Macroeconomic Effects of COVID-19 Across the World Income Distribution *

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Abstract

The macroeconomic effects of the COVID-19 pandemic were most severe for emerging market economies, representing the middle of the world income distribution. This paper provides a quantitative economic theory for why emerging markets fared worse, on average, relative to advanced economies and low-income countries. To do so we adapt a workhorse incomplete-markets macro model to include epidemiological dynamics alongside key economic and demographic characteristics that distinguish countries of different income levels. We focus in particular on differences in lockdown stringency, public insurance programs, age distributions, healthcare capacity, and the sectoral composition of employment. The calibrated model predicts greater output declines in emerging markets, as in the data, and greater excess mortality, albeit to a smaller extent than what is observed in the data. Quantitatively, stricter lockdowns and a higher share of jobs requiring social interaction explain a large fraction of the especially severe outcomes in emerging markets. Low-income countries fared relatively better mainly due to their younger populations, which are less susceptible to the disease, and larger agricultural sectors, which require fewer social interactions.

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1. Introduction

While every country has been badly affected by the coronavirus pandemic, the damage it has wrought varied widely around the world. In this paper, we investigate how and why the pandemic's macroeconomic consequences have differed (so far) across the world income distribution. We focus in particular on variation in output and excess mortality across three broad groups of countries: low-income economies, emerging markets, and advanced economies, as classified by the International Monetary Fund's (IMF). As we detail below, data from a variety of sources reveal that the pandemic's cost in terms of lives and livelihoods was roughly U-shaped in national income, with emerging markets experiencing the worst public health and macroeconomic consequences. For instance, GDP per capita in emerging markets declined by 6.7 percent on average from 2019 to 2020, compared to 2.4 percent in advanced economies and 3.6 percent in low-income countries. Excess mortality has exhibited a similar pattern. According to estimates by *The Economist,* excess mortality was 75 percent higher in emerging markets than in advanced economies. While credible excess mortality data for low-income countries are still largely unavailable, the few existing estimates similarly point to lower mortality rates than in emerging markets.

We assess the extent to which policy responses and certain preexisting differences in economic and demographic conditions can explain the cross-country variation we observe in the data. In part, these outcomes could stem from differences in government policy responses to combat the coronavirus pandemic. While most countries enacted similar "lockdown style" policies and expanded social insurance programs, the scope of such efforts varied substantially. According to the Oxford Coronavirus Government Response Tracker, the stringency of lockdown policies aiming to restrict individual behavior (such as school and workplace closures) were most strict in emerging markets. The generosity of social insurance programs, in contrast, appears to increase linearly with a country's GDP per capita. Accounting for these differences in policy is important because they can directly affect both fatalities and growth during the pandemic.

The cross-country variation may also arise from the stark underlying differences in economic and demographic characteristics that predate the pandemic. Low-income economies may have faced very different public health risks than wealthier ones due to their substantially younger populations but also their less developed healthcare systems. Furthermore, systematic variation in the sectoral composition of employment across the world income distribution creates differences in the ability of workers to preserve income while mitigating health risks or coping with extended lockdowns. Lower-income countries may benefit from large rural agricultural sectors, which provide a resilient source of income that can be sustained while limiting contacts. On the other hand, Gottlieb, Grobovsek, Poschke, and Saltiel (2021b) show that in urban areas, the ability to work from home is far more limited in lower income countries. Combining their estimates with data on urbanization rates, we can measure the share of labor in *social* and *non-social* employment across countries, as in Kaplan, Moll, and Violante (2020), to capture differences in the ability to work without social interactions. Our composite measure shows that emerging markets have the highest share of workers in social employment, with their largely urban workforces concentrated in high-contact sectors such as manufacturing and retail trade. In contrast, low-income countries have the smallest social employment shares, due to the predominance of rural agricultural work.

To investigate the extent to which these factors can explain the differential mortality and output losses in the data, this paper follows the newly emerged literature on the macroeconomics of pandemics by combining a variant of the SICR model standard in epidemiology with a workhorse macro model. In particularly, our model builds on the heterogeneous-agent incomplete-markets model of Aiyagari (1994), Bewley (1977) and Huggett (1996). This setting allows us to capture the individual trade-off between maintaining consumption levels and preserving health that has been the focus of economic analysis of behavior during the pandemic. The model distinguishes between social and non-social jobs, so that individuals differ in the ability to work effectively from home. We incorporate age heterogeneity following Glover, Heathcote, Krueger, and Ríos-Rull (2020) and allow death rates to depend on the infected person's age, consistent with a vast medical literature. Our model also allows for a time-varying infection rate that captures, in a reduced-form way, the various other non-modeled determinants of disease progression, such as seasonal conditions, improved treatment, or virus mutation. Finally, we include constraints on peak healthcare capacity, which capture differential ability for healthcare systems to treat many patients at once, stemming from the availability of hospital beds or supplemental oxygen.

In the model, the propagation of disease depends in large part on individual household choices on whether or not to work from home. The model thus features a public health externality, creating space for welfare improving government interventions. We model lockdown policy in a simple way that is consistent with policy variation observed during the pandemic. Specifically, we feed in time-varying lockdown measures that replicate the changing stringency of government policies over the course of the pandemic, as measured by the Oxford Coronavirus Government Response Tracker. In the model, lockdown policies confine individuals to their home, where they are less likely to become infected but incur income losses depending on their job type. More stringent lockdowns confine a larger share of the population to their home. While we do not allow individuals to disobey lockdowns, households can voluntarily elect to work from home at any point in time.

To evaluate the quantitative importance of each of these channels, and their interactions, in explaining the facts at hand, we parameterize the model to match key pre-pandemic economic and demographic characteristics of the United States. Parameters governing the epidemiological process are set using estimates from the relevant medical literature. We compute the models equilibrium response to the COVID-19 pandemic as a surprise "MIT shock," where a small exogenous fraction of the population becomes infected with the virus, and then allow the disease to spread endogenously through the populous. We feed in the time-series of vaccination rates, as reported by OxCGRT, allowing a random fraction of the population to be vaccinated in each period, consistent with rates we observe in the data. We set the non-parametric component of the infection probability so that the model's endogenous disease path (nearly) exactly replicates the time-path of fatalities from COVID-19 in the United States during the pandemic. We calibrate the productivity penalty incurred during lockdowns to match the cumulative 2019-2020 year-on-year employment loss in the United States. We also allow for a one-off shock to aggregate total factor productivity (TFP), which is calibrated to match the cumulative 2019-2020 year-on-year decline in U.S. real GDP per capita.

We use the calibrated model to simulate how the United States would have fared during the pandemic if it had counterfactually had the characteristics of emerging economies. Comparing these counterfactual predictions to the actual outcomes allows us to assess the importance of each characteristic in explaining the higher GDP declines and mortality rates in emerging markets. Including all emerging-market characteristics, the model predicts a substantially larger decline in GDP during the pandemic, consistent with larger decline in emerging markets in the data. The model also predicts a larger mortality rate with the emerging markets' characteristics, but quantitatively the gap is significantly smaller than in the data. The latter result implies that the higher excess mortality in emerging markets was likely driven by factors other than those modeled here, in particular the greater prevalence of social employment and lower ICU capacity. Possible missing factors include other existing co-morbidities, less prevalent mask use, or other other deficiencies in the medical system.

The final set of counterfactuals we run simulate the effects of the pandemic in the United States assuming it had the features of low-income countries. We find that with the younger demographics and sectoral composition of employment of low-income countries, the pandemic would have been much less pronounced in terms of GDP declines and fatalities. The less intense lockdowns and weaker ICU capacity both would have raised mortality, though only modestly. The combined effects of all of these features lead to substantially lower mortality, which is consistent with the limited available evidence on excess deaths in Africa.

We conclude by reporting multiple correlations between cross-country changes in GDP-per-capita during the pandemic and covariates representing the channels embodied in our model. The data show that agricultural employment shares are strong positive correlates of GDP changes during the pandemic, while lockdown stringency is a strong negative correlate. Median age and an economic support index exhibit weaker correlations. Altogether, the covariates greatly reduces the observed U-shape pattern in GDP declines across the world income distribution. The result suggests that this parsimonious set of variables is empirically relevant in explaining cross-country macroeconomic outcomes during the pandemic.

Taken together, our analysis suggest that the comparatively worse outcomes experienced by emerging markets, and comparably better outcomes of low-income countries, may have been in large part pre-determined by underlying economic and demographic conditions, rather than by policy failures or successes during the pandemic. The greater size of the social sector in emerging markets, which limited the ability of individuals to work from home, was an important factor in their greater economic losses, whereas their somewhat younger age structure had only a modest impact on their mortality rates. In low income countries, the large rural agriculture sectors and young age structure was a central factor in keeping their GDP losses and mortalities lower than they otherwise would have been. A valuable goal for future research would be to help refine the quantitative importance of different policy decisions across countries in determining macroeconomic outcomes during the pandemic.

Our work builds on the first generation of papers addressing the aggregate effects of COVID-19 in the developing world, which were largely written in the early months of the pandemic (Loayza and Pennings, 2020; Alon, Kim, Lagakos, and VanVuren, 2020; Alfaro, Becerra, and Eslava, 2020; von Carnap, Almås, Bold, Ghisolfi, and Sandefur, 2020; Djankov and Panizza, 2020). The current paper differs in its efforts to explain observed macroeconomic outcomes through the first year and a half of the pandemic, in particular the larger declines in GDP and employment in emerging markets. Sanchez (2021) also notes the larger decline in GDP middle-income countries, but does not attempt to explain this finding. We also emphasize the inability of individuals in emerging market economies to work from home, following Gottlieb, Grobovsek, Poschke, and Saltiel (2021a,b), though we argue that low-income developing countries, on account of their large agriculture sectors, are better able to work without social interactions.

On the modeling front, our study most closely follows the structural macro work on the pandemic using models of heterogeneity in income, age and sector of employment (e.g. Acemoglu, Chernozhukov, Werning, and Whinston, 2020; Bairoliya and Imrohoroglu, 2020; Kaplan, Moll, and Violante, 2020; Glover, Heathcote, Krueger, and Ríos-Rull, 2020; Brotherhood, Kircher, Santos, and Tertilt, 2021). Our model of disease dynamics features endogenous behavioral responses to changes in infection rates, even in the absence of government intervention, as in Greenwood, Kircher, Santos, and Tertilt (2019); Alvarez, Argente, and Lippi (2020); Krueger, Uhlig, and Xie (2020) and other studies. To our knowledge ours is the first to evaluate the quantitative predictions of a model of this sort for how the experience of emerging markets differed from richer (or poorer) countries.

Our study abstracts from many important features of reality that may also be relevant for the effects of the pandemic outside of the world's advanced economies, such as negative impacts through shocks to global supply chains (Cakmakli, Demiralp, and Ozcan, 2020; Bonadio, Huo, Levchenko, and Pandalai-Nayar, 2021), the ability to issue sovereign debt (Arellano, Bai, and Mihalache, 2020), or the ability to test and trace infections (Berger, Herkenhoff, and Mongey, 2020). We also abstract from differences in the prevalence of co-morbidities, such as diabetes and cardiovascular disease, and differential ability or willingness or ability to mask or get vaccinated. These issues would be valuable to consider in future studies trying to explain cross-country differences in the macroeconomic effects of the pandemic.

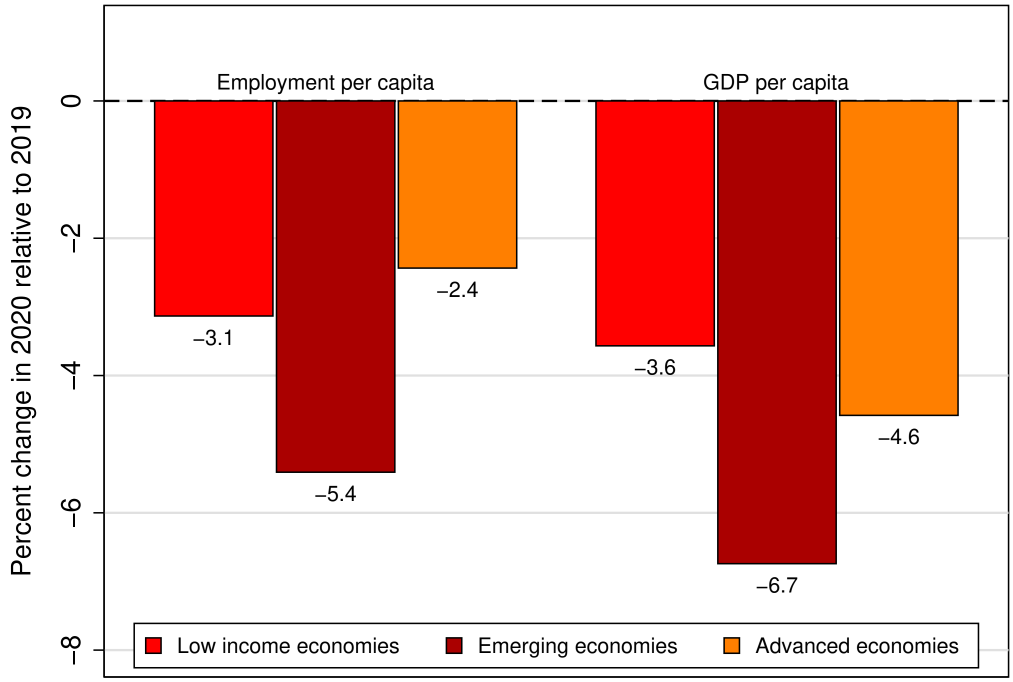
2. Macroeconomic Effects of the Coronavirus Pandemic by Income Level

This section presents the main facts regarding excess mortality and output losses across the world income distribution resulting from the coronavirus pandemic. Following the IMF classification, we focus in particular on three major income groups: low-income economies, emerging markets, and advanced economies. In 2019, the median GDP per capita of these three country groups was \$1,124, \$6,700, and \$43,144, respectively, in constant 2010 USD. While there is interesting variation even with these group, we focus the main part of our analysis on just the three aggregate groups. Section 5 of the paper looks at empirical patterns in the full set of countries for which data are available. Here, drawing on various data sources, we show that both output losses and excess mortality exhibit hump-shaped outcomes with middle income countries experiencing the worst. We then present in a systematic way the important differences in policy and underlying economic and demographic conditions. For each, we briefly discuss their relevance for the pandemic's impact in order to help motivate the model and quantitative analysis which follows.

