shock via sectoral I-O linkages.[4]

The heterogeneity in infection rates by the job type and age are critical in our framework as this heterogeneity will deliver the sectoral heterogeneity in terms of output losses. In no lockdown scenario, most of the population is fully exposed to the outbreak. Nevertheless, the working population is under higher risk compared to the non-working population. In partial lockdown scenario, teleworkable occupations start working from home and hence the base infection rate declines for this group. It is important to note that the individuals in the highest risk group, ages 65 and above, as well as the younger people are assumed to have lower infection rates because they do not work or because they switch to distanced learning. This is consistent with the optimal setting identified by Acemoglu et al. (2020). The infection rate is still high for the on-site workers. In full lockdown, we assume that only the essential sectors require their non-teleworkable employees on-site. This is why the infection rate declines substantially for the remainder of the population that stays home under full lockdown and therefore normalizing the demand.

Our benchmark estimates of economic costs are in the absence of any policy action. Costs might decline when fiscal and monetary policy responses are taken into consideration. We prefer to provide our baseline estimates based on no policy action so that the minimum magnitude of the fiscal policy packages can be identified. This approach makes our findings particularly 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. In-

[4]In our follow-up paper we illustrate an even bigger amplification mechanism once international production linkages are incorporated into our model on top of the final good trade linkages that we have here. In that framework, a supply shock in one country can affect all its trading partners through trade in intermediate inputs. In a model with no infection dynamics (SIR), Baqaee and Farhi (2020a) exploit nonlinear production networks in a general equilibrium framework and show that non-linearities amplify the impact of COVID-19 between 20 to 100 percent. See also Baqaee and Farhi (2020b). The work by Guerrieri et al. (2020) does not include an infection dynamics model either but underlines the importance of a multi-sector economy, where supply shocks can turn into larger aggregate demand shocks.

deed, 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.[5]

Last but not least, we evaluate the role of fiscal policy and show that capital flows can make up for the limited domestic fiscal packages in emerging markets. We illustrate that sectors with stronger international connections suffer more from the pandemic due to a significant decline in external demand. Such costs are positively associated with the absence of effective lockdown measures in the trading partners, but negatively associated with large fiscal stimulus packages in these same trading partners. We show that capital inflows into sectors with large losses are particularly effective in mitigating those losses under a coordinated global lockdown.

We organize the remainder of the paper as follows: Section 2 describes the literature. In Section 3, we briefly go over the background for Turkey. Section 4 describes the model. Section 5 presents our quantitative results. Section 6 concludes.

2 COVID-19 Literature and Our Contribution

The literature on understanding the economic impact of COVID-19 pandemic has resulted in an ever-growing list of papers. To capture the infection dynamics, many studies use SIR models or its extensions. Papers such as Stock (2020) and Alvarez et al. (2020) consider a standard SIR model and focus on the trade off between unemployment that arises from lockdowns versus the number of deaths due to the pandemic. They reach the conclusion that the optimal policy is a full lockdown that covers the majority of the population where the restrictions are removed gradually afterwards. Acemoglu et al. (2020) consider a multi-risk SIR model by focusing on the structural differences in the severity of infections for distinct age groups that affect lockdown policies and economic costs. They show that targeted measures such as full lockdown for the elderly group could be more effective. Alon et al. (2020) also consider a closed economy model but approaches the problem from the developing country perspective, considering market distortions and the presence of an informal sector and hand to mouth consumers. They realize that such economies cannot fully lockdown and

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

argue that lockdowns on the elderly population might be better.

Combining supply and demand in a SIR framework Farboodi et al. (2020) internalize the individual choices for social distancing and study both laissez-faire and social optimum scenarios. They find that even in the laissez-faire case individuals choose to sharply reduce their activity but the socially optimal response imposes severe restrictions at the onset of the outbreak. Eichenbaum et al. (2020) incorporate supply and demand in a SIR model as well, where the government is assumed to alter the individuals' activities through a consumption tax and again find that relatively severe containment at the beginning of the pandemic is the most socially optimum response. Krueger et al. (2020) extends the model by Eichenbaum et al. (2020) and introduces differential transmission rates based on the consumption or employment choice. They aim to capture the interplay between infection dynamics and the demand side or the supply side –but not both of them simultaneously.

The above cited literature do not feature *sectoral heterogeneity* for demand and supply shocks together. However, the pandemic evidence shows the magnitude of the demand shock to be very large and vary by sector, as we model. Specifically, using granular data, Chetty et al. (2020) analyzed the consumer spending during the first month of the pandemic in the United States and found that the spending declined by 39% for consumers in the top-quartile and 13% in the bottom quartile of the income distribution. The observed decline exhibits heterogeneity across sectors, with drastic decreases in industries requiring in-person interactions.

Our paper is unique in combining supply and demand shocks at the sectoral level with a SIR model for an open economy. Our open economy framework makes the role of global coordination clear. If the lockdown can be implemented with global synchronization, the pandemic will be controlled faster. As the number of infections decline globally, demand returns to pre-pandemic levels faster as both domestic and foreign demand normalize sooner.

3 Background: Turkey

This section summarizes the economic environment in Turkey before the pandemic to provide a background on initial conditions.

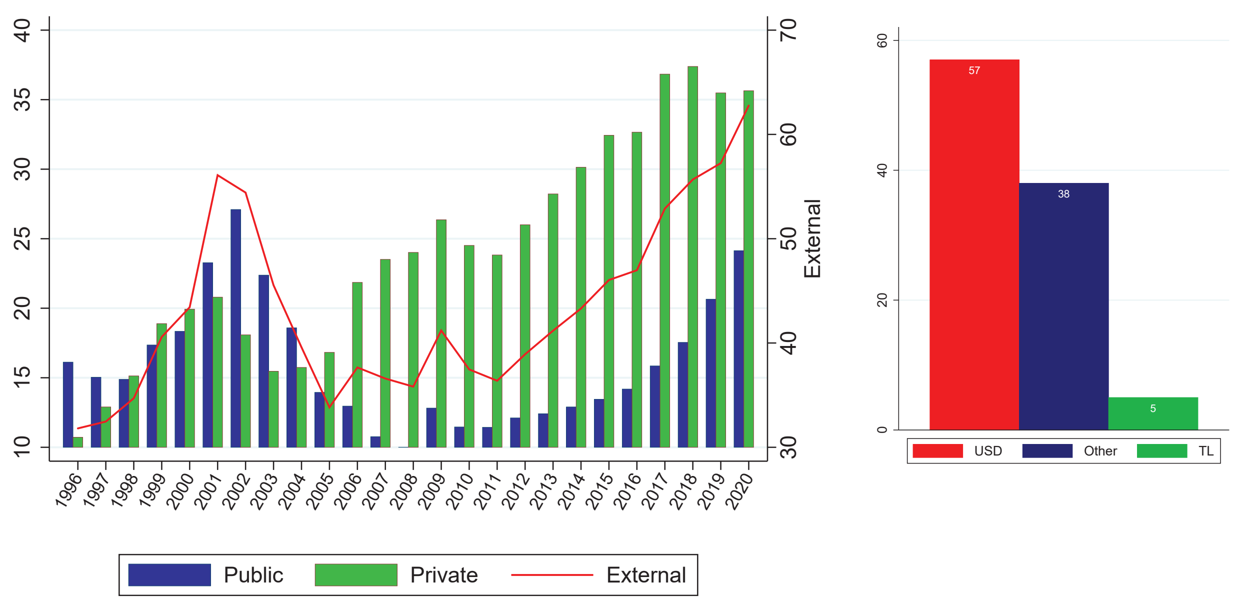
Since 2017, the inflation rate had been on the rise while Turkish Lira (TL) depreciated. Triggered by the political tension between Turkey and US, August 2018 marked the beginning of an exchange rate crisis, where rapidly depreciating TL brought many companies with FX debt to the edge of bankruptcy. The significant decline in economic growth led to an improvement in the current account deficit because Turkey's production heavily relies on imports of intermediary goods. The growth rate in the first quarter of 2020 reached 4.5 percent and the unemployment rate declined to 12.7 percent.

Capital outflows by non-residents during COVID-19 led to a wave of depreciation in TL, which required FX interventions and brought FX reserves to low levels. As of June 11, 2021, *net* reserves of Central Bank of the Republic of Turkey (CBRT) stood at $14.9 billion. IMF-defined budget deficit that excludes one-time transfers stands close to 5 percent of GDP while the current account deficit is around 2.5 percent of GDP, as an average over the last 5 years.