2.1. The Impact of COVID-19

The first fact we highlight is the differential impact of the pandemic on output losses and employment declines across the world income distribution. Figure 1 displays the data by plotting changes in output and employment for low-income, emerging, and advanced economies. While there is considerable variance even within groups, a clear U-shaped patterns emerges in which

Figure 1: GDP and Employment Growth from 2019 to 2020 by National Income

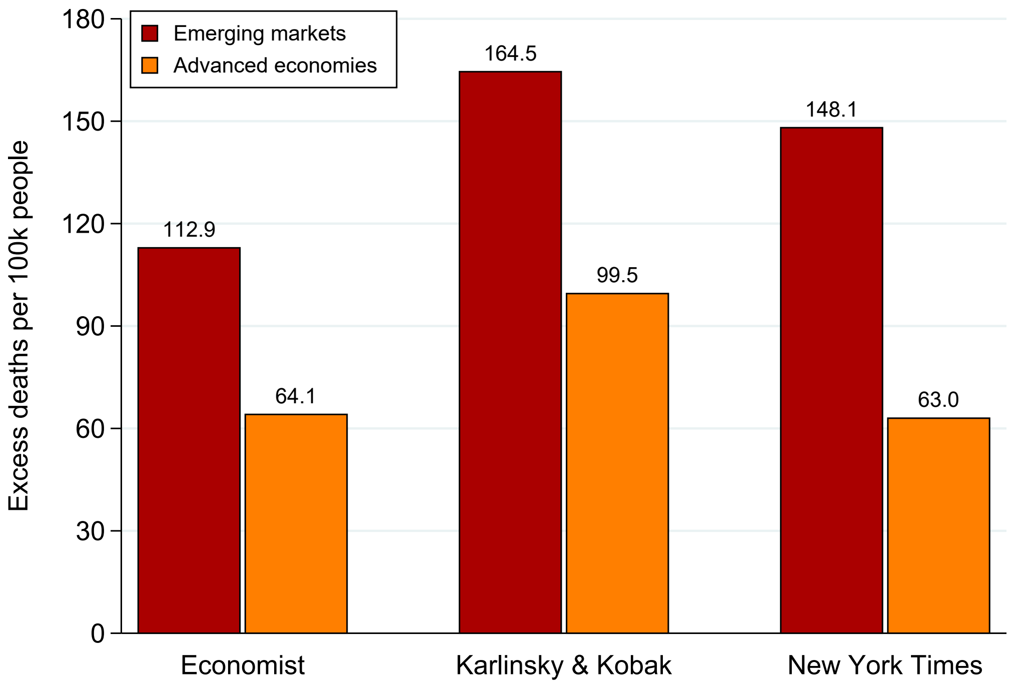


Note: Employment data comess from he ILO Statistical Database and data on GDP-per-capita is taken from the World Bank World Development Indicators.

output losses were greatest in emerging economies. GDP-per-capita fell by 6.7 percent and employment by 5.4 percent in emerging economies, considerably worse than both wealthier countries where output and employment losses were 4.6 percent and 2.4 percent, respectively, and lower income countries where those losses stood at 3.6 and 3.1 percent. Figures A.2 and A.1 illustrate that the relationship also hold sin the un-binned data and Figure A.3 displays similar trends in cross-country consumption data. Interestingly, these data also suggest that declines in output and consumption may have been greater in advanced economies than in low-income ones. Such outcomes are surprising given the tremendous resources and technology that wealthy countries brought to bare in combating COVID-19, resources that low-income countries had no ability to marshall or match in any comparable way.

The second important fact pertains to the fatalities caused by COVID-19. These deaths are commonly measured using excess mortality, the difference between total deaths in a given month of the pandemic and those that would be normally expected, measured as expected deaths during the same month over the previous (typically five) years. Figure 2 displays the data by comparing mortality outcomes in advanced and emerging economies. As with output losses, we find that the emerging economies experienced the worst outcomes. According to

Figure 2: Excess Deaths from 2019 to 2020

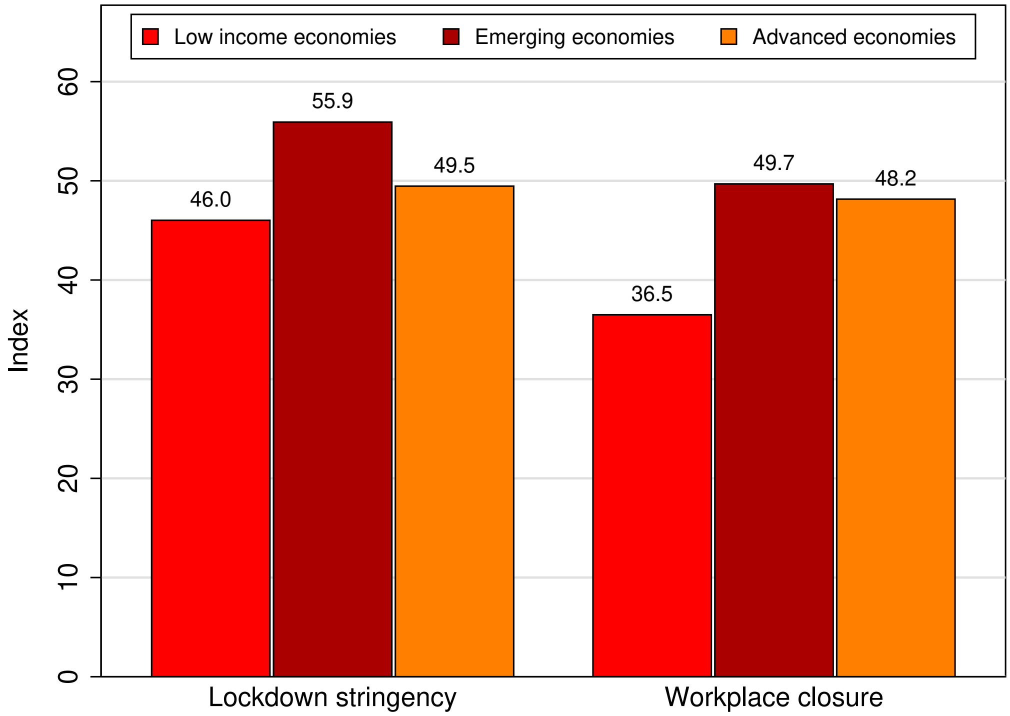


Note: Data sourced from the New York Times and Economist excess mortality trackers, and Karlinsky and Kobak's (2021) World Mortality Database.

estimates *The Economist*, excess deaths in emerging economies stands at 112.9 per hundred thousand people, which is around 75 percent higher than the average estimate for advanced economies, which experienced 64.1 excess deaths per hundred thousand. Estimates from the World Mortality Database of Karlinsky and Kobak (2021) show 164.5 excess deaths per hundred thousand people, or 65 percent larger than the 99.5 deaths per hundred thousand of advanced ones. The gap is even wider in the New York Times mortality tracker which records 148.1 deaths per hundred thousand in emerging economies, compared to 63 in advanced ones.

Internationally comparably data on excess mortality in low-income countries are more difficult to find. The most comparable statistics of which we are aware contain very few observations from low-income countries (see Figure A.4 and Figure A.5). These data, from *The Economist* and Karlinsky and Kobak (2021), have two and five observations from the low-income group respectively. Deaths for this small set of countries average around 100 excess deaths per hundred thousand people, putting them well below the level of the emerging markets. Official data on deaths from COVID-19 in low-income show remarkably low levels of fatalities (see e.g. Figure A.6), though there is widespread belief that official statistics undercount deaths

Figure 3: Oxford Lockdown Stringency Index



Note: The Government Stringency Index is taken from the Oxford Government Response Tracker (OxCGRT). GDP per capita is expressed at PPP and taken from Penn World Table 9.1 (Feenstra et al., 2015).

there. Our read of the literature is that there is still no clear consensus on what the true death rates have been in low-income countries, though it seems unlikely that they are worse than the high rates estimated in emerging markets such India (Deshmukh et al., 2021; Ramachandran and Malani, 2021), Mexico (Dahal et al., 2021) and Brazil (Yamall Orellana et al., 2021).

Taken together, the data reveal that the impact of the COVID-19 pandemic across the world income distribution has been highly non-linear. Emerging economies have been hit the hardest most in terms of output losses and likely in terms of excess mortality as well. Equally surprising is that the data suggest that low-income countries have fared better than advanced economies in terms of output losses, and possibly also in terms of mortality rates, despite the far greater economic and technological resources mustered by the latter to combat the crisis.

2.2. Differences in Policy Response

A natural candidate explanation for the cross-country variation is that they reflect differences in policy responses to the COVID-19 pandemic. While nearly all countries implemented some sort of lockdown and transfer programs, they varied widely both in the stringency of restrictions and in the generosity of transfers. The policy distinction matters for how well countries manage the endogenous path of infections through the public health externality and for the ability of households to protect themselves by staying home for prolonged periods without income.

By lockdown policies, we refer to those whose primary aim is to restrict individual behavior and social interactions to stem the spread of disease. These include school closures; workplace closures; public event cancellations; restrictions on public gatherings; closure of public transport; stay-at-home requirements; public information campaigns; and domestic and international travel restrictions. The Oxford Coronavirus Government Response Tracker's (OxCGRT) *stringency index* provides a parsimonious quantifiable measure of how strict these policies were across countries. Figure 3 plots the index of each country group, and shows that the most stringent lockdown policies were implemented by emerging economies (the un-binned data are displayed in Figure A.7). When we simulate lockdown policies, we implement them using the time-series of workplace closures reported by OxCGRT to be consistent with how such policies are represented in the model. As the data show, cross-country variation in these programs is similar to the overall stringency of policies. The time-series dynamics of their implementation within countries also appears similar (see Figure A.14)

Another important dimension of the policy response in nearly all countries was the expansion of social insurance payments, such as unemployment benefits. These payments are viewed as critical to offsetting lost income and make isolating at home economically feasible for those with low savings or little income. However, as the crisis unfolded it quickly became clear that governments in many developing countries lacked the fiscal capacity to sustain substantial transfers to major segments of their population for very long. Consequently, we observe substantially more cross-country variation in the size and scope of social insurance programs than in lockdown policies.

Figure 4 provides two measures capturing the scope and generosity of transfer programs implemented in response to COVID-19 across the world income distribution. The left side histogram plots national pandemic spending as a share of GDP, which includes comprehensive measures of budgetary fiscal support to individuals and firms estimated by the IMF. While pandemic spending appears similar in low-income and emerging economies, they are only about one-third the spending undertaken by advanced economies which reached nearly 10 percent of GDP. The right side histogram displays the Oxford's Government *Economic Support Index* which records financial assistance programs such as income replacement and debt relief for individual citizens. The index should be interpreted as an ordinal measure of economic assistance for individual citizens in that it does not include support to firms or business and does not take into account the total fiscal value of economic support programs. Nevertheless, the

Table 1: Oxford Covid-19 Government Response Indices in 2020

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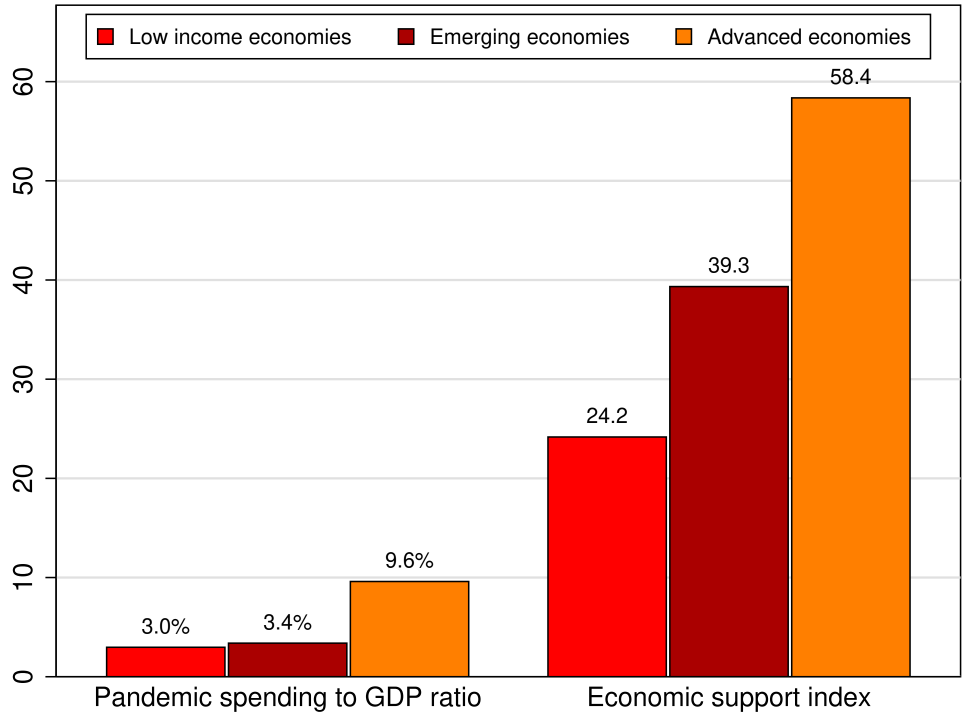
	Country Income Group		
Index	Low-Income	Emerging Markets	Advanced Economies
Panel A: Included in both Stringency and Health & Containment Indices			
School closures	53.8	64.8	50.1
Workplace closures	34.6	47.0	45.1
Cancellation of public events	57.0	69.4	63.7
Restrictions on public gatherings	50.9	59.5	61.3
Closure of public transport	22.5	32.0	17.8
Stay at home requirements	25.0	35.7	24.9
Restrictions on internal movements	32.9	47.7	31.8
International travel controls	57.6	63.6	63.4
Public information campaigns	79.7	83.8	87.0
Panel B: Included only in Health & Containment Index			
Contact tracing policy	54.4	61.5	67.6
Facial coverings	43.8	46.4	37.3
Testing policy	37.9	52.2	58.8
Vaccination policy	22.8	31.3	35.3
Protection of the elderly	19.4	40.8	57.3
Panel C: Included only in Economic Support Index			
Income support	17.3	29.3	57.8
Contract/Debt relief	31.0	49.6	58.9
Observations	52	67	33

Note: Countries are grouped into low income, emerging markets, and advanced economies using the IMF's economic classification of countries. Data in the table is the average level of the Oxford Covid-19 government response tracker by country income group.