Figure 1: External Debt and Currency Decomposition

(a) Decomposition in terms of Ownership

(b) Currency Decomposition



NOTES: (a) This panel plots external debt (right x-axis) alongside with its public-private composition (left x-axis) for Turkey. Debt values are expressed as percentage of GDP. (b) This panel shows the currency composition of total external debt as of December 2020. Source: Turkey Data Monitor

Turkey relies heavily on capital flows to finance its external debt, which stood at 63 percent of

GDP at the end of 2020. Figure 1a shows the changes in the composition of external debt over time. In 2001, total external debt was 57 percent of GDP. Of this, public sector debt was 24 percent, while the private sector debt was 22 percent.[6] After the 2001 crisis, external debt was reduced at first, but it gradually built up in the years that followed. By the time we reached 2019, total external debt was once again comparable to 2001 levels with 56 percent of the GDP. Different from 2001, however, this time the lion's share was held by the private sector debt which was 36 percent of the GDP while the public debt was 21 percent of GDP. Another interesting pattern that is observed in Figure 1a is the increasing trend in public borrowing in the period after 2012. As of December 2020, almost 60 percent of total external debt is denominated in USD (see Figure 1b).

4 The Framework

In this section, we develop a model that illustrates how COVID-19 affects the economy. 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. In the model we do not quantify the economic costs of lost lives (see e.g., Greenstone and Nigam (2020)) under alternative lockdown scenarios. Had we incorporated the costs of deaths, the superiority of full lockdown would be even more striking.

[6] The sub-components do not add up because the remainder of the external debt is held by CBRT.

4.1 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 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

[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.

trajectories. We assume that the industries that require a greater degree of physical proximity would be more prone to infections.[8]

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 5.1 for details). One caveat with this approach is that during the pandemic the physical proximity requirements of industries could

[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/

be adjusted downwards (Eichenbaum et al., 2020). 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 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.

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

[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 .

4.2 Production

We specify a simplified version of the production function where output is a linear function of labor. This treatment emphasizes the impact of the pandemic on production through changes in labor supply. Here, we implicitly assume that the amount of the capital stock remains the same in the short-run, and therefore, can be omitted during normal times as well as the pandemic period. We model production as a function of the number of workers in industry i as:

$$Y_i = Z_i L_i \tag{11}$$

where Z_i denotes the productivity of workers in sector i.

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:

$$\tilde{L}_{i,t} = (N_i - I_{i,t}) + TW_i \left(1 - \frac{I_{0,t}}{N_0}\right) \tag{12}$$

Since we assume a linear production function, the output in industry i decreases due to the ongoing pandemic with the levels at:

$$Y^S_{i,t} = Z_i \tilde{L}_{i,t} = Y_i \frac{\tilde{L}_{i,t}}{L_i}. \tag{13}$$

4.3 Demand

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.

In modeling the demand side in terms of the domestic and foreign demands, we assume that for a country $c = 1, ..., C$, a representative agent allocates her income optimally among different final goods, by maximizing her utility function through expenditures on these goods. Here, we use a Cobb-Douglas specification for the utility function of the representative agent in line with the literature on input-output analysis (e.g., Acemoglu et al. (2012), among others). Specifically, we use the following utility function:

$$U(e_1, \ldots, e_n) = \prod_{i=1}^{n} e_i^{\alpha_i}, \tag{14}$$

where e_i is the expenditure on the final good of industry i and α_i refers to industry i's share in total expenditure together with $\sum_{i=1}^{n} \alpha_i = 1$ and $0 < \alpha_i < 1 \forall i = 1, \ldots, n$. As a natural consequence of the Cobb-Douglas formulation, α_i represents the share of expenditures on the final good i in the budget of the representative agent. Suppose that the income (wage) of the representative agent is w. Then the expenditure in industry i can be written as $e_i = \alpha_i w$.

The pandemic alters the demand profile and expenditure shares in each country. We assume that demand is affected through two distinct channels during the pandemic. The first channel is the effect of the pandemic on the priorities, and thus, on preferences. In this case, the sectoral weights in the budget change following the changes in preferences. The utility function changes with the

[11] We present these demand changes and related data resources in Table A.3 of the Appendix.

weights as follows:

$$\tilde{U}(e_1, \ldots, e_n, I_c) = \prod_{i=1}^{n} e_i^{\tilde{\alpha}_i(I_c)}, \tag{15}$$

where the Cobb-Douglas exponents depend on the number of infections in each country, denoted as I_c for $c = 1, ..., C$. $\tilde{\alpha}_i(I_c) = \alpha_i$ for a small number of infections, i.e., $I_c \leq 0.1\bar{I}_c$, where $\bar{I}$ is a scaling parameter for infections. In the Turkish context, we set $\bar{I}_c$ to 50,000 to capture a relevant range for the number of infections (see below for our simulations). Likewise, in the international case we set $\bar{I}_c$ proportional to 50,000 with proportionality computed as the ratio of the population of the foreign country to the population of 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_c, the limit level is defined as $\lim_{I_c \to \infty} \tilde{\alpha}_i(I_c) \equiv \bar{\alpha}_i$ with $\sum_{i=1}^{n} \bar{\alpha}_i = 1$ and $0 < \bar{\alpha}_i < 1$ for all $i = 1, \ldots, n$.

In addition to the changes in preferences during the pandemic, demand also changes due to the income effect. We assume that the available income for expenditure decreases by a ratio of $1 - \eta(I_c)$ compared to normal times for countries $c = 1, ..., C$. We assume that $\eta(I_c)$ is a decreasing function of the number of infections and satisfies $\eta(I_c) = 1$ for $I \leq 0.1\bar{I}_c$. For large I_c, i.e., $\lim_{I \to \infty} \eta(I_c) = \bar{\eta}$ with $0 < \bar{\eta} \leq 1$. In this set up, the minimum level of income that is necessary for survival at the brunt of the pandemic is given by $\bar{\eta} \times w$, which can be achieved through transfer payments.

Fiscal policies introduced by governments to mitigate the effects of the pandemic could also be modeled by changing the levels of η function. While we capture the effects of the pandemic by modelling the demand parameters α and η as a function of the number of infections, the specification can be generalized to include consumer sentiment or the trustworthiness of the policies as the determinants of these key demand parameters. Hence, the impact of a decline in capital inflows, or a decline in policy credibility during the pandemic can be analyzed by adjusting the demand parameters within our framework.

To determine the level of output implied by the changes in demand during the pandemic, we first express the expenditure in each industry as a function of the number of infections. Next, we construct a ratio, $\delta_i(I_c)$, that depends on the number of infections in countries. The numerator shows the level of expenditure when the number of active cases is I_c, while the denominator shows the level of expenditure when there is no infection at all. The numerator in this ratio is dependent on both the income channel and changes in priorities. By combining both channels, we can write $\delta_i(I_c)$ as:

$$\delta_i(I_c) = \frac{\tilde{\alpha}_i(I_c)\eta(I_c)}{\alpha_i}. \tag{16}$$

When the number of infections is small, the demand ratio approaches 1. When the number of infections soars, the preferences change dramatically with the heat of the pandemic. We specify the limiting cases for $\delta_i(I_c)$ using this ratio corresponding to the brunt of pandemic. We further assume that demand remains unaffected for a small number of infections, $0.1\bar{I}_c$, when the society believes that the pandemic is contained. This implies that for $I \leq 0.1\bar{I}_c$, $\delta_i(I_c) = 1$. At the peak of the pandemic, when the number of infections soars, $\lim_{I_c \to \infty} \tilde{\alpha}_i(I_c) \equiv \bar{\delta}_i = \frac{\bar{\alpha}_i\bar{\eta}}{\alpha_i}$. For the specific sectors, such as the airline industry, the demand might completely stall due to travel restrictions. For these sectors, $\bar{\delta}_i = 0$. On the contrary, the demand might remain intact for the other sectors, such as the food industry. In this case $\bar{\delta}_i = 1$. To sum up, $\bar{\delta}_i$ 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 dataset 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 $\bar{\delta}_i$ and 1, representing the two limiting cases. We use an inverse hyperbolic functional form to achieve this

[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.

property as:[13]

$$\delta_i(I_c) = \begin{cases} 1 & \text{if} \quad I_c \le 0.1\bar{I}_c \\ \bar{\delta}_i \frac{1+(I_c/\bar{I}_c-0.1)}{\bar{\delta}_i+(I_c/\bar{I}_c-0.1)} & \text{if} \quad I_c > 0.1\bar{I}_c. \end{cases} \tag{18}$$

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 $\bar{I}_c$ and δ_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.

With industry specific $\delta_i(I_c)$ values in hand, we can now estimate the output of industries that would satisfy these demand levels. Let's show the final demand levels (expenditures) of industry i in country c with $F_{c,i}$. During the pandemic, when the number of infections is I, the final demand can be written as:

$$\tilde{F}_{c,i}(I) = F_{c,i}\delta_i(I) \tag{19}$$

where the demand during the pandemic is represented by $\tilde{F}_{c,i}(I)$.