Figure 4: Pandemic Spending and Economic Support



Note: The left side histogram plots the ratio of pandemic spending to GDP, taken from the IMF. The right side histogram displays the Oxford Economic Support Index available through the Oxford Coronavirus Government Response Tracker's (OxCGRT).

data reveal a similar pattern with spending on economic support rising monotonically with national income. The greater cross-country variation in economic support policies, as compared to lockdown policies, is most apparent in thes underlying data which is displayed in appendix Figures A.8 and A.9.

These cross-country differences in lockdown policies and public insurance programs are even more apparent when one examines the underlying components of the OxCGRT's indices which are displayed in Table 1. The first noticeable feature is that low-income countries have the least stringent policies in every lockdown category, and in all other categories except "Facial Coverings." The near opposite is true for emerging economies which have the most stringent policies across all sub-categories of lockdown measures (Panel A) except "Public Information Campaigns." The largest deviations in emerging economy lockdowns pertain to the closure of public transport, stay at home orders, and restrictions on internal movements. This is notable since these measures likely imposed the largest restrictions on commercial activity, especially in emerging economies where the ability to work from home is not widespread (see section 2.5) and substituting to e-commerce and delivery services is limited by infrastructure. Finally, it is interesting to note that the stringency of emerging economy policies does not extend beyond lockdowns; as Panels B and C show, direct public health interventions and economic support policies were generally less encompassing in emerging economies. Taken altogether, the scope of differences in the stringency and aim of policies across the world income distribution offer ample scope for them to drive the differences in outcomes we observe in the data.

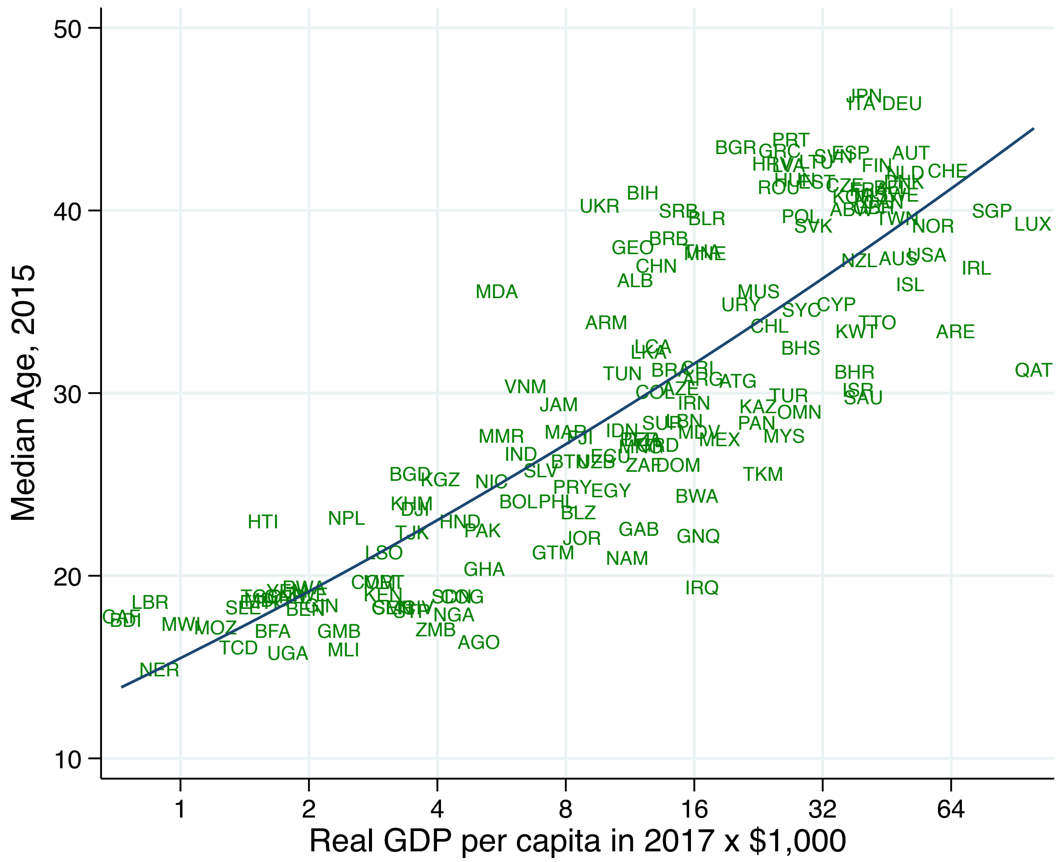
2.3. Differences in Population Structure

It has been well known since the beginning of the pandemic that COVID-19 poses dramatically greater health risks to older individuals, in particular those over the age of 65 (Ferguson et al., 2020; Glynn, 2020). Early centers of infection in the west, such as Italy, experienced health impacts concentrated on those in this older age range, with particularly severe fatality rates for those in their 80s and 90s. At the same time, the number of deaths linked to COVID-19 for those under 20 has been negligible, though certainly not zero.

A basic demographic difference between advanced and developing economies is that populations are far younger in the developing world. Since fatality rates from COVID-19 are very low for young individuals but rise sharply with age, these demographic differences suggest much smaller populations of vulnerable individuals in the developing world. One can see these demographic differences starkly when looking at cross-country data on the median age. Figure 5 plots the median age against GDP per capita in a set of 158 countries using data from UN Population Division and Penn World Tables. Data from the UN Population Division show that countries in the bottom quartile of the world income distribution have a median age of 19.1 years. Nigeria, Africa's most populous country, has a median age of 17.9, while countries like Angola and the Democratic Republic of the Congo have median ages of just 16.4 and 16.8 years old. By contrast richer countries like Italy, the United Kingdom and France have median ages of 45.9, 40.2 and 41.2, respectively.

Another statistic indicative of the much smaller vulnerable population in the developing world is the cross-country data on the population above 65. Figure A.10 plots the fraction of the population that is above 65 against GDP per capita in a set of 162 countries using data from the World Bank and the Penn World Tables. In the world's poorest countries the fraction of the population that is above age 65 is negligible, with an average of around 3 percent for countries in the bottom quartile of the world income distribution. The older population is much larger as a fraction of the total in richer economies, and reaches around one quarter of the population in Japan. Among countries in the topic quartile of the world, the average is about 15 percent of the population being above age 65.

Figure 5: Median Age of the Population



Note: Median age data corresponds to 2015 and is from the UN Population Division. GDP per capita is expressed at PPP and taken from Penn World Table 9.1 (Feenstra et al., 2015).

It is hard to look at statistics like these and not see how different the impacts of COVID-19 will be in less developed countries. Concretely, while almost everything about COVID-19 suggests a more severe impact in less-developed countries, the far younger demographic is clearly in their favor.

2.4. Differences in Healthcare Capacity

Developing countries typically have substantially less ability to control disease than do richer countries. Sanitation and hygiene are more of an issue given the lack of widespread piped water and functioning sewage systems. Health infrastructure, especially hospital and health clinic capacity, is also less developed. For mild cases of COVID-19 infections, this may make little differences, as bed rest is likely to suffice in these mild cases. However, for critical cases, the lack of intensive-care capacity is a clear disadvantage for developing countries in their attempts to save lives during the pandemic.

Figure A.11 plots the number of hospital beds per 10,000 people, as reported by the World Health Organization (WHO), against GDP per capita. The number of hospital beds is an imperfect measure of hospital capacity for many reasons, most importantly because it is not a bed per se that helps critical patients recover from COVID-19 but trained doctors, equipment like ventilators, and appropriate pharmaceuticals. Still, for lack of more comprehensive cross-country data, we take hospital beds as a proxy for medical care capacity.

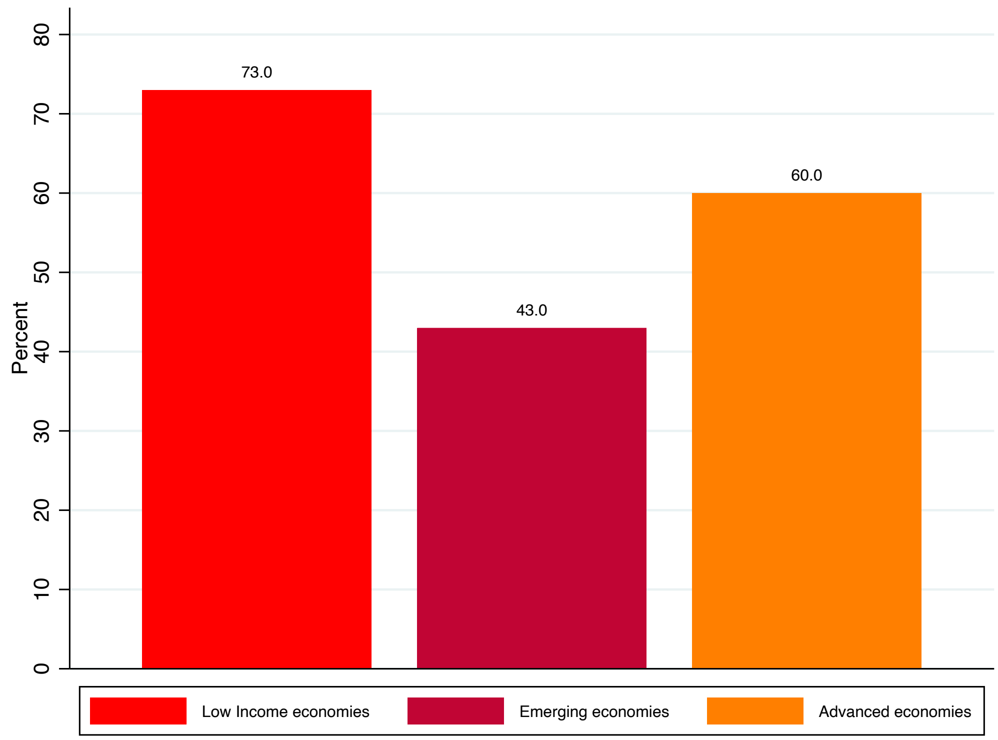
By this metric there are stark differences in healthcare capacity across countries. Richer countries, which have quite some range amongst themselves, average around 49 hospital beds per 10,000 people. Countries like Japan and Korea have even more beds per capita, having 134 and 115 beds per 10,000 people, respectively. This is still far higher than the capacity in developing countries, which is a paltry 12 beds per 10,000 people on average in the bottom quartile of the income distribution. In Appendix Table B.1, we report the availability of intensive care unit (ICU) beds and per capita healthcare costs across a limited set of countries. Consistent with the patterns observed from the number of hospital beds, it appears that low income countries possess significantly fewer ICU beds than high income countries.

2.5. Differences in Sectoral Composition of Employment

It is widely known that the sectoral composition of employment varies systematically with economic development. These differences are important because commercial disruptions brought on by COVID-19 and the resulting lockdowns differed substantially by occupation. Non-essential jobs that could not be performed remotely or while socially distancing experienced the largest and most sustained drops in employment throughout the recession; in contrast, occupations that were amenable to working from home experienced minimal disruption and some even flourished during the pandemic. In our model, we highlight two systematic differences in the composition of employment between advanced and developing economies which are relevant to the pandemic's macroeconomic outcomes across countries: the share of rural employment and the extent to which the urban workforce can work from home.

It is well known that the share of agricultural employment varies widely with economic developmnt (see Figure A.12). In the poorest countries, up to 70% of the population can be engaged in agricultural work, often subsistence farming on family plots; in advanced economies, that share is in the low single digits. The high agricultural share, while often considered a drag on economic modernization, offers a resilient source of income during pandemics. A good deal of agriculture in the developing world takes place on household-run farms, allowing it to continue during "stay-at-home" orders. Even in the absence of lockdowns, farming can often continue

Figure 6: Non-Social Sector Employment Share



Note: The non-social sector includes rural employment and urban jobs that can be done from home, as estimated by Gottlieb et al. (2021b). See text for details. GDP per capita is expressed at PPP and is taken from the Penn World Table 9.1 (Feenstra et al., 2015).

while socially distanced or with contact restricted to household members. Agricultural workers therefore do not face the same stark trade-offs in choosing between protecting their health or incomes since farming can often continue without substantially increasing the risk of infection. Consequently, while agricultural workers may be vulnerable because of low wages, their employment is more resilient to large losses from lockdowns or voluntary self-isolation.

Outside of the agriculture sector, labor markets in lower income countries are characterized by widespread informality and employment concentrated in high-contact sectors.[1] Large informal sectors will generally make economies more vulnerable to COVID-19 since, like agriculture, these jobs generally pay low wages while, unlike agriculture, most informal jobs cannot be performed from home or while socially distancing. To summarize these effects at the country level, we follow (Kaplan et al., 2020) and aggregate employment into *social* and *non-social* sectors. Social sector workers have limited ability to work from home and suffer large income

[1] According to the International Labor Organization (ILO), informality rates in the non-agricultural sector can be as high as 80% of employment in the lowest income countries, but falls drastically with GDP-per-capita to less than half that level.

losses during lockdowns, while non-social sector workers can substitute more easily to remote work. We calculate the non-social sector share to include rural employment and all urban jobs that can be worked from home. For the latter, we use the cross-country estimates of (Gottlieb et al., 2021a) which are constructed using worker level data on the task-content of jobs in urban labor markets. Figure 6 displays the resulting estimates of non-social employment and illustrates that it varies substantially across countries. Emerging market economies have the lowest ability to work from home, with only 43% employed in non-social, low-contact jobs. In advanced economies, the non-social share is 60%, due to the greater number of high skill, professional jobs. However, the non-social share is largest in low-income countries, at 73% of aggregate employment, driven by the large agricultural labor force.