We map the changes in the final demand for each sector to the output level in each industry using the input-output framework. We account for the international linkages to fully capture the impact of final demand on production with OECD Inter-Country Input-Output (ICIO) Tables.[14] ICIO provides us with inter-industry input usages of industry i in country c from other industries form any country as well as final usage of this industry. ICIO consists of 36 industries and 65 entities (corresponding to 64 countries and another entity representing rest of the world). The input-output portion of ICIO is a matrix of 2484×2484 entries. The final demand vector has 2484 entries for each industry in every country. We calculate the direct requirements matrix $\mathbf{A}$ by dividing the rows of IO matrix with the

[13]This inverse hyperbolic functional form provides a smooth transition between the two limiting cases, for small and large I_c, where the marginal impact of the number of infections changes at a rate that is inversely proportional to the number of infections. The flexibility in this specification allows for changes across sectors as $\bar{I}_c$ and δ_i are the tuning parameters that determine the limits and the speed of the convergence. The following functional forms for $\eta(I_c)$ and $\tilde{\alpha}_i(I_c)$ for $i = 1, \ldots, n$ lead to the smooth function in Equation 18.

$$\begin{aligned} \eta(I_c) &= 1 \quad \text{and} \quad \tilde{\alpha}_i(I_c) = \alpha_i & \text{if } I_c \le 0.1\bar{I}_c \\ \eta(I_c) &= \bar{\eta}\frac{1+(I_c/\bar{I}_c-0.1)}{\bar{\eta}+(I_c/\bar{I}_c-0.1)} \quad \text{and} \quad \tilde{\alpha}_i(I_c) = \frac{\bar{\alpha}_i}{\alpha_i}\frac{\bar{\eta}+(I_c/\bar{I}_c-0.1)}{\bar{\delta}_i+(I_c/\bar{I}_c-0.1)} & \text{if } I_c > 0.1\bar{I}_c \end{aligned} \tag{17}$$

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

total output of industry. The direct requirement matrix reflects the need from each intermediate input to make $1 worth of output. For any industry, its output is either used as a final good or an intermediate input. We can write this relationship in a matrix notation as:

$$Y = F + \mathbf{A}Y \tag{20}$$

where Y captures output vector of size 2484×1 and F is the final demand vector. For both of these vectors, each entry corresponds to a country industry combination of (c, i) combinations.[15] Solving for output in terms of the final demand yields: satisfy the final demand as:

$$Y = (\mathbf{I} - \mathbf{A})^{-1} F \tag{21}$$

where $(\mathbf{I} - \mathbf{A})^{-1}$ is the well-known Leontief inverse. Hence, the total output of country c is:

$$Y_c = \sum_{i=1}^{n} Y_{c,i} \tag{22}$$

During the pandemic, with an infection level of I_t, the expenditures on the final demand change according to Equation (19). Therefore, the output to satisfy this final demand can be calculated using Equation 21:

$$Y_t^D = (\mathbf{I} - \mathbf{A})^{-1} \tilde{F}(I_t). \tag{23}$$

where Y_t^D denotes the output implied by the demand and $\tilde{F}(I_t)$ represents the altered demand vector due to infections at t. This relationship pins down the output as a function of infections due to demand changes.

4.4 Equilibrium

We calculate the output implied by supply using Equation 13 and the output implied by demand using Equation 23. We take the minimum of these outputs to calculate the equilibrium. Formally,

[15] In our formulation, with a slight abuse of the notation, variables missing a subscript refers to vectors or matrices.

the output is calculated as:

$$Y_t^{EQ} = \min(Y_t^S, Y_t^D) \tag{24}$$

where the min is element-by-element minimum function for two output vectors corresponding to outputs implied by supply, Y_t^S, and demand, Y_t^D.

In practice, we are interested in calculating the GDP decline associated with the pandemic. We assume that value added shares of the industries do not change during the pandemic. Let $VA_{c,i}$ denote the value-added in industry i in country c. Then, value added during the pandemic can be written as::

$$VA_{t,c,i}^{EQ} = Y_{t,c,i}^{EQ} \frac{VA_{c,i}}{Y_{c,i}} \tag{25}$$

GDP of a country is the sum of the value-added from all its industries:

$$GDP_{t,c}^{EQ} = \sum_{i=1}^{n} VA_{t,c,i}^{EQ} \tag{26}$$

5 Quantitative Analysis

5.1 Data

In our analysis, we use OECD ICIO Tables from 2015. 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.2.

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.[16] 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 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. 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 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.2 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.

[16] 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.

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.5. 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.3 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.4 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.6 of the Appendix.

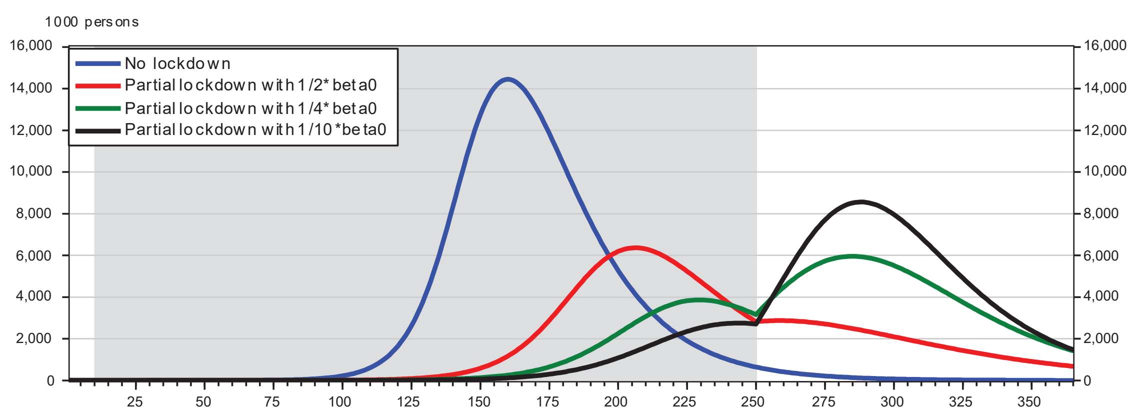
5.2 Infection Rates under Alternative Lockdown Scenarios

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. These simulations allow us to calculate the economic costs of alternative lockdown scenarios.[17]

We start with the no lockdown scenario and compare it to partial lockdown where certain restrictions are imposed on daily life to incorporate social distancing rules 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 $i = 1, \ldots, n$ remain unchanged. We consider three cases of partial lockdown where the infection rate, β_0 is reduced by the proportion of 0.5, 0.25 and 0.10 compared to the reference setting. Figure 2 displays the evolution of the number of infected patients under these four scenarios when a hypothetical lockdown is implemented for 240 days, starting early on the 10^{th} day and remains active until the 250^{th} day.

Figure 2: No lockdown versus Partial Lockdown Scenarios



As can be seen from the figure, in case no action is taken against the COVID-19 pandemic, which

[17] 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.

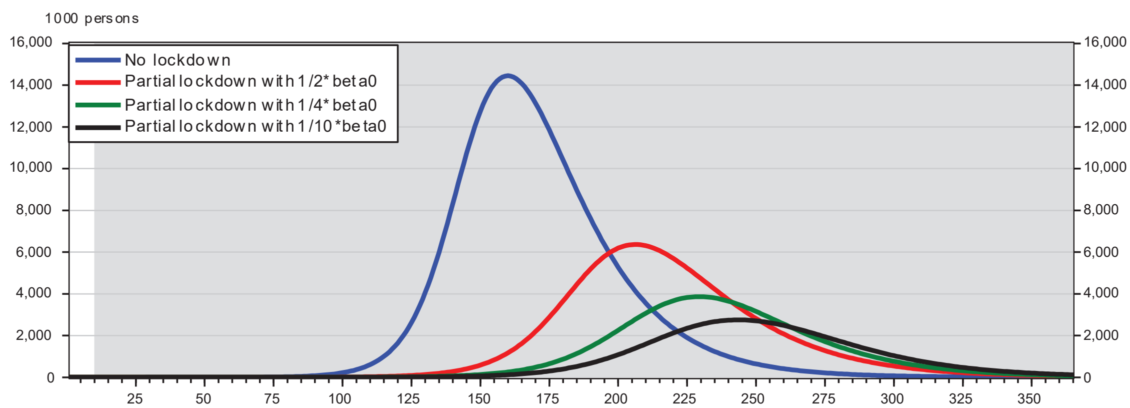
is shown with the blue line, the pandemic advances at a rate implied by the benchmark reproduction rate of $R_0 = 2$. This implies that the pandemic reaches its peak around the 150^{th} day with a total toll of around 14 million infections. Following this state of "herd immunity", the number of infections 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 11.0% 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.