As a consequence of theses differences in the sectoral composition of employment, emerging market economies are more exposed to economic losses during the pandemic. Having less jobs that can be done from home or while socially distanced leads to greater economic losses during lockdowns and workplace closures. Moreover, in the absence of robust transfers, many social sector workers can become desperate and so voluntarily elect to continue working, rather than shelter at home, during times of peak infection. Such decisions will generally provide only marginal income gains, while amplifying the infection risk for the whole population through the public health externality. Large social sector employment can therefore be a liability for emerging market countries fighting COVID-19, as these workers are particularly vulnerable with limited options to avoid increasing their risk of becoming infected, or infecting others.

3. Model

Our analysis draws on a quantitative heterogenous-agent macroeconomic model with epidemiology as in the SICR model to analyze how policy responses to the COVID-19 pandemic should differ in developing countries. The model is equipped with several features that vary between advanced and developing economies that are relevant for the pandemic response, as motivated by the data presented in the previous section. These include uninsurable idiosyncratic health and income risks, age heterogeneity, fiscal capacity constraints, healthcare capacity, and availability to work from home across sectors. This section now presents these features in detail.

3.1. Households and Preferences

The economy is populated by a unit mass of heterogenous individuals who make consumption and savings decisions subject to idiosyncratic income and health risks. Individuals differ in their age $j \in \{\text{young adult}, \text{old adult}\}$ and permanent labor productivity $z \sim G$. Time is discrete and each period represents two weeks. Preferences are given by:

$$U = \mathbb{E}\left[\sum_{t=0}^{\infty} \beta_j^t \left\{\log(c_t) + \bar{u}\right\}\right], \tag{1}$$

where the discount factors β_j^t capture age heterogeneity in the population, and $\beta_{\text{young}} < \beta_{\text{old}}$. This specification follows the tractable formulation of Glover et al. (2020) that abstracts from explicitly modeling age, appealing to the logic that pandemics are sufficiently short-lived relative to entire lifetimes. It thus suffices to model only the expected number of years left to live, which is captured by the heterogeneity in discount factors. The term $\bar{u}$ represents the flow utility value of being alive, following the specification of Jones and Klenow (2016), and represents the reason that model households try to avoid fatality risk. Once an individual dies, they receive a fixed utility level that potentially depends on their individual characteristics, as we describe below.

There are two sectors, which we denote as social ($s = S$) and non-social ($s = N$). We assume that households are born with the sector they supply labor and cannot switch sectors. The social sector represents the workers with little availability of remote work. Examples of the occupations in the social sector includes waitresses, hair dressers, to name a few. The non-social sector represent the occupations that can be done with low level of social contacts. Such occupations include farmers in agricultural sector who can work while distancing from others, or college professors who can easily work remotely. Households in sector s supply their labor to a representative firm where they can earn wage w_s per effective hour worked.

At the beginning of life, workers draw their permanent productivity, $z \sim G$. Incomes in both sectors are also subject to idiosyncratic productivity shocks as in Bewley (1977), Huggett (1993) and Aiyagari (1994). Specifically, we assume that individual labor productivity in each sector is composed of the sector-specific permanent component z and an idiosyncratic component v following the stochastic process:

$$\log v_{t+1} = \rho_v \log v_t + \epsilon_{t+1}, \qquad \epsilon_{t+1} \sim F(0, \sigma_v). \tag{2}$$

We include idiosyncratic income risk because developing countries are far from having full insurance, and so accounting for how people insure themselves in response to policies which may keep them away from work for prolonged periods of time is a first order consideration.

After observing their income realization, households make consumption and savings decisions given the interest rate, r, and subject to a no-borrowing condition, $a \geq 0$. Formally, the budget constraint of a household in sector s before the pandemic is given by:

$$c + a' \leq (1-\tau)w_s z v n + (1+r)a + T \tag{3}$$

where τ is the income tax rate and T is government transfers.

3.2. Aggregate Production Technology

The economy produces a single final good by combining capital with labor services supplied by the three sectors. The aggregate production technology is given by:

$$Y = AL^{\alpha}K^{1-\alpha},$$

where A is the total factor productivity and $0 < \alpha \leq 1$ is labor's share of value-added. We abstract from the domestic capital market. The aggregate capital stock is composed entirely of foreign sources, $K = K^F$, which can be rented at an exogenously given international rental rate r^F and which depreciates at rate δ. Aggregate labor depends on the total supply of labor services from the social and non-social sector,

$$L = L_S + L_N$$

3.3. Credit and Capital Markets

Credit market incompleteness prevents households from borrowing against future earnings. As a result, individuals must maintain non-negative assets in formulating their consumption plans subject to (3), giving rise to hand-to-mouth consumers as well as a precautionary savings motive in response to idiosyncratic health and income risks. The precautionary motive is important for getting aggregate welfare measurements correct since it creates another feedback between the epidemiological and economic dynamics, as individuals withhold some consumption to increase precautionary savings in response to the pandemic's onset.

3.4. Public Health and Hospital Capacity

Households face idiosyncratic health risk which can reduce their labor productivity and increase the probability of dying. Susceptibility to infection is determined in part by economic decisions taken by households. Once infected, progression of the disease depends on an individual's age and the availability of public health infrastructure offering treatments.

Health risks are modeled using an SICR epidemiological model with five health states: susceptible ($\mathbb{S}$), infected ($\mathbb{I}$), critical ($\mathbb{C}$), recovered ($\mathbb{R}$), and deceased ($\mathbb{D}$). We denote by N_t^x the mass of individuals in each health state $x \in \{\mathbb{S},\mathbb{I},\mathbb{C},\mathbb{R},\mathbb{D}\}$ at time t and use $N_t = N_t^{\mathbb{S}} + N_t^{\mathbb{I}} + N_t^{\mathbb{C}} + N_t^{\mathbb{R}}$ to measure the non-deceased population. Figure 7 illustrates how these states evolve:

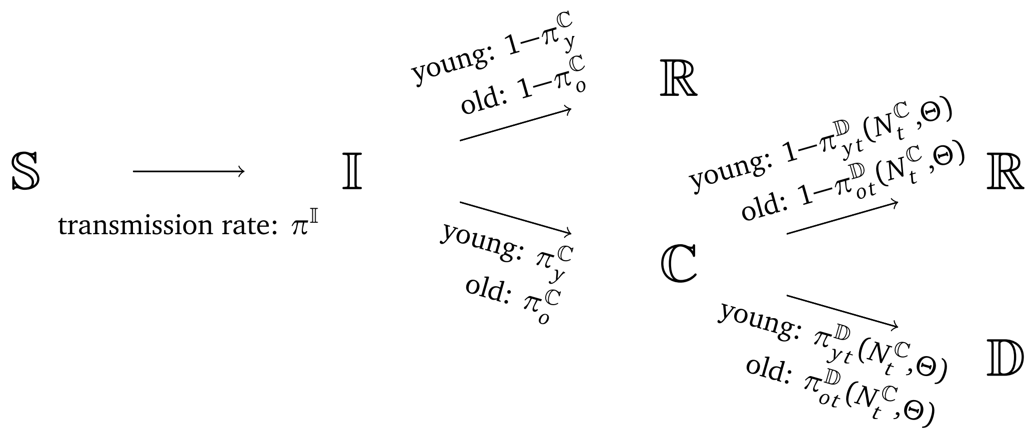


Figure 7: Dynamics of Health States and Transition Probabilities

The probability a susceptible person becomes infected is given as:

$$\pi_t^{\mathbb{I}} = \beta_t^{\mathbb{I}} \times \frac{N_t^{\mathbb{I}}}{N_t}$$

where $\beta_t^{\mathbb{I}}$ is the "behaviorally-adjusted infection rate," which accounts for both the diseases biological transmission rate as well as population wide behavioral responses to avoid being infected. The explicit dependence of $\beta_t^{\mathbb{I}}$ on time reflects the time-varying and population-wide behavioral responses to avoid being infected such as improved hygiene, social distancing, and learning about the best-pratice behavior during a pandemic.

Individuals who contract the virus experience a proportional drop in productivity of $1-\eta$ for one model period (two weeks), at which point they either recover or enter a critical health state. The probability of becoming critically ill depends on an individual's age and is given by π_j^C. Those in critical health are unable to work and require hospitalization. The likelihood of recovery in the hospital depends again on their age in addition to the availability of public health infrastructure, such as ICU beds and ventilators. In particular, the fatality rate of a critically ill patient of age j is given by:

$$\pi_{jt}^{\mathbb{D}}(N_t^{\mathbb{C}},\Theta) = \begin{cases} \pi_j^{\mathbb{D}} & \text{if assigned ICU bed} \\ \kappa \times \pi_j^{\mathbb{D}} & \text{if not assigned} \end{cases}$$

where π_j^D is a baseline fatality rate for age j individuals in critical health and κ governs the impact on fatality rates of strained hospital resources. Whether or not a critically ill patient receives an ICU bed depends on overall hospital capacity and the number of other patients. Specifically, letting Θ denote hospital ICU capacity, the probability a new patient receives an ICU bed is given by $\min\{\Theta/N_t^C, 1\}$. In other words, all critically-ill patients receive an ICU bed if hospital capacity constraints are not binding, and beds are rationed amongst the critically-ill with probability Θ/N_t^C when constraints bind.

3.5. Voluntary Substitution Away From Workplace and Lockdowns

Voluntary Subtitution While the diseases progression is exogenous, the probability a susceptible person becomes infected depends on endogenous economic decisions and the prevalence of infections in the population. To incorporate the feedback from economic behavior to infections, we allow individuals to lower the degree of exposure to the virus by voluntarily substitution away their labor supply to remote work. Specifically, we allow workers to choose between going to workplace and working remotely in each period. Remote work involves less social contacts, providing protection from being infected. Specifically, remote work lowers the probability of infection by ξ.

While it provides protection from being infected, working remotely is also less productive than going to the workplace. The productivity penalty of working remotely is parameterized by ϕ_s, where $s \in \{S, N\}$, by assuming that the effective labor supply of an worker in sector s can provide is given as $\phi_s n$, where $0 \leq \phi_s < 1$. We assume that $\phi_S < \phi_N < 1$, implying that the jobs in the non-social sector are more suited to be done remotely. Consequently, the probability a susceptible person becomes infected is given by:

$$\pi_t^{\mathbb{I}} = \begin{cases} \beta_t^{\mathbb{I}} \times N_t^{\mathbb{I}}/N_t & \text{if go to workplace} \\ \beta_t^{\mathbb{I}} \times N_t^{\mathbb{I}}/N_t \times \xi & \text{if work remotely} \end{cases}$$

Lockdowns Infection rates can be further mitigated by containment policies, such as lockdowns. As in Kaplan et al. (2020), we model lockdowns contrain a certain fraction of workforce to work remotely through stay-at-home orders. Under a lockdown, households who would otherwise go to workplace hours are forced to substitute switch to remote work. The stringency of lockdown varied across time and countries. Following Bick et al. (2020), we assume that 70% of the workers are forced to work at home under a full lockdown. Because remote work lowers the number of new infections, lockdowns mitigate the pandemic by exogenously decreasing the aggregate supply of workplace labor.

3.6. Vaccinations

Susceptible individuals can obtain immunity through vaccination as well. In each period, a susceptible individual draw a nonnegative probability of receiving vaccination. Once vaccinated, the individual obtains immunity and joins the recovered population. The exact probability of vaccination in each time period is taken from the actual path of vaccination in the US. We will explain it in more details in the calibration section.

3.7. Government and Taxation

The government has power to tax, transfer, and impose economic lockdowns subject to the constraints imposed by limited fiscal capacity and labor market informality. We further require that the government run a balanced flow budget which satisfies,

$$B_t + \tau \int y(a,x,v)dQ = T$$

where $y(a,x,v)$ is pretax income for individual $(a,x,v) \sim Q$, τ is the prevailing tax rate, and T is aggregate transfers to households. In addition to tax revenue, we allow developing countries access to emergency bonds, B_t, which can be used to finance additional welfare transfers during government imposed lockdowns. The source of these funds is international donors and multinational institutions such as the IMF, World Bank, and World Health Organization. Funds borrowed for emergency transfers accrue interest at rate $1+r^F$ until the pandemic ends, at which they are repaid through annual annuities. Formally, emergency transfers are given by:

$$B_t = \begin{cases} \bar{B} & \text{during the lockdown} \\ -\frac{r^F}{1+r^F} \times \sum\limits_{t_l - t_s}^{t_l - t_e} \left(1+r^F\right)^t \bar{B} & \text{after pandemic ends} \\ 0 & \text{otherwise} \end{cases}$$

where $\bar{B}$ is the size of per-period emergency transfers during lockdown, which we take parametrically, and t_s, t_e, and t_l index the lockdown's start, the lockdown's end, and the pandemic's end, respectively.

4. Quantitative Analysis

In this section, we discuss the calibration strategy, validate the model's fit, and present our counter-factual results. To evaluate the quantitative importance of each channel in explaining the cross-country variation in outcomes, we calibrate the model to match the U.S. economy and then vary key economic and demographic characteristics of the U.S. to match those of low-income and emerging economies. For each variation, we display the dynamic path of output and fatalities predicted by the model. To identify the most salient channels, we report the cumulative effects of each counterfactual on the U.S. economy compared to the calibrated benchmark.

4.1. Data Sources and Calibration

For expositional clarity, we divide the calibrated targets into three broad categories corresponding to those governing economic mechanisms, those controlling epidemiological dynamics, and those delineating differences between the advanced, emerging, and low-income countries.

Table 2: Calibration of Economic Parameters

Var	Description	Value	Source / Target
r^F	Exogenous interest rate	0.0006	Pre-COVID T-Bills rate 1.5%
ρ_v	Persistence of idiosyncratic income shock	0.91	Floden and Lindé (2001)
σ_v	St.Dev of idiosyncratic income shock	0.04	Floden and Lindé (2001)
α	Labor share	0.6	Gollin (2002)
β_y	Discount factor for the young	0.9984	Glover et al. (2020)
β_o	Discount factor for the old	0.9960	Glover et al. (2020))
σ_g	Variance of remote / non-remote work taste shock	0.0101	Pre-COVID Remote Workers 8.2%
ϕ_n	Productivity remote work, non-social sector	1	Barrero et al. (2021)
ϕ_s	Productivity remote work, social sector	0.62	COVID-19 Employment Declines - 6.4%
$A(P)$	Pandemic Total Factor Productivity	1.042	COVID-19 Output Declines -4.1%

Table 2 reports the parameters that govern the core economic dynamics of the model. Population demographics are modeled using age dependent discount factors accounting for differences in the remaining years of life for young and old workers. The age specific discount factors are taken from Glover et al. (2020), and the stochastic income processes are taken from Floden and Lindé (2001), who estimate similar income processes in the United States and Sweden. The taste-shock for remote work σ_g is chosen so that 8.2% of the pre-pandemic laborforce works remotely, consistent with the estimates in Bick et al. (2020). Finally, labor's share of income comes from Gollin (2002), and the rental rate of capital is set to the two-week return on pre-COVID Treasury Bills. We set the productivity penalty for remote work in the nonsocial sector, ϕ_n, to unity, consistent with evidence of small productivity losses for these workers in most cases, and potentially even productivity gains in some cases (Barrero et al., 2021). Finally, the penalty for remote work in the social sector, ϕ_s, and the TFP shock accompanying the pandemic $A(P)$, are jointly calibrated to match aggregate 2019-2020 year-on-year

Table 3: Calibration of Epidemiological Parameters

Var	Description	Value	Source or Target
η	Effect of infection on productivity	0.3	Alene et al. (2021)
ξ	Reduction of infection probability by working from home	0.6	Mossong et al. (2008)
κ	Impact of hospital overuse on fatality	2	Glover et al. (2020)
$\pi_y^{\mathbb{C}}$	Rate of young entering $\mathbb{C}$ from $\mathbb{I}$	6.7%	Ferguson et al. (2020)
$\pi_o^{\mathbb{C}}$	Rate of old entering $\mathbb{C}$ from $\mathbb{I}$	38.0%	Ferguson et al. (2020)
$\pi_y^{\mathbb{D}}$	Rate of young entering $\mathbb{D}$ from $\mathbb{C}$	2.7%	Glynn (2020)
$\pi_o^{\mathbb{D}}$	Rate of old entering $\mathbb{D}$ from $\mathbb{C}$	9.0%	Glynn (2020)

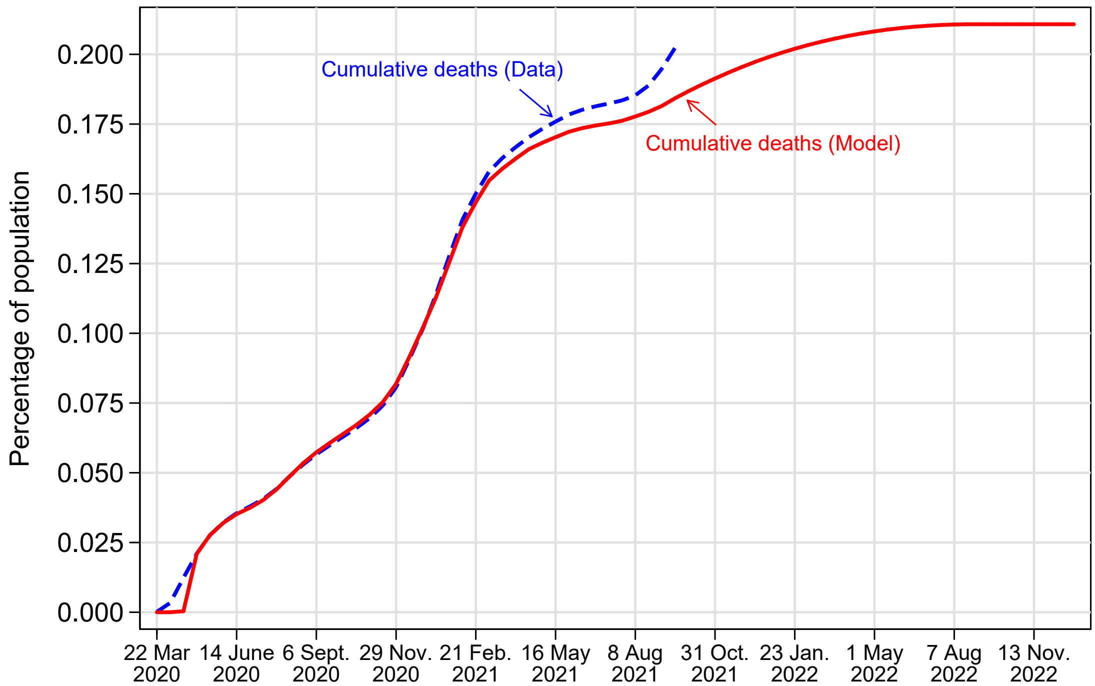
employment and output declines in the United States.[2]

Table 3 reports parameters controlling the epidemiological transmission of disease and their interactions with public health infrastructure and lockdown policies. We take parameters governing the fatality infection rates from Glynn (2020) and the rates of infected cases becoming critical from Ferguson et al. (2020). The effect of hospital congestion on disease fatality rates, κ, is taken from Glover et al. (2020). The productivity penalty of becoming infected, η, is set to match a 30 percent share of asymptomatic infection cases, as estimate in the meta-analysis of Alene et al. (2021). Such a choice is motivated by the observation that those known to be infected cannot work, and so have productivity of zero, while those who are infected but asymptomatic may continue to work unhindered. Finally, we choose the time-varying behavioral-adjusted infection probability, $\beta_t^{\mathbb{I}}$, so that the model's endogenous path of fatalities precisely matches the experience of the United States. The simulated endogenous path of the virus also account the time path of vaccinations and lockdowns in the U.S.. Vaccination data is taken from the COVID-19 Data Repository by CSSE at John Hopkins University, and we assume vaccination rates continue to grow at 1% per period after the last available data point, until period 60. The time path of lockdown policies comes from the Oxford Coronavirus Government Response Tracker (see Figure A.14). We assume lockdown policies are gradually lifted starting in the last period of available data until they are completely discontinued by period 60. Figure 8 plots the fitted results and validates the model's ability to replicate these dynamics exactly.

Table 4 summarizes parameters which vary across advanced and developing countries. The tax rates for the advanced and developing countries are taken from Besley and Persson (2013). Age demographics ω_y come from the World Bank and measure the share of the population under 65. The youth share in advanced economies corresponds to the U.S. economy, as it

[2]Appendix Table B.2 summarizes the internally calibrated parameters and the model's fit to the data. Note that TFP in normal times, $A(N)$ is set to one, so that $A(P)$ should be interpreted as a relative TFP shock in effect during the Pandemic.

Figure 8: Predicted and Actual COVID-19 Mortality in the United States



Note: Time path of U.S. COVID-19 mortality taken from the COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at John Hopkins University.

is our benchmark calibration, and we set the shares for emerging and low-income countries to their group averages. The share of workers in the social sector, ω_s, is constructed using estimates from Gottlieb et al. (2021b) on the share of urban labor that can work from home and adjusting the ratio to account for the rural population. Specifically, we take the shares of urban and rural labor from the UN Population Division and assuming the entire rural sector is non-social, calculate the ω_s as the weighted average of the urban and rural populations.

The flow value of life, $\bar{u}$, is calibrated using the value of statistical life (VSL) approach. Following Glover et al. (2020), we set the per-period statistical value of life to \$515,000 for advanced economies, equal to 11.4 times average US consumption. The value for $\bar{u}$ is then computed so that the behavioral response to a marginal increase in the risk of death is consistent with the VSL. Specifically, we get $\bar{u}$ by solving,

$$\text{VSL} = \frac{dc}{d\rho}|_{E(u)=k,\rho=0} = ln(\bar{c}) - \bar{u}$$

where ρ is the risk of death and $\bar{c}$ is average consumption. Absent better evidence, we assume the VSL has unitary income elasticity and adjust $\bar{u}$ for developing countries accordingly.

Table 4: Calibration of Parameters Varying Across Advanced and Developing Economies

Var	Description	Advanced Economies	Emerging Economies	Low-Income Economies	Source or Target
$\bar{u}$	Flow value of being alive	$11.4\bar{c}^{US}$	$11.4\bar{c}^{MID}$	$11.4\bar{c}^{DEV}$	Glover et al. (2020)
τ	Marginal tax rate	0.25	0.20	0.15	Besley and Persson (2013)
ω_y	Share of young in population	83%	84%	92%	UN Population Division
ω_s	Share of social sector workforce	40%	57%	27%	Gottlieb et al. (2021b)/IPUMS
Θ	Hospital capacity per capita	0.00042	0.00025	0.00011	Glover et al. (2020) / WHO

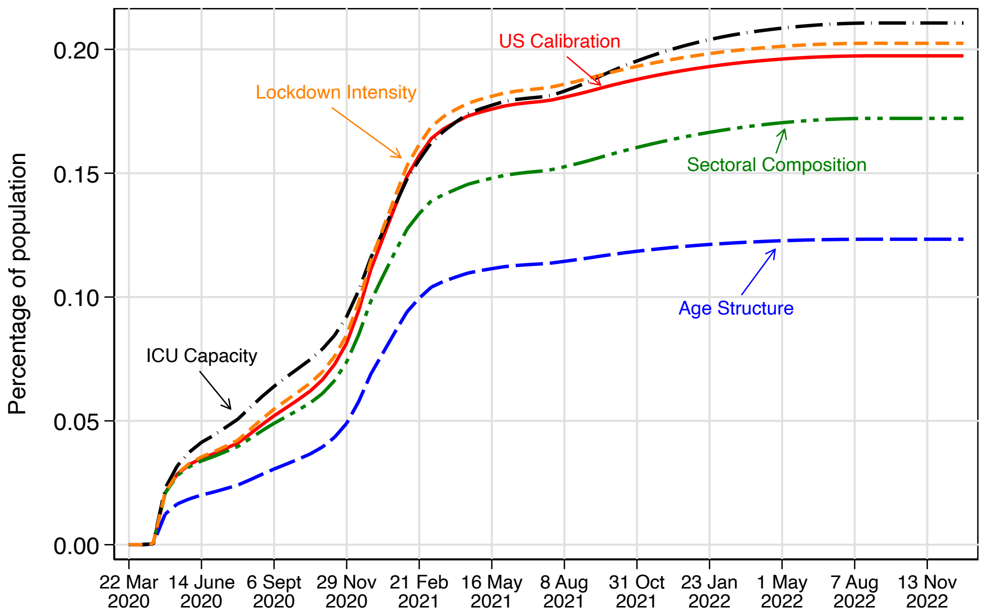
The final cross-country parameter to be set govern the ICU hospital capacity in developing and developed countries. One challenge is that while many countries report hospital bed capacity, few developing countries distinguish explicitly between general hospital capacity and ICU capacity in the data. To address this, we assume the ratio of hospital beds to ICU beds is constant across countries, and calibrate Θ by adjusting WHO data on the availability of hospital beds in the top and bottom quartiles of country income levels (as in Figure A.11) by the ratio of hospital beds to ICU beds taken from Glover et al. (2020).

4.2. Economic and Demographic Sources of Cross-Country Differences

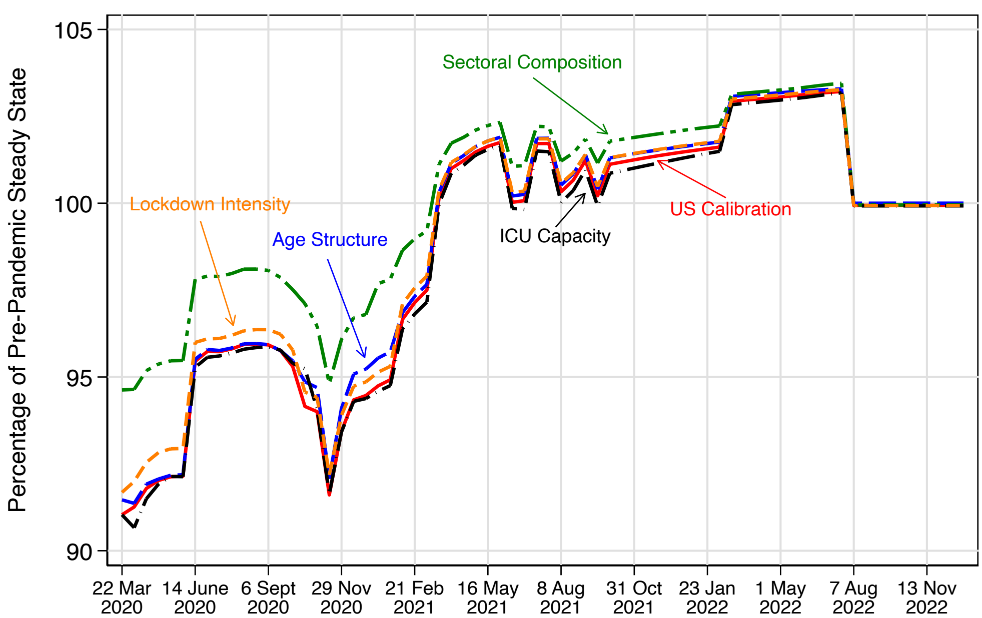
Figure 9 and 10 plot the dynamic path of GDP-per-capita and fatalities as a percentage of population during the COVID-19 pandemic in the United States in each of our counterfactual simulations. The top panels display results for cumulative fatalities, the bottom panels display results for output. Each figure provides five simulated paths: the benchmark U.S. calibration and the four counterfactual exercises which vary demographics, the sectoral composition of employment, public healthcare capacity, and the stringency of lockdowns in the United States. Figure 9 reports counterfactuals that endow the U.S. economy with the characteristics of low-income countries; Figure 10 reports the results of endowing the U.S. with emerging market economy characteristics.