Under partial lockdown scenarios, the reproduction number declines below 2 due to lower infection rates but remains above 1 in all three scenarios. Specifically, we assume that the lower infection rate dampens the rate at which the pandemic evolves, nevertheless it is not sufficient to contain it altogether. This is due to the fact that businesses remain open, which feeds the virus within the industries and affects the overall course of the pandemic. If the infection rate is relatively high ($0.5 \times \beta_0$), which is shown with the red line, the GDP declines 11.6 percent. If the infection rate is moderate ($0.25 \times \beta_0$), shown with the green line, the GDP declines by 10.9 percent. If the infection rate is relatively low ($0.1 \times \beta_0$), shown with the black line, the GDP declines by 10.5 percent.

None of the 240-day partial lockdown scenarios that we considered in Figure 2 were successful in containing the pandemic. When the lockdown is removed on day 250, all three partial lockdown scenarios have approximately the same number of infections. Once the lockdown is removed, however, the virus follows a different course in each scenario. For the low infection rate scenarios (green and black lines) the number of new cases increase rapidly, leading to peak levels within 50 days after the lockdown. Meanwhile the high infection rate 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 scenarios, shown by the area under the black and green lines. Hence, by the time the lockdown is removed, the number of susceptible people are significantly higher under the low infection rate scenarios, 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. Figure 3 shows the simulation results if partial lockdown lasts for a full year. As in Figure 2, we assume that the industries are operating as usual and thus

β_i's (for $i = 1, \ldots, K$) remain unaffected. 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.

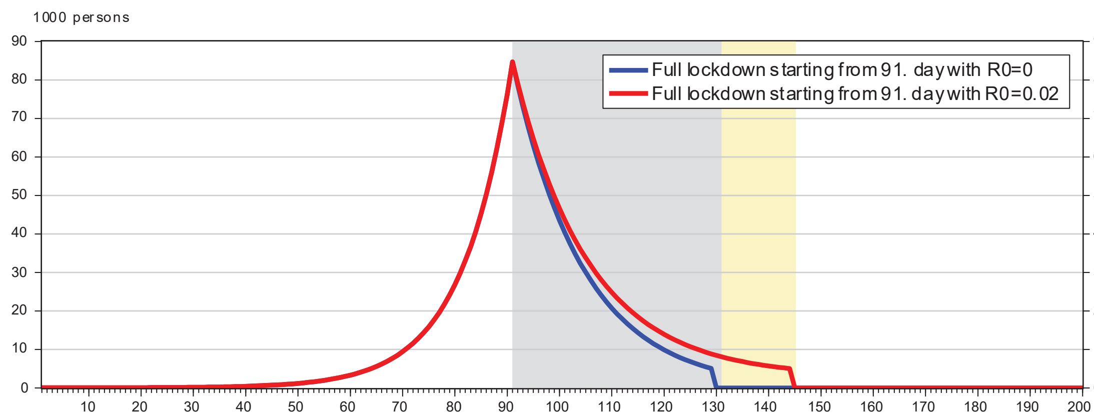
Figure 3: Alternative Scenarios under Partial Lockdown for Full Year



Compared to Figure 2, 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. In terms of the economic costs, the additional economic costs of the longer partial lockdown hover around 0.5 percent of the GDP. The added costs despite the extended duration of the lockdown are limited. This is due to the fact that the decline in demand already reaches a maximum level at the earlier stages of the lockdown and successive reductions in production only reflect the decline in supply due to increased number of infections.

Figure 4 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). The consequent decline in GDP is about 5.8 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 7.6 percent.

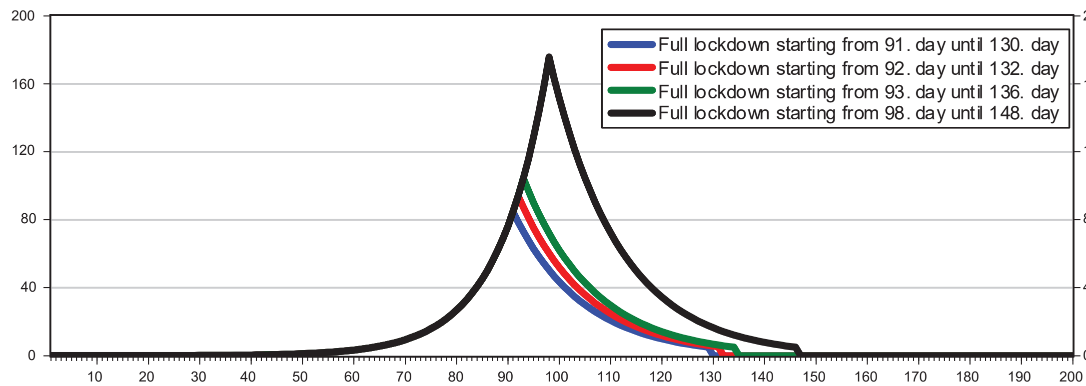
Figure 4: Alternative Scenarios under Full Lockdown



The costs of delaying full lockdown are shown in Figure 5. The benchmark scenario that is illustrated in Figure 4 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 to 5.9 percent of the GDP. If there is a two-day delay (the green line), this time the duration of the lockdown increases to 43 days and the decline in GDP is 6.2 percent. If the lockdown is delayed by one week (the black line), the decline in GDP is 7.3 percent. After 100 days, the virus starts to spread again and hence prematurely ending the lockdown is rather ineffective.

As we compare the economic costs under full lockdown (Figures 4 and 5) with those of partial lockdown (Figures 2 and 3), we note that the costs of full lockdown are lower than any of partial

Figure 5: Costs of Delay in Implementing Full Lockdown



lockdown scenarios.

As we compare the the number of deaths under alternative scenarios, 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. If partial lockdown is extended to a full year, then the number of deaths decline to about 0.5 percent of the population.

5.3 The Role of External Demand Shocks

The aggregate costs of COVID-19 shock that we calculated in the previous section embeds supply and demand channels in Turkey as well as abroad. In this section, we illustrate the role of external demand and supply in total costs. In order to better illustrate the role of international linkages for the Turkish economy, we consider two alternative scenarios.

Assuming a parallel progression of pandemics, we arrive at Equations 21, 23 and 19 to quantify demand change and final output implied by this change. Here, different than Equation 19, in this section we allow for country specific demand shocks. The matrix for intermediate goods is obtained from the direct requirements matrix and the output vector:

$$\overline{INT} = \mathbf{A}\bar{Y}. \tag{27}$$

Each entry of the matrix INT corresponds to the usage of intermediate goods by industry i in country c from industry i' in country c'. Combining imports of intermediate goods and final goods, we write the total imports for country c as:

$$\overline{\text{imports}}_c = \sum_{c' \neq c} \sum_{i=1}^{n} \left(\bar{F}_{c,c',i} + \sum_{i'=1}^{n} \overline{INT}_{c,i,c',i'} \right) \tag{28}$$

Similarly the total exports by country c is:

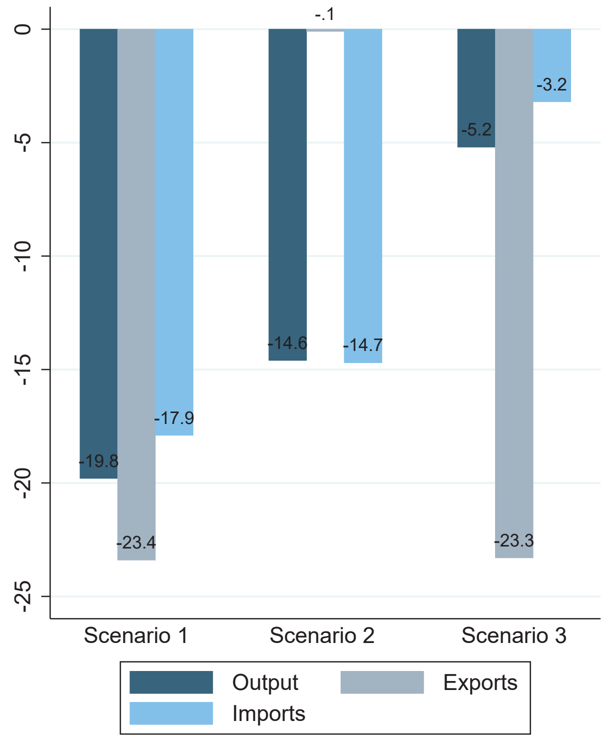
$$\overline{\text{exports}}_c = \sum_{c' \neq c} \sum_{i=1}^{n} \left(\bar{F}_{c',c,i} + \sum_{i'=1}^{n} \overline{INT}_{c',i',c,i} \right) \tag{29}$$

As a result, a decline in foreign demand for final goods will create sectoral output declines in many domestic sectors, which will add to aggregate output decline in Turkey. To highlight this mechanism, we present three scenarios.

Scenario 1 assumes the same proportionate demand shock in Equation 19 for the whole world. For example, if we estimate that the demand for automobiles decline by 60 percent based on Turkish data, we assume that the demand for automobiles declines by 60 percent throughout the world. Figure 6 shows how much total output, exports and imports change at the brunt of the pandemic relative to normal times for alternative scenarios. In the baseline scenario, the decline in terms of total output is 19.8 percent (Scenario 1 in Figure 6). Interestingly, imports decline less (17.9 percent) compared to exports (23.4 percent). This is consistent with the nature of the Turkish economy which is highly dependent on imports of intermediate goods. On the exports side, a further breakdown indicates that the 27.4% decline in terms of final goods is higher than the 18.8% decline in intermediate goods (not shown). Similarly, on the imports side, the 19.7% decline in intermediate goods is higher than the 16.1% decline in final goods (not shown).

Under scenario 2, we assume that the demand in Turkey declines but the international demand for final goods is back to its normal (see Scenario 2 in Figure 6). Using the automobile example above, this implies that the domestic demand for automobiles shrinks to 60% of normal levels but the international demand remains at its normal levels. In this setting, the decline in terms of total output is 14.6 percent at the brunt of the pandemic. The decline in imports is 14.7% but the decline

Figure 6: Demand Shocks for an Open Economy with I-O Links



NOTES: This graph illustrates the impact of three different scenarios for demand shocks. In the first scenario, all the countries are assumed to experience the same demand shifter during the pandemic. In the second scenario, only Turkey experiences a demand shock but the international demand levels are intact. In the final scenario, the international demand levels are down but the demand in Turkey is at pre-pandemic levels. The number written on each bar corresponds to the percentage change in the relevant variable in the underlying scenario relative to its pre-pandemic level.

in exports is only 0.1%.

Lastly, in scenario 3, we model the setting where the demand in Turkey is intact but the demand in international markets has plummeted (see Scenario 3 in Figure 6). Under this scenario, the decline in output is 5.2% solely because of international linkages. As expected, the exports are hit the hardest with a decline of 23.3% and imports decline by 3.2%.

If we compare Scenario 1 and Scenario 3, we can see the role of demand in total economic costs. The decline in foreign demand solely account for almost 27 percent of the decline in aggregate output. Notice that we run these scenarios under no lockdown policy in the absence of any policy action.

5.4 Globally Uncoordinated Lockdowns and the Role of Fiscal Policy

So far we assumed that the countries act in global coordination and take measures similar to Turkey during the pandemic. In this section, we relax this assumption to calculate the economic costs in an environment of uncoordination. The purpose of this exercise is to take a closer look at the role of foreign demand on the domestic recovery through two channels: First, we want to determine the additional costs that will be borne by the small open economy, if its trade partners do not take effective lockdown measures to contain the pandemic. Second, we want to quantify the role of fiscal stimulus that is provided by the trade partners on domestic recovery.

In order to compute these alternative scenarios, we make several simplifying assumptions. Specifically, we assume that countries consider either full lockdown or partial lockdown during the pandemic. In a full lockdown, many industries are either fully or partially closed, hence, their supplies are lower. We further simplify our definition of a partial lockdown. In the previous section, both demand and supply shocks were present during a partial lockdown. In this section, we ignore the supply effects through the labor force due to sick workers. This enables us to pinpoint solely the foreign demand related losses in the home country due to the lack of global coordination. Furthermore, this simplification is strengthened by our findings in the next section where we find that the demand shock is more assertive than the supply shock during a partial lockdown (Figure 9, panel c).

When the lockdowns are not coordinated, we assume that the countries in the rest of the world choose between a full lockdown and a partial lockdown when the home country (i.e. Turkey) implements full lockdown. In this manner, we calculate the additional costs that Turkey would bear due to the decline in external demand, depending on the number of infections in its trade partners.

To allow for different lockdown decisions and hence differential progression of the pandemic in countries, we ignore the sectoral heterogeneity and assume a single β for a country. Lockdown decisions affect this β value. Full lockdowns bring $\beta = 0$ and partial lockdown bring it down to half the value, i.e., $\beta = 0.14/2$.

In this section, we assume that the countries start the pandemic with the same number of infections. Once the infection levels reach $I_c = \text{population}_c/1000$ for country c, it goes into lockdown. With these simplifying assumptions, the decision of an initial lockdown coincides across countries.

Table 1: ECONOMIC COSTS OF THE PANDEMIC UNDER DIFFERENT GLOBAL SCENARIOS

Scenario:	**Coordinated FL (ρ=1)** (1)	**Uncoordinated FL (ρ=0.5)** (2)	**Uncoordinated FL (ρ=0)** (3)
(1) **Without stimulus**	5.8	6.9	7.8
(2) **With stimulus**		6.6	7.4

NOTES: Table 1 reports the economic costs of the pandemic under different scenarios. Coordinated FL (ρ=1): A lockdown is put into practice between the 91^{st} and 131^{st} days of the pandemic and is fully effective with zero reproduction number in Turkey and the rest of the world coordinates with Turkey i.e., the probability of coordination (ρ) equals 1; Uncoordinated FL (ρ=0.5): A lockdown is put into practice in between the 91^{st} and 131^{st} days of the pandemic and is fully effective with zero reproduction number within Turkey and a randomly selected 50 percent of the countries in the world cooperate with Turkey i.e., ρ=0.5; Uncoordinated FL (ρ=0): A lockdown is put into practice in between the 91^{st} and 131^{st} days of the pandemic and is fully effective with zero reproduction number within Turkey, but the rest of the world does not cooperate with Turkey i.e., ρ=0. The economic costs are computed also for additional scenarios where the countries that implement partial lockdown consider stimulus packages or not.

However, further lockdown decisions can take place at different times since some countries choose partial lockdown while others engage in full lockdown and follow different paths. We model several scenarios that are summarized in Table 1.

In our baseline scenario, all countries go into full lockdown simultaneously and the disease is controlled globally after 39 days. The results from this scenario were reported in the previous section 5.2 where the total costs were estimated to be 5.8 percent. We replicate this figure in Table 1 for comparison purposes (column 1). In the two alternative scenarios, we allow for uncoordination and let a certain fraction of the countries adopt partial lockdown while Turkey still maintains a full lockdown. The additional cost incurred by Turkey, compared to our baseline scenario reflects the impact of foreign demand on Turkey's pandemic-related costs.

In the second scenario, we assume that Turkey goes into full lockdown and all other countries are assigned to full or partial lockdown with equal probability (Table 1, column 2). We run this scenario 200 times to control for the effect of random assignment and to establish confidence intervals. We note that the economic costs borne by Turkey increase to 6.9 percent when some of its trade partners suffer from a prolonged pandemic and reduce their demand for Turkish goods. In the third scenario, we provide an upper bound for the additional costs that are accrued due to lower external demand. This time, we assume that Turkey goes into full lockdown and all other countries engage in partial lockdown. This scenario yields the highest costs of 7.9 percent (Table 1, column 3).

Next, we consider a framework where the countries that implement partial lockdown consider stimulus packages to offset the sizable reduction in demand in their economies. In our set up, this corresponds to increasing η by 5 percent in Equation 16. With this interpretation, the stimulus packages enable the consumers to increase their budget for the expenditures and lead to a milder decline in the demand profile. In other words, we assume that the fiscal stimulus that is given to the consumers result in a 5% increase (i.e. $1.05 \times \eta$) in spending at any point of the pandemic.

Let us again remind the readers that the next section compares the relative importance of supply and demand factors under alternative lockdown scenarios. In that section we illustrate that the demand effect is dominant in a partial lockdown, which drags economic costs (Figure 9, panel c). Thus, policies that are aimed to stimulate demand are most effective in a partial lockdown.[18] In light of this finding, we consider stimulus programs only under partial lockdown. The second row in Table 1 illustrates that total economic costs in the home country decline by about 0.3 to 0.4 percent of the GDP if the countries that adopt partial lockdowns offset some of the drag in their economies through stimulus packages.

We note that the costs of uncoordinated lockdown that we estimated in this section do not incorporate the potential future waves once the home country considers an effective full lockdown and reduces the number of infections to 5000. In our stylized model, we assume that the home country can implement effective contact tracing and keep the pandemic contained moving forward. In real life, an uncoordinated lockdown in the absence of vaccinations magnifies global and domestic economic costs by causing the virus to circulate and present potential risks for the home country.