Looking across the panels, one can see that all four mechanisms play an important role to some degree, but differences in age demographics and the sectoral composition of employment are the most quantitatively prominent. In determining the trajectory of fatalities, age demographics are the most important for understanding differences between low-income and advanced economies, while the sectoral composition of employment is most relevant for differences between emerging markets and advanced economies. The high agricultural employment share in low-income countries also greatly reduces fatalities there. In emerging market economies, lockdown policies also played an important role, on par with age-demographics, suggesting the especially stringent policies enacted there were tied to the more serious public health

Figure 9: Time Path of Cumulative Deaths and GDP: Low Income Economies

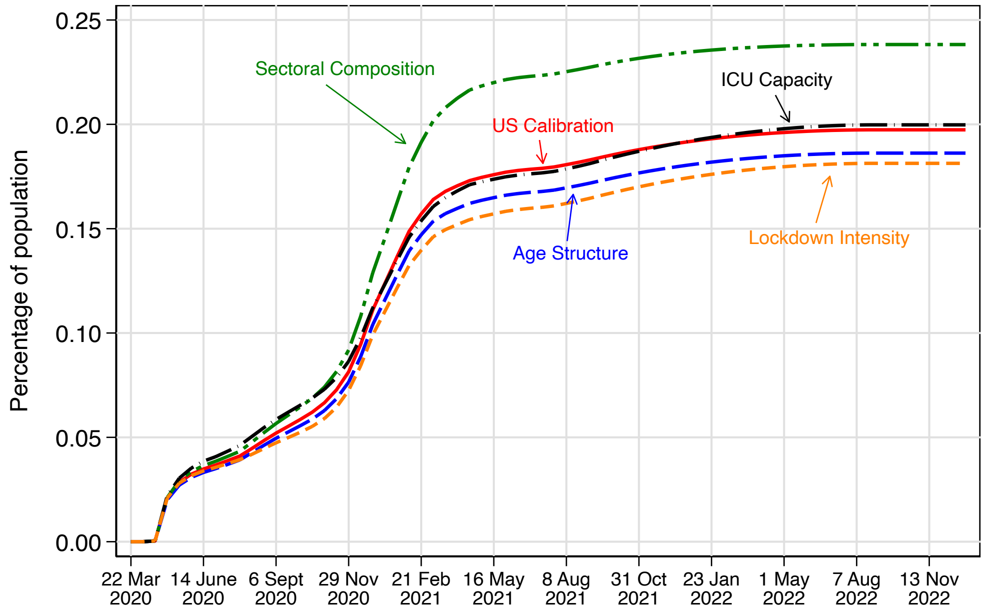


(a) Cumulative Death, US with Low Income Economies' Features

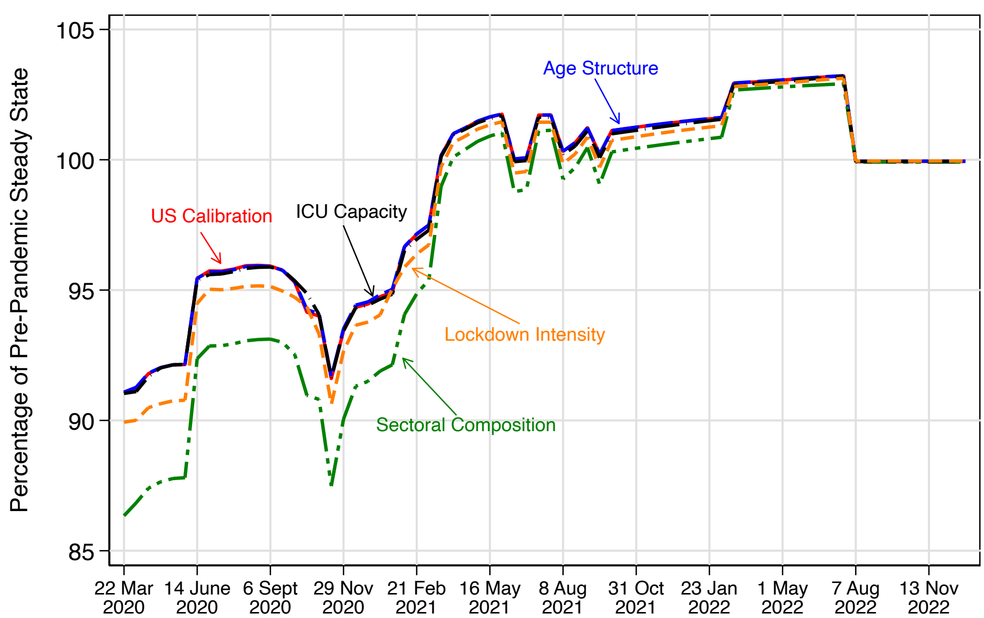


(b) GDP per capita, US with Low Income Economies' Features

Figure 10: Time Path of Cumulative Deaths and GDP: Emerging Economies



(a) Cumulative Death, US with Emerging Economies' Features



(b) GDP per capita, US with Emerging Economies' Features

Table 5: Cumulative Counterfactual Effects of the COVID-19 Pandemic

Panel (a): GDP Changes from 2019 to 2020			
	Data	Model	
		All Features	Age/Sector/ICU
Advanced Economies	-4.60	-4.01	-4.01
Emerging Economies	-6.70	-7.36	-6.40
Ratio	1.46	1.84	1.60
Panel (b): Excess Mortality			
	Data	Model	
		All Features	Age/Sector/ICU
Advanced Economies	64.10	197.39	197.39
Emerging Economies	112.90	208.03	236.55
Ratio	1.76	1.05	1.20

emergency; Our simulations suggests deaths would have been considerably higher without them.

The output counterfactuals exhibit less variation than what we see in fatalities, suggesting the mechanisms we study contribute more equally to observed economic declines. Among the channels, only the sectoral composition of employment stands out as having an especially important quantitative role. In low-income countries, economic losses were moderated by a large agricultural sector that was minimally disrupted by lockdowns and social distancing requirements. In emerging markets, high levels of urban employment in jobs that cannot be done from home explains a substantial part of their larger economic losses.

To assess what may be driving the especially bad outcomes observed in emerging markets, Table 5 reports the cumulative effect of our counterfactuals on 2019-2020 year-on-year changes in GDP and fatalities. For comparison, the first data column displays the data for advanced and emerging economies discussed in the introductory sections (see Figures 1 and 2). The second data column reports the simulation outcomes when all features are allowed to vary (i.e. demographics, sectoral employment, ICU capacity, and lockdown policies). The entry for advanced economies corresponds to our benchmark calibration to the United States data; the entry for emerging economies corresponds to the simulation which endows the United States with all the features of emerging economies. The third column reports results when we endow the United States with only the age demographics, sectoral employment, and ICU capacity of emerging economies. We distinguish these features since we view them as largely immutable throughout the pandemic's duration. To facilitate comparisons, the final row of each column reports the ratio of outcomes in emerging markets relative to advanced economies.

In panel (a) we see that the model does relatively well at replicating variation in GDP. In the data, GDP in advanced economies contracted by -4.6% while emerging economies shrank by -6.7%. The benchmark model generates a -4.01% decline in advanced economies–matching the U.S. data target – and predicts a decline of -7.3% for emerging economies. The model therefore over-accounts for GDP declines, predicting that emerging markets would experience contractions in GDP that are 86% greater than those advanced economies, while the data show declines that are roughly 46% larger. One reason the model may over-predict GDP declines is that official lockdowns could overstate de facto lockdowns in emerging markets, where governments have more limited enforcement capability.

Panel (b) reports excess mortality per hundred thousand people in advanced economies and emerging markets, both in the data and full counterfactual. The model substantially over-predicts the total fatality rate since the benchmark advanced economy calibration is set to match the United States, which has been a outlier in terms of reported COVID-19 mortality amongst advanced economies. Endowing the United States with all the features of an emerging market economy leads to a 5% rise in excess mortality. Since the data show mortality was 76% higher in emerging markets, the counterfactual simulation can only explain about 6.5% of the overall difference. These results suggest that there may exist other important public health differences between countries that are missing from our model. Examples include lower overall healthcare capacity in developing economies and a greater prevalence of co-morbidities.

Finally, in light of the large differences in emerging economies, it is natural to ask if there is anything emerging market economies could have done differently to improve their outcomes. While we do not model the optimality of different policies, our framework allows us to study the extent to which outcome differences depend on features that are outside the control of policymakers throughout the pandemic's duration. In particular, we view a country's age demographics, sectoral composition of employment, and healthcare capacity to be largely fixed throughout the pandemic. That governments cannot choose the age of their population is obvious. Similarly, it's generally widely held that the industrial composition of the economy is rigid in the short-run. While public healthcare capacity can in principle be expanded (and was, rather rapidly in a few places like China), we believe that emerging market economies by and large only had limited ability to do so during the pandemic, especially given the concurrent global competition for medical equipment, oxygen, and protective gear. The final column of Table 5 reports the cumulative counterfactual impact on output and fatalities if only these immutable characteristics varied between emerging markets and advanced economies. For output, these characteristics alone lead to a -6.4% decline in GDP, compared with -6.7% in the data. For mortality, these fixed features lead to a 20% rise in fatalities, accounting for over 25% of the 76% mortality gap observed in the data. Taken together, the simulations suggest that the unusually bad outcomes in emerging markets were largely outside the control of policymakers, depending instead on prevailing demographic and structural differences that cannot be easily changed. In fact, the more stringent policy response of policymakers in emerging markets appears to have drastically reduced the fatalities they've experienced during the pandemic while leading to an additional 1 percentage point decline in GDP.

5. Empirical Correlates of GDP Declines During the Pandemic

In this section we explore the empirical correlates of changes in GDP per capita from 2019 to 2020, focusing on the same variables emphasized in the model. We make no claim at uncovering causal patterns in this section. Instead, we assess the extent to which correlations between aggregate income changes during the pandemic and a country's demographic, economic, and policy characteristics are consistent with the model's predictions and quantitative exercises.

We begin with the basic relationship between declines in GDP per capita and pre-pandemic level of GDP per-capita. The first column of Table 6 shows that this relationship is U-shaped, as we argued earlier. Both the level and quadratic coefficients on GDP per capita in 2019 are statistically significant at the five-percent level, with the former negative and latter positive. The second column includes controls for the agricultural employment share. The variable exhibits a significant positive correlation with changes in GDP, holding constant differences in national income, means that countries with larger percentages of their workforce in agriculture also experienced smaller declines in national income, all else equal. Interesting, the coefficients on GDP-per-capita and its square are now statistically indistinguishable from zero, with the former switching signs. The third column includes median age as a control which exhibits no significant correlation, somewhat puzzlingly. The fourth column controls for the stringency of lockdowns, which is positive and statistically significant. The fifth column adds controls for the generosity of economic support programs during the pandemic, which turns out ot be statistically insignificant.

Column six of Table 6 adds all the covariates at once. This specification shows that agriculture's employment share remains a strong positive correlate of GDP changes, while lockdown stringency remains a strong negative correlate. Median age and the economic support index continue to be insignificant. This results do not change significantly under alternative specifications of the regression model (see Table B.3). Collectively, the inclusion of these controls

Table 6: Correlates of GDP per Capita Change from 2019 to 2020

	Dependent variable: GDP per capita change from 2019 to 2020					
Independent variables	(1)	(2)	(3)	(4)	(5)	(6)
GDP per capita in 2019	-0.10**	0.037	-0.17*	-0.076*	-0.11	-0.052
	(0.046)	(0.068)	(0.094)	(0.044)	(0.068)	(0.11)
GDP per capita in 2019^2	0.0014**	0.00021	0.0020*	0.0011*	0.0014*	0.00084
	(0.00066)	(0.00071)	(0.0010)	(0.00063)	(0.00080)	(0.0011)
Agriculture emp. share		0.076***				0.062**
		(0.027)				(0.030)
Median age			0.083			0.074
			(0.079)			(0.082)
Lockdown stringency				-0.13***		-0.13**
				(0.043)		(0.053)
Economic support					0.0042	0.024
					(0.036)	(0.038)
Constant	-4.21***	-8.03***	-5.67***	2.38	-4.29***	-2.97
	(0.60)	(1.66)	(1.48)	(2.07)	(1.09)	(3.34)
Observations	144	144	144	140	140	140
R^2	0.031	0.071	0.037	0.129	0.030	0.163

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

eliminates the statistical significance of the original U-shape pattern in GDP-per-capita, and substantially reduce the magnitude of the original correlations. We take this as suggestive evidence that these variables are important empirical determinants of macroeconomic performance across the world income distribution, at least thus far, during the pandemic.

6. Conclusion

The macroeconomic impact of the COVID-19 pandemic was most severe in emerging market economies, which represent the middle of the world income distribution. This paper provides a quantitative economic theory to explain why these economies fared so poorly compared to both poorer and wealthier nations. Our model is motivated by key economic and demographic differences across the world income distribution, including variation in lockdown policies, public insurance, demographics, healthcare capacity, and the sectoral composition of employment.