In terms of the fiscal policy implementation, the stimulus package announced by the Turkish government in March 2020 was consistent with the general framework adopted by other countries. There was postponement of tax obligations, social security premiums and credit payments of the companies in the services sector. The limits of the Credit Guarantee Fund were increased to make bank loans more accessible. Temporary income support was provided to those workers whose companies have ceased production due to the pandemic. Furthermore, a cash assistance program for needy families was launched. IMF data notes that once equity, loans, and guarantees are excluded,

[18] In contrast, supply side pressures characterize total costs in a full lockdown. Therefore, we do not consider demand-side policies if the countries adopt full lockdown

fiscal spending in Turkey was less than 2 percent in 2020, the third lowest among EMs after Mexico and Egypt. This reflects the limited fiscal space relative to other EMs and advanced economies.[19]

5.5 Sectoral Breakdown of Economic Costs

In this section, we analyze the economic costs at the sectoral level. Heterogeneity in sectoral costs may stem from several channels. Sectors that are closed down due to isolation measures (i.e. nonessential sectors), those that are hit hardest by the collapse in demand such as the services sectors, or those industries where teleworking is not very feasible will be hit harder. As for the role of international linkages, those sectors with greater exposure to international spillovers, particularly with those countries that had larger domestic outbreaks would be more affected. Similarly, those industries that rely more on external finance would experience the pinch of tightening in global financial conditions. In the next sub-section, we focus on the role of trade linkages. In the following sub-section, we calculate the sectoral economic costs in our framework under different scenarios. Using these sectoral costs, in the last sub-section, we disentangle the role of trade and external funding in sectoral costs in a regression framework.

5.5.1 The Role of Trade Linkages in Sectoral Costs

We investigate the role of international linkages in determining the heterogenetiy in sectoral costs. International linkages would affect economic costs through trade relationships as well as capital inflows, both at the sectoral level. Those sectors that are more closely connected to international value chains as well as those sectors that are dependent on external funding would be affected more from the COVID-19 shock.

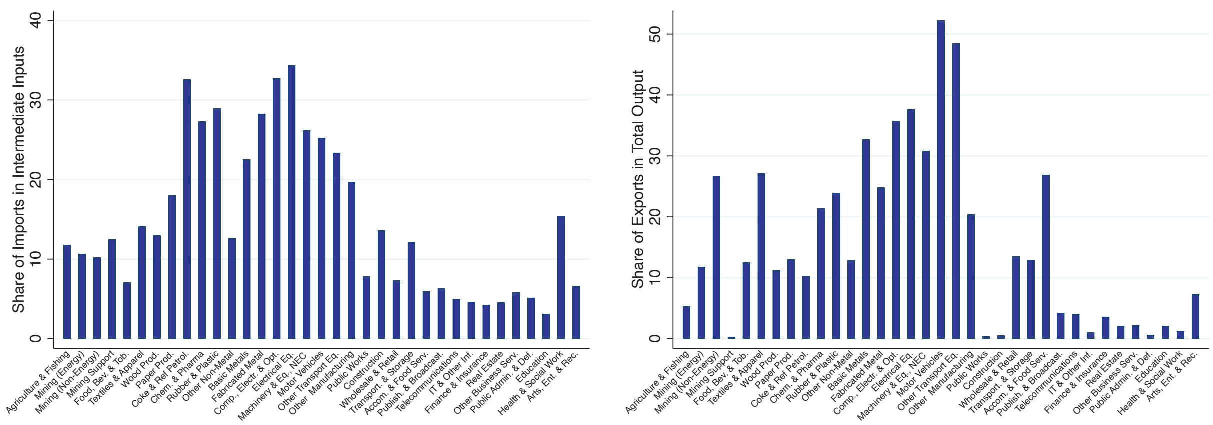
Figure 7 allows us to get a glimpse of the role of trade. The figure illustrates the share of imports in total intermediate inputs (the left panel) and the share of exports in total output (the right panel). We would expect those sectors that rely on imports and exports to be more affected. For example, motor vehicles, transportation equipment, electrical equipment, computer and electronics, and tourism-related services sectors such as accommodation and food services are the sectors that

[19] https://www.imf.org/en/Topics/imf-and-covid19/Fiscal-Policies-Database-in-Response-to-COVID-19.

rely more on external demand. Thus, the deep recessions that are expected in Turkey's major export markets such as the Euro Area, UK, or the US would hit these sectors the most, consistent with our analysis in Figure 6.

Figure 7: Import and Export Share

(a) Import Share in Intermediate Inputs (b) Export Share in the Output



NOTES: (a) This figure plots the share of imports in the intermediate inputs. (b) This figure plots the exports as a share of output for each sector. Source: OECD ICIO Tables.

5.5.2 The Role of Lockdowns on Sectoral Costs

Figure 8 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).

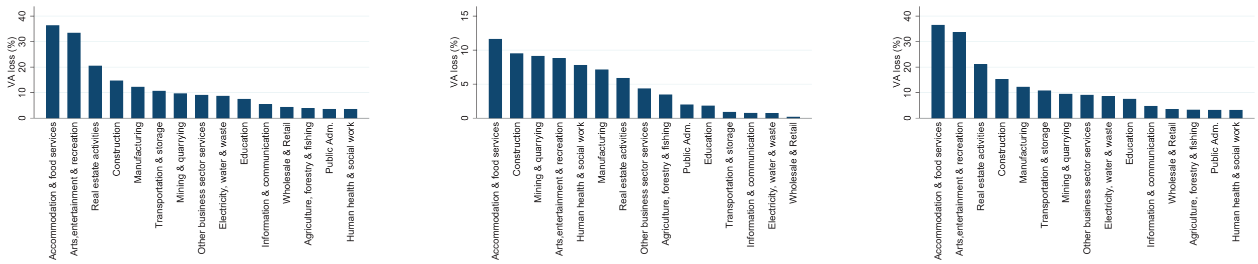
After documenting the heterogeneous economic costs of the pandemic for different sectors, we investigate whether these costs are accrued from demand or supply pressures. Figure 9 counts the days in which output implied by the demand channel or supply channel prevails to bring about the equilibrium output in a given industry.

Figure 8: Sectoral Heterogeneity in terms of Economic Cost of COVID-19 Shock

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

(b) **Scenario 2:** Full Lockdown, 91-131, $R_0 = 0$

(c) **Scenario 3:** Partial Lockdown, 10-250, $0.25 \times \beta_0$

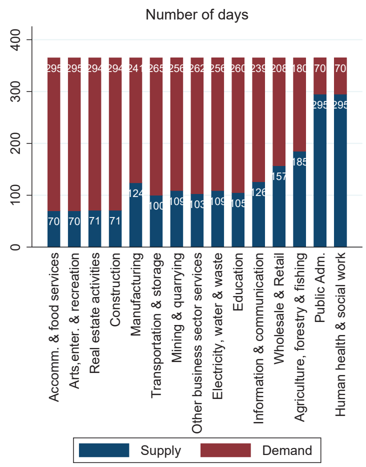


NOTES: This figure shows how the economic cost of COVID-19 shock differs across sectors in a particular lockdown scenario. The panels show three alternative scenarios: (a) No action is taken against the COVID-19 pandemic; (b) A lockdown is put into practice between the 91^{st} and 131^{st} days of the pandemic and is fully effective with zero reproduction number; (c) A partial lockdown is put into practice between 10^{th}-250^{th} days of the pandemic that evolves with a moderate infection rate ($0.25 \times \beta_0$). 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.