Our quantitative model predicts greater declines in employment and output in emerging market economies, as in the data. It also predicts the higher excess mortality in middle income countries, albeit to a substantially smaller extent than in the data. The modest excess mortality predictions of the model suggest that the higher COVID-19 fatalities in middle-income countries is likely driven by factors other than ICU capacity and the ability to work from home (e.g. co-morbidities, hospital quality, etc.). Among the channels we study, age demographics and the sectoral composition of employment are the most quantitatively important. Low-income countries fare well because of their younger demographic and large agricultural population, which provide a resilient source of income during lockdowns and while socially distancing. A large share of jobs which require social interaction and stringent government lockdowns explains a large fraction of the worse outcomes in emerging market economies. Quantitatively, the results suggest that cross-country differences are mostly driven by factors outside the short-term control of government officials, and so there is likely little policy makers in middle-income countries could have done differently to avert the especially severe outcomes they experienced.

Overall, our findings suggest that much of the variation in aggregate outcomes across country income groups during the pandemic can be attributed to a small set of economic characteristics and broad policy choices. Though substantial gaps are still left unexplained by these factors, suggesting that other forces must be playing important roles. Absent from this study are policy decisions regarding school closings (e.g. Fuchs-Schündeln, Krueger, Ludwig, and Popova, 2020), mask use (e.g. Abaluck et al., 2021; Karaivanov et al., 2021), testing and tracing policies (e.g. Berger et al., 2020), and vaccine provision (e.g. Arellano, Bai, and Mihalache, 2021). Future research could also fruitfully assess the quantitative importance of other policy choices for cross-country macroeconomic performance during the pandemic.

Another key limitation of our analysis is that it relies on a large exogenous time-varying component of the infection rate in order to match the observed path of excess deaths in the United States. In reality, however, much of the time variation in infection probabilities is likely due public policy choices that are not modeled here. These include policies that increase the prevalence of mask wearing, the development of better treatments for the infected, the rate of vaccination, or general knowledge about how COVID-19 can and cannot be transmitted. Future research should more explicitly consider the role these factors play in determining cross-country differences in aggregate outcomes during the pandemic.

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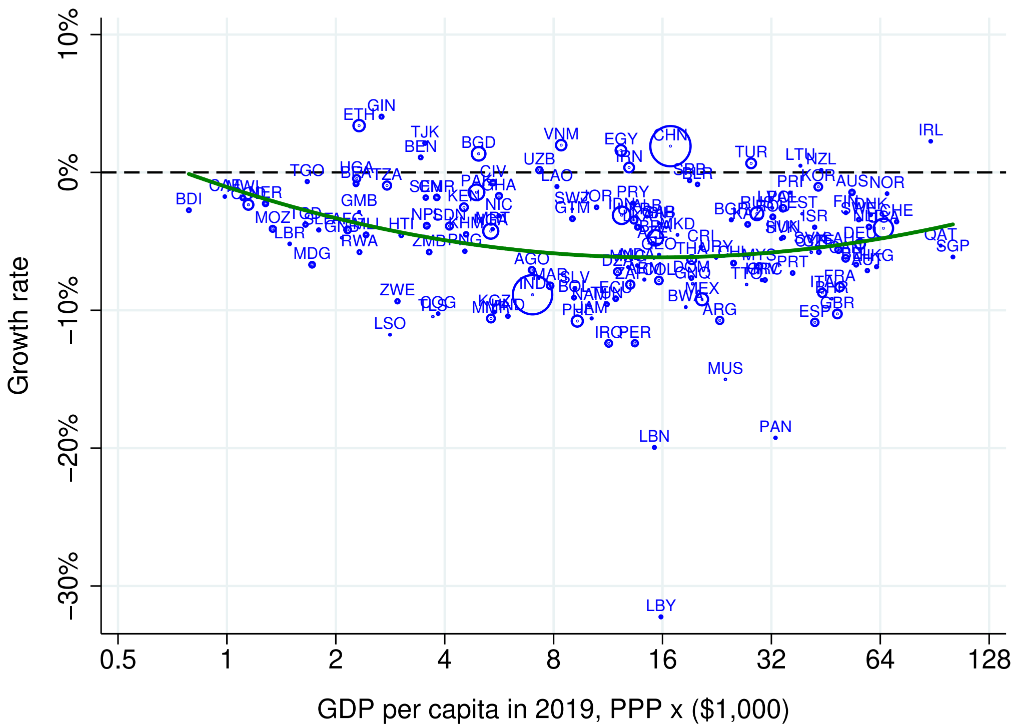
Appendix

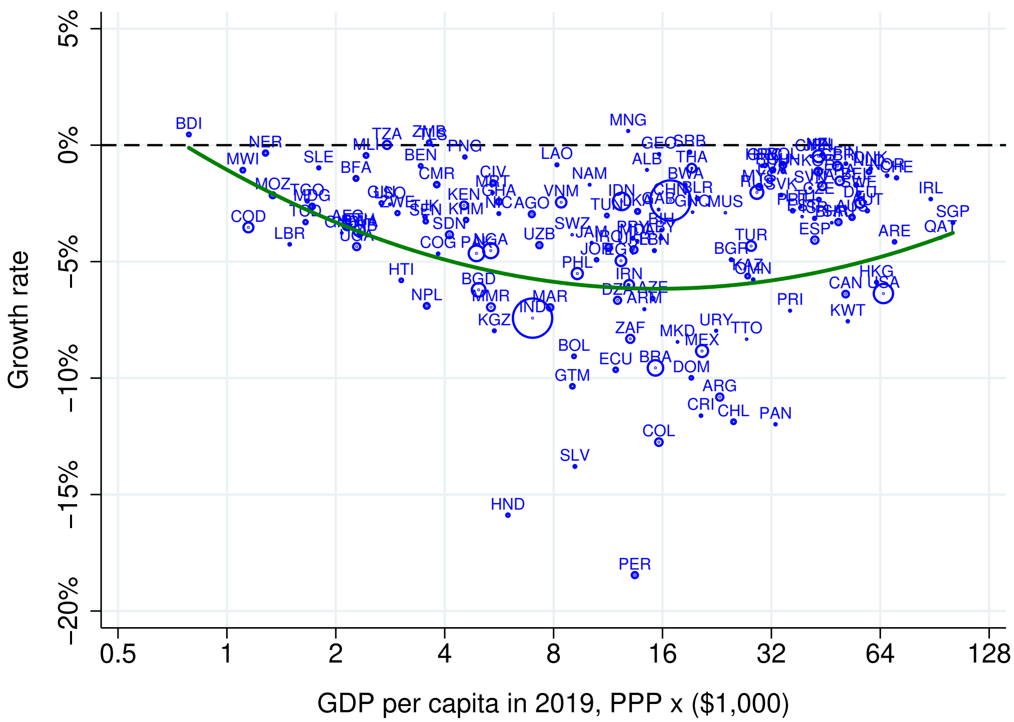
A. Appendix Figures

Figure A.1: GDP-per-capita Growth from 2019 to 2020



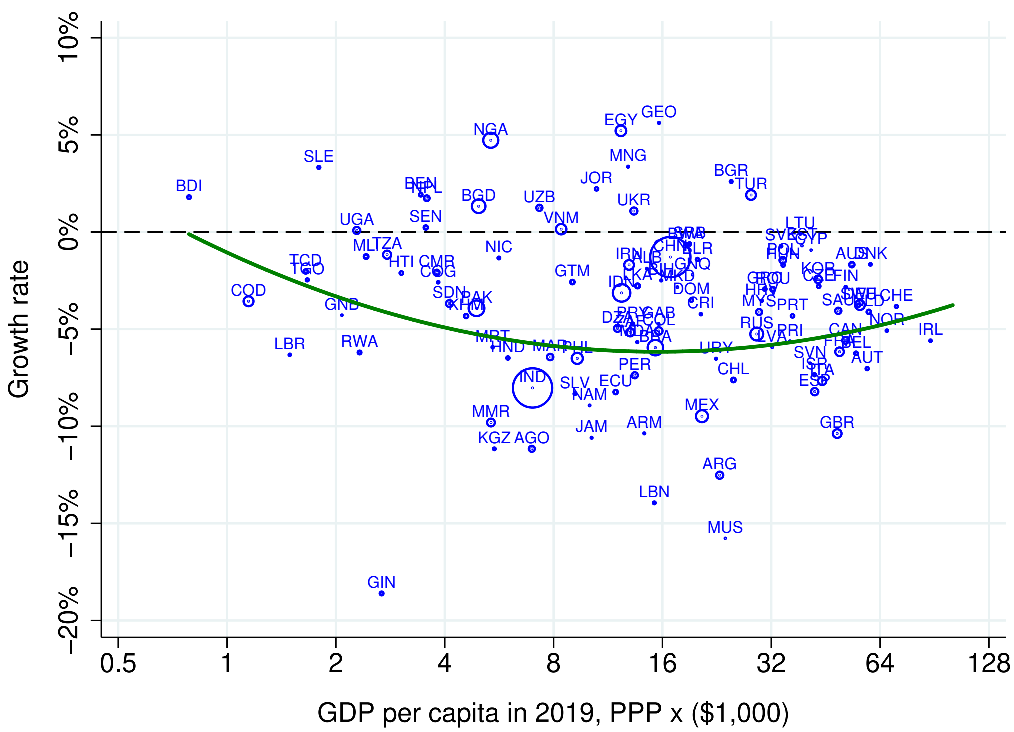
Note: GDP-per-capita data comes from the World Bank World Development Indicators. GDP per capita is expressed at PPP and is taken from the Penn World Table 9.1 (Feenstra et al., 2015).

Figure A.2: Employment Growth from 2019 to 2020



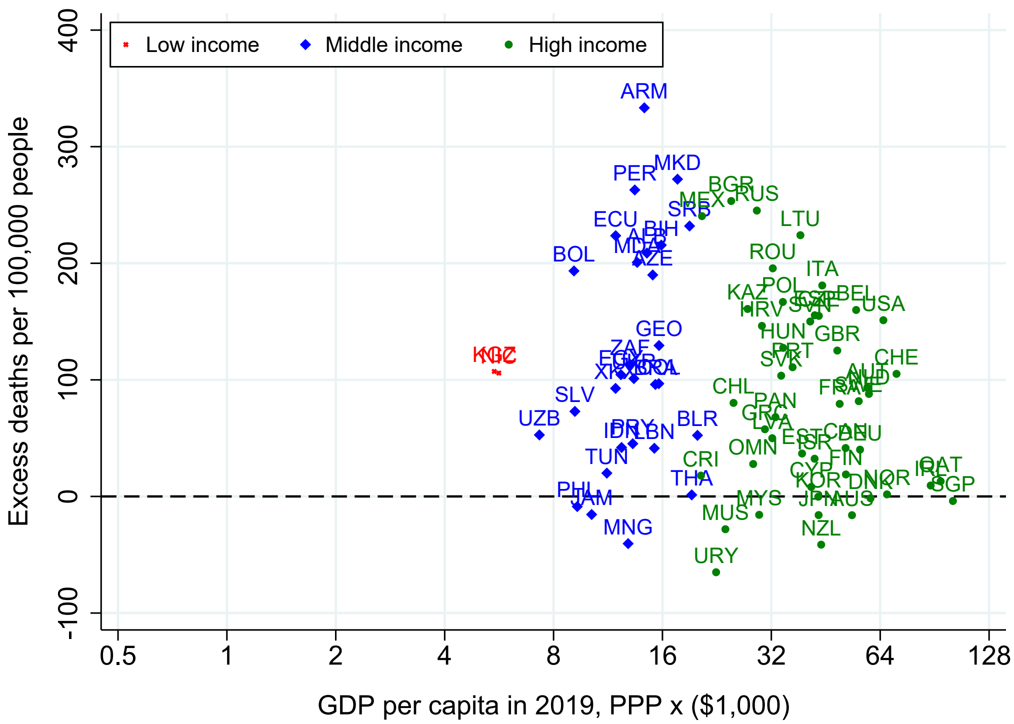
Note: Employment data comes from the ILO Statistical Database. GDP per capita is expressed at PPP and is taken from the Penn World Table 9.1 (Feenstra et al., 2015).

Figure A.3: Consumption-per-capita Growth from 2019 to 2020



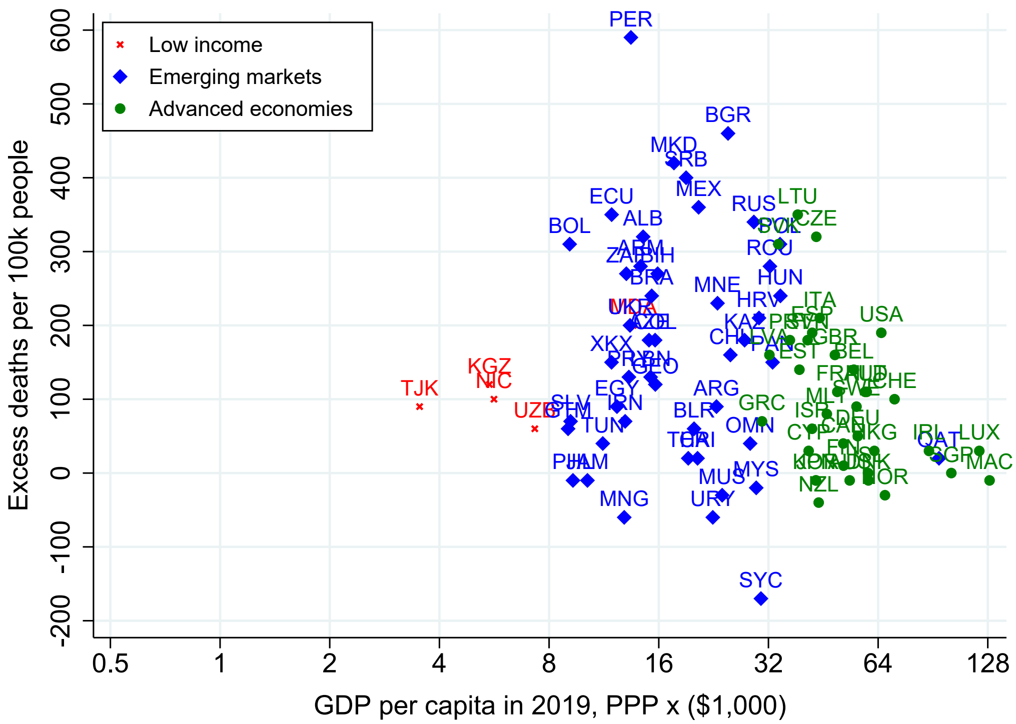
Note: Consumption data comes from the World Bank World Development Indicators. GDP per capita is expressed at PPP and is taken from the Penn World Table 9.1 (Feenstra et al., 2015).