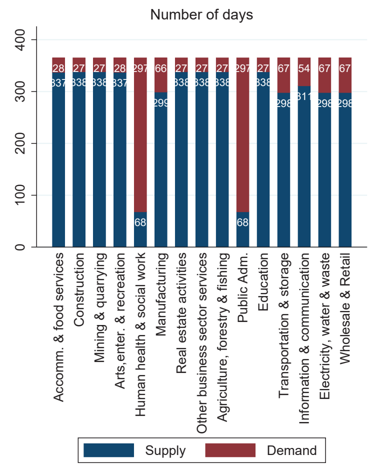
To interpret the findings present in this figure, we consider three benchmark scenarios: Panel (a) compares the no lockdown (blue line in Figure 2) scenario against full and effective lockdown (blue line in Figure 4), and partial lockdown with moderate infection rate (green line in Figure 3). Panel (a) suggests that under the no lockdown scenario, the demand channel, shown by the red bars, drives output in almost all days until the virus is fully contained. The supply channel, presented by the blue bars, prevails only in the early days of the pandemic (not shown). Among the 15 industry groups, "Accommodation and food services," "Arts, entertainment, recreation and other service activities," and "Real estate activities" are those that result in the highest economic costs of 36%, 33%, and 20% of the value added generated in those sectors, respectively. This is not only because goods produced in those categories (which are all provided by the services sector) cannot be consumed from home, but also because people prefer delaying their consumption until the uncertainty regarding the containment of the pandemic resolves. 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 9: Supply and Demand Pressures under Benchmark Lockdown Scenarios

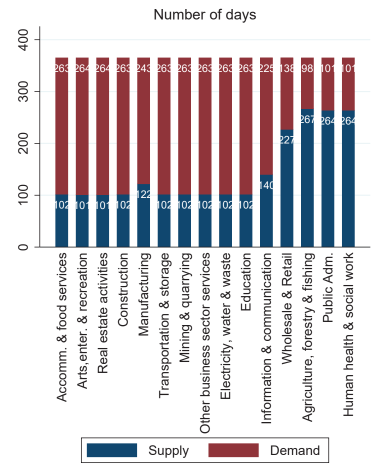
(a) **Scenario 1:** No Lockdown, $\beta = 0.14$



(b) **Scenario 2:** Full Lockdown, 91-131, $R_0 = 0$



(c) **Scenario 3:** Partial Lockdown, 10-250, $0.25 \times \beta_0$



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) A lockdown is put into practice between the 91^{st} and 131^{st} days of the pandemic and is fully effective with zero reproduction number; (c) A partial lockdown is put into practice between 10^{th}-250^{th} days of the pandemic that evolves with a moderate infection rate ($0.25 \times \beta_0$). 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, "Accommodation and food services," "Construction" and "Mining and non-quarrying of non-energy producing products" are those that result in the highest economic costs of 12%, 9.5%, and 9.1% 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 moderate infection rate ($0.25 \times \beta_0$), the supply channel dominates in the first 100 days of pandemic. On the other hand, demand drives output for the rest of the year, including the days in which new peak levels are reached after the partial lockdown is prematurely removed. This is because of the fact that businesses remain open, which feeds the virus within the industries and increases the uncertainty about the containment of the pandemic. Among the 15 industry groups, "Accommodation and food services," "Arts, entertainment, recreation and other service activities," and "Real estate activities" are those that result in highest economic costs of 36%, 34%, and 21% 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.

5.5.3 The Role of External Finance in Sectoral Costs

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 (a) in Figure 9 that in the case of a global no lockdown, demand channel drives output, 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

Table 2: SECTOR-LEVEL REGRESSIONS

Scenario:	**No Lockdown**		**Uncoordinated FL (ρ=0)**				**Uncoordinated FL (ρ=0.5)**				**Coordinated FL (ρ=1)**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dep. Var: VA Loss												
(1) Trade	16.0273**	16.5283**	6.1316*	6.5342**	5.5668*	5.9434**	4.5942*	4.9384**	4.2206*	4.5493**	1.1996	1.4767
	(6.388)	(6.412)	(3.039)	(2.925)	(2.876)	(2.772)	(2.340)	(2.223)	(2.243)	(2.132)	(1.919)	(1.847)
(2) Capital Flows	34.9502*	35.8033**	15.9595	16.6450*	14.0993	14.7406*	12.2088*	12.7950*	11.0549	11.6147*	4.8717	5.3435
	(17.331)	(17.234)	(9.638)	(9.201)	(8.973)	(8.571)	(6.979)	(6.558)	(6.623)	(6.222)	(5.274)	(4.988)
(3) FX		0.1572**		0.1263**		0.1182**		0.1080**		0.1031**		0.0869**
		(0.076)		(0.041)		(0.039)		(0.032)		(0.031)		(0.034)
Stimulus package	No	No	No	No	Yes	Yes	No	No	Yes	Yes	No	No
R^2	0.12	0.2	0.041	0.19	0.039	0.19	0.032	0.19	0.03	0.18	0.0036	0.11

NOTES: Table 2 reports the results of estimation of Equation 30 for four alternative scenarios. No Lockdown: No action is taken against the COVID-19 pandemic; Coordinated FL (ρ=1): A lockdown is put into practice between the 91^{st} and 131^{st} days of the pandemic and is fully effective with zero reproduction number in Turkey and the rest of the world coordinate with Turkey i.e., the probability of coordination (ρ) equals 1; Uncoordinated FL (ρ=0.5): A lockdown is put into practice in between the 91^{st} and 131^{st} days of the pandemic and is fully effective with zero reproduction number within Turkey and a randomly selected 50 percent of the countries in the world cooperate with Turkey i.e., ρ=0.5; Uncoordinated FL (ρ=0): A lockdown is put into practice in between the 91^{st} and 131^{st} days of the pandemic and is fully effective with zero reproduction number within Turkey, but the rest of the world do not cooperate with Turkey i.e., ρ=0. 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.

sectoral trade.[20,21] And then we run the following regression for sector i:

$$\Delta Y_i = \beta_0 + \beta_1 \text{Trade}_i + \beta_2 \text{Capital Flows}_i + \varepsilon_i \tag{30}$$

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 positive and highly signif-

[20]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.

[21]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.

icant coefficient estimates in the first two columns of Table 2 confirm the importance of international linkages on sectoral COVID losses under no lockdown scenario. 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 who finance these stronger production links through capital flows (row 2) and sectors with higher FX exposure (row 3) suffer even more, highlighting the additional adverse impact of COVID-19 on EMs with high external debt and domestic FX debt. We control sectoral FX debt (measured as the ratio of foreign currency debt in total debt as of 2016) because this variable captures domestic sectoral borrowing in foreign currency as opposed to international borrowing that we want to capture and hence will create an omitted variable bias.

Columns (3) to (12) illustrate the regression results where we use the sectoral COVID losses that are estimated under uncoordinated and coordinated full lockdown scenarios. In an uncoordinated lockdown where the rest of the world adopts partial lockdown while Turkey implements full lockdown (columns (3) to (6)), there is still a significant positive relationship between the sectoral costs and trade linkages, stemming from the decline in demand for Turkish exports despite the containment of the pandemic in Turkey. Columns (3) and (4) illustrate that the coefficient estimates associated with trade linkages decline more than 50 percent compared to the no-lockdown scenario thanks to the improvement in external demand due to lockdown measures abroad. The coefficient estimates decline further if the countries that implement partial lockdown provide stimulus packages (columns (5) and (6)) to support their recovery. The consequent improvement in the export revenue reduce the pandemic related costs at the home country.

If half of the world adopts full lockdown together with Turkey (columns (7) to (10)), then the empirical relationship weakens further because foreign demand strengthens as more countries adopt stricter lockdown measures. Within this scenario, adoption of fiscal stimulus programs further weaken the relationship as shown in columns (9) and (10). If the lockdown is completely coordinated and all countries adopt full lockdown (columns (11) and (12)), this time external demand fully normalizes. Indeed, in this scenario, the significant relation between sectoral output losses and trade and finance linkages disappears as the export revenue rebounds quickly following the containment of pandemic in all trade partners of Turkey. Put differently, now there is almost no sectoral variation on the left hand side that can be linked to open economy linkages. The coefficient on FX debt remains positive and significant with a similar magnitude. This debt is mostly borrowed domestically and hence still linked to the sectoral variation in COVID losses. Specifically, sectors with higher FX debt will suffer from COVID related deprecation, incurring higher COVID losses.

5.6 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.[22] 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 10 illustrates the course of the pandemic for a selected group of countries including Italy, 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 10 while the rest of the countries mimic partial lockdown with premature opening scenario illustrated in Figure 2.

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.[23]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.

[22]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%.

[23]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

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.

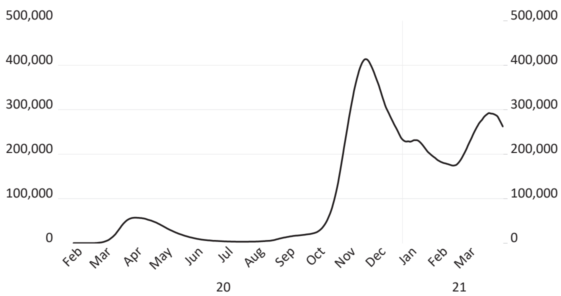
In the model, we did not explicitly incorporate expectations about infections and implicitly assumed that the two are highly correlated. Meanwhile, one can imagine a forward looking demand curve, which could be a function of infection expectations rather than the actual number of infections. In this 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.

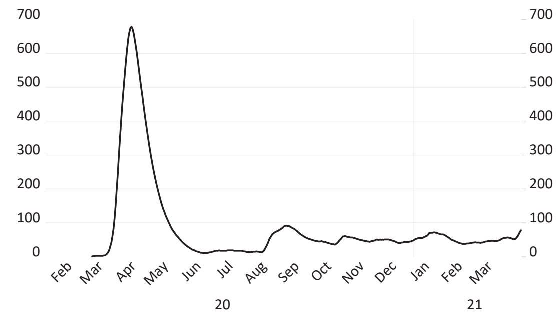
Our theoretical predictions are highly accurate for the Turkish economy where a relatively successful first wave was followed by an early opening and thus a sizable second and third waves. The consequent slowdown in demand was offset with an unsustainable credit growth policy through low interest rates, which led to further vulnerabilities for the economy.

Figure 10: The Progression of COVID-19 Pandemic

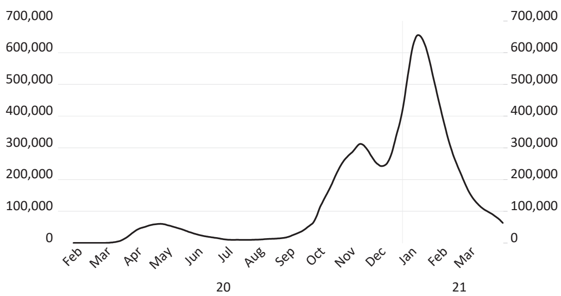
(a) Italy



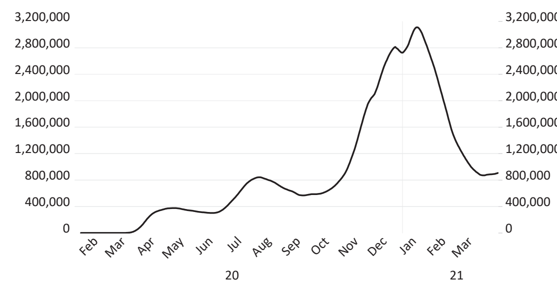
(b) New Zealand



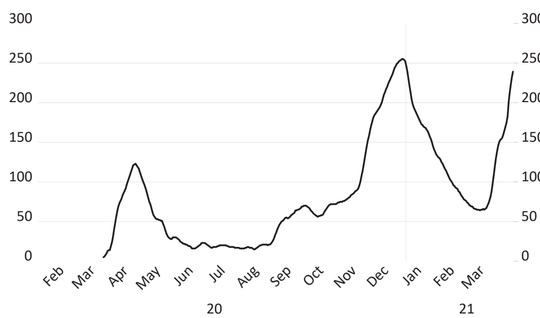
(c) The United Kingdom



(d) The United States



(e) Turkey



NOTES: Panels (a)-(d) plot the number of daily active cases in Italy, New Zealand, the United Kingdom and the United States, respectively. Panel (e) plots the number of daily deaths in Turkey.

A quickly implemented stimulus package that compensates the income loss due to the lockdown and enables a faster recovery would minimize the long term damage in the production capacity. If the stimulus packages are delayed, on the other hand, more companies would fail, more workers would be laid-off, and demand would decline further. This would then feed into more bankruptcies and elevate the economic costs that quickly become unmanageable. In fact, just as a drowning person needs immediate help or else her organs start to fail, the economy needs immediate help before the companies start to fail. Fiscal transfers can help to ensure that the supply chains are not destroyed, the economic units are functional and ready to go back to production once the pandemic is contained and demand returns. Fortunately, many governments around the world took decisive action. In the case of EMs, however, policy options were limited given the limited fiscal space. As put by former Colombian finance minister, Mauricio Cardenas: "We do not live in whatever it takes region, we can do whatever we can."[24] The generous fiscal packages that were released by Turkey's trade partners supported the positive growth rate registered by the Turkish economy in 2020 and formed expectations of export driven growth for the Turkish economy in the years that follow. However, as noted in IMF's country report for Turkey as of June 2021, potential GDP in Turkey is expected to decline in the post-pandemic era, likely reflecting limited domestic fiscal expansion during the pandemic that was unable to offset permanent damage.[25]

6 Conclusion

Containing the pandemic as soon as possible is an urgent obligation to save human lives. While the introduction of vaccines is a game changer, there is still substantial inequality in vaccine distribution, particularly among the emerging markets and developing countries, which threatens full global recovery (Çakmaklı et al., 2021).[26] 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 multiple waves and differential domestic and foreign sectoral demand 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 that depends on the recovery of the other countries. We show that foreign demand may amount to 15 to 30 percent of the total costs.

Our findings show the importance of globally coordinated lockdowns and fiscal spillovers from

[24] The Economist, May 25, 2020.

[25] See https://www.imf.org/en/Publications/CR/Issues/2021/06/11/Turkey-2021-Article-IV-Consultation-Press-Release-Staff-Report-and-Statement-by-the-50205/

[26] See Baker et al. (2020) and Ludvigson et al. (2015) on the role of uncertainty shock linked to COVID-19.

one country to other. We illustrate that stimulus programs allow for a faster recovery abroad. In turn, the stronger global recovery increases the demand for exports from the home country. We illustrate that globally uncoordinated lockdowns increase the economic costs of the pandemic by almost 2 percent of the GDP, while stimulus packages abroad can lower these costs by about 0.5 percent of the GDP.

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. This way, it eliminates the fear factor and allows the economies to recover through demand normalization.

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A APPENDIX

List of Figures and Tables:

Table A.1: 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.2: 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.[27] 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.3: DEMAND CHANGES ACROSS INDUSTRIES

OECD ISIC	Definition	Change	Explanation
01T03	Agriculture, forestry and fishing	100%	Based on projections on the manufacturing sector using data on credit card spending from the database of CBRT and computations using historical data.
05T06	Mining and extraction of energy producing products	100%	Based on projections on the manufacturing sector using data on credit card spending from the database of CBRT and computations using historical data.
07T08	Mining and quarrying of non-energy producing products	100%	Based on projections on the manufacturing sector using data on credit card spending from the database of CBRT and computations using historical data.
09	Mining support service activities	100%	Based on projections on the manufacturing sector using data on credit card spending from the database of CBRT and computations using historical data.
10T12	Food products, beverages and tobacco	100%	Based on projections on the manufacturing sector using data on credit card spending from the database of CBRT and computations using historical data.
13T15	Textiles, wearing apparel, leather and related products	50%	Based on estimates using data on credit card spending from the database of CBRT.
16	Wood and products of wood and cork	90%	Based on projections on the manufacturing sector using data on credit card spending from the database of CBRT and computations using historical data.
17T18	Paper products and printing	90%	Based on projections on the manufacturing sector using data on credit card spending from the database of CBRT and computations using historical data.
19	Coke and refined petroleum products	75%	Based on estimates using data on credit card spending from the database of CBRT.
20T21	Chemicals and pharmaceutical products	90%	Based on estimates using data on credit card spending from the database of CBRT.
22	Rubber and plastic products	90%	Based on projections on the manufacturing sector using data on credit card spending from the database of CBRT and computations using historical data.
23	Other non-metallic mineral products	90%	Based on projections on the manufacturing sector using data on credit card spending from the database of CBRT and computations using historical data.
24	Basic metals	90%	Based on computations using 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%	Based on computations using historical data and sectoral reports.
26	Computer, electronic and optical products	100%	Based on estimates using data on credit card spending from the database of CBRT.
27	Electrical equipment	90%	Based on projections on the manufacturing sector using data on credit card spending from the database of CBRT and sectoral reports, https://www.ibisworld.com/industry-insider/media/4637/covid-19-special-report.pdf
28	Machinery and equipment, nec	90%	Based on projections on the manufacturing sector using data on credit card spending from the database of CBRT and computations using historical data.
29	Motor vehicles, trailers and semi-trailers	70%	Based on other countries' experiences 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%	Based on projections on the manufacturing sector using data on credit card spending from the database of CBRT and computations using historical data.
35T39	Electricity, gas, water supply, sewerage, waste and remediation services	100%	No change.
41T43	Construction	75%	Based on computations using 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%	Based on estimates using data on credit card spending from the database of CBRT.
49T53	Transportation and storage	80%	B ased on other countries' experiences 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%	Based on estimates using data on credit card spending from the database of CBRT.
58T60	Publishing, audiovisual and broadcasting activities	85%	Based on estimates using data on credit card spending from the database of CBRT.
61	Telecommunications	100%	Based on estimates using data on credit card spending from the database of CBRT.
62T63	IT and other information services	100%	Based on other countries' experiences 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%	Based on estimates using data on credit card spending from the database of CBRT.
68	Real estate activities	60%	Based on estimates using data on credit card spending from the database of CBRT.
69T82	Other business sector services	85%	Based on estimates using data on credit card spending from the database of CBRT.
84	Public admin. and defence; compulsory social security	125%	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%	Based on other countries' experiences 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%	Based on other countries' experiences 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.4: 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.5: 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.6: 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%.