Figure A.4: Excess Deaths Estimated by *The Economist*



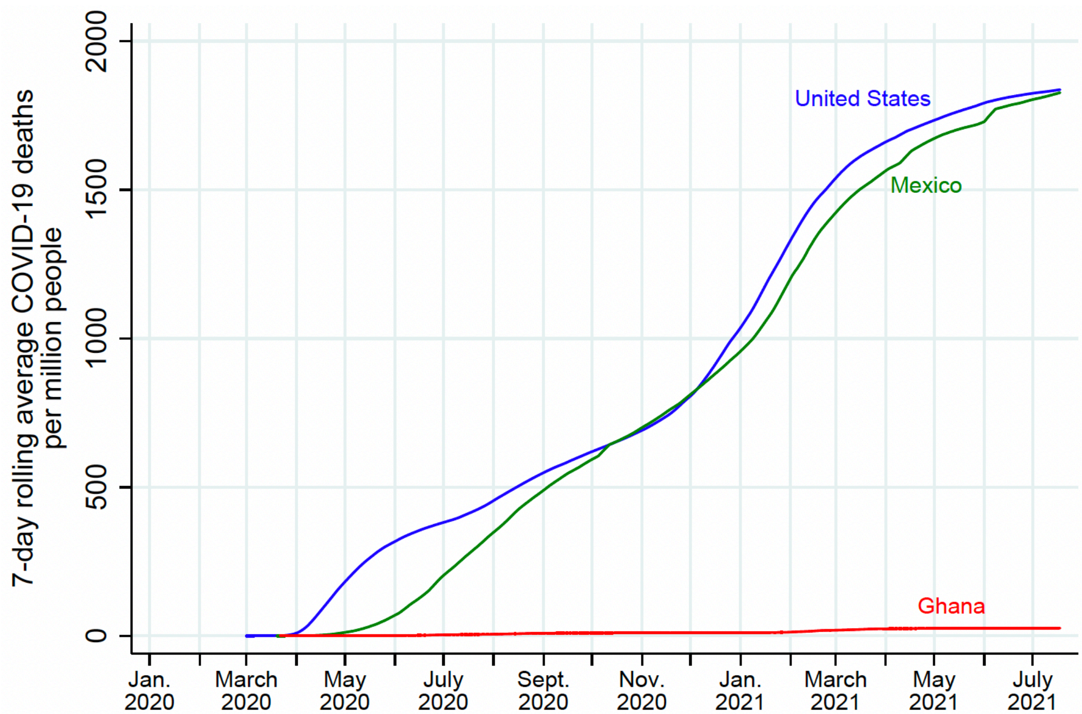
Note: Data sourced from the Economist excess mortality tracker.

Figure A.5: Excess Deaths Estimated by Karlinsky & Kobak (2021)



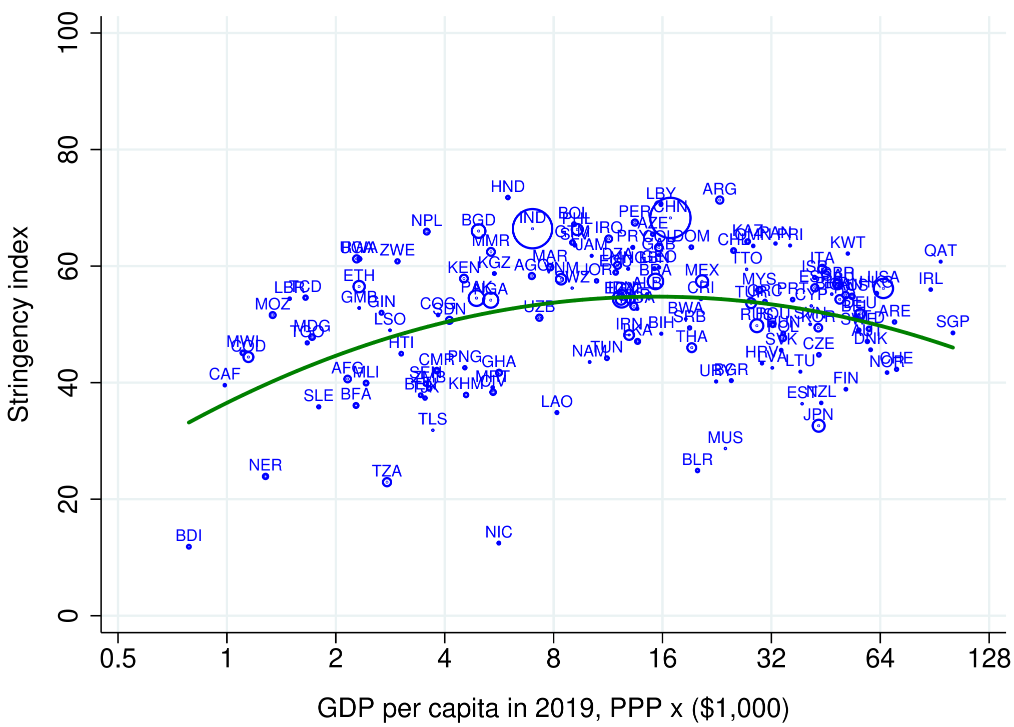
Note: Data sourced from Karlinsky & Kobak (2021)'s World Mortality Database.

Figure A.6: Official COVID-19 Deaths in the United States, Mexico and Ghana



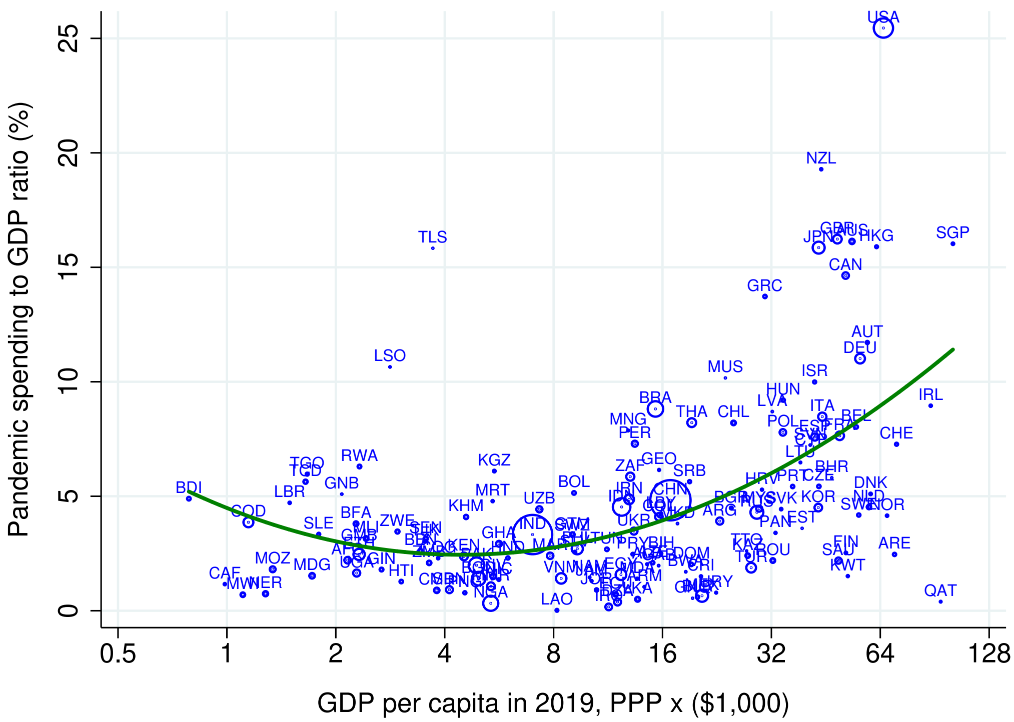
Note: This figure plots cumulative official deaths from COVID-19, according to Our World in Data, in the three focus countries: the United States, Mexico and Ghana.

Figure A.7: Oxford Lockdown Stringency Index



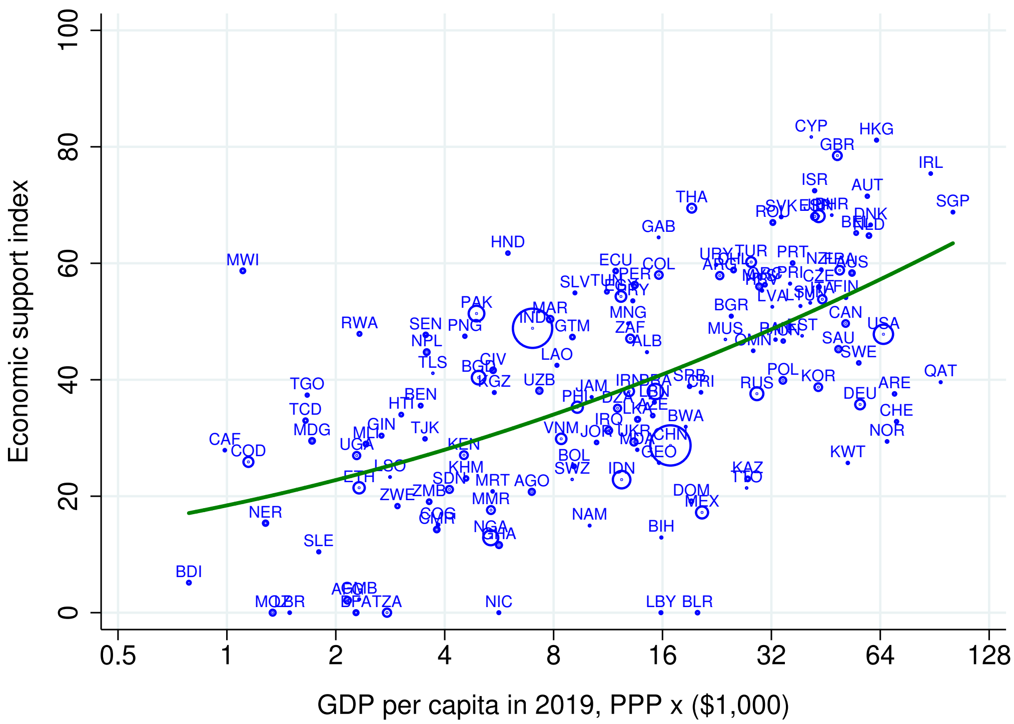
Note: The Government Stringency Index is taken from the Oxford Government Response Tracker (OxCGRT). GDP per capita is expressed at PPP and taken from Penn World Table 9.1 (Feenstra et al., 2015).

Figure A.8: Pandemic Spending as Share of GDP



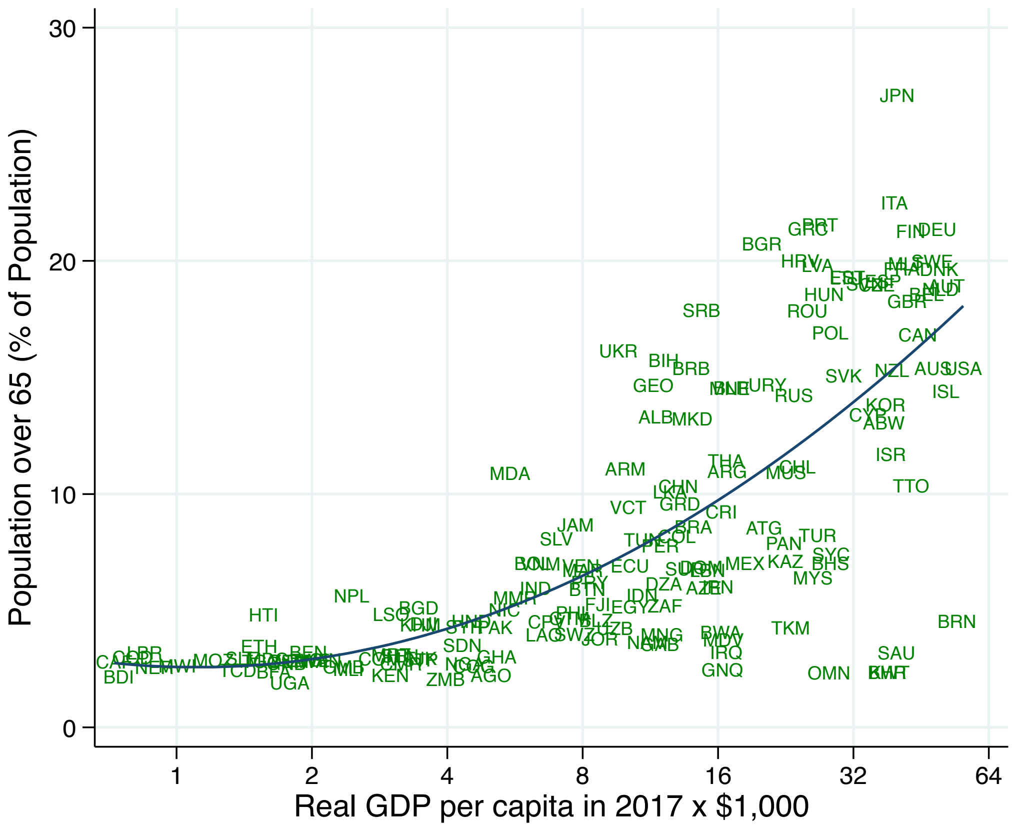
Note: Data on pandemic spending come from the IMF Fiscal Monitor Database. GDP per capita is expressed at PPP and taken from Penn World Table 9.1 (Feenstra et al., 2015).

Figure A.9: Economic Support Index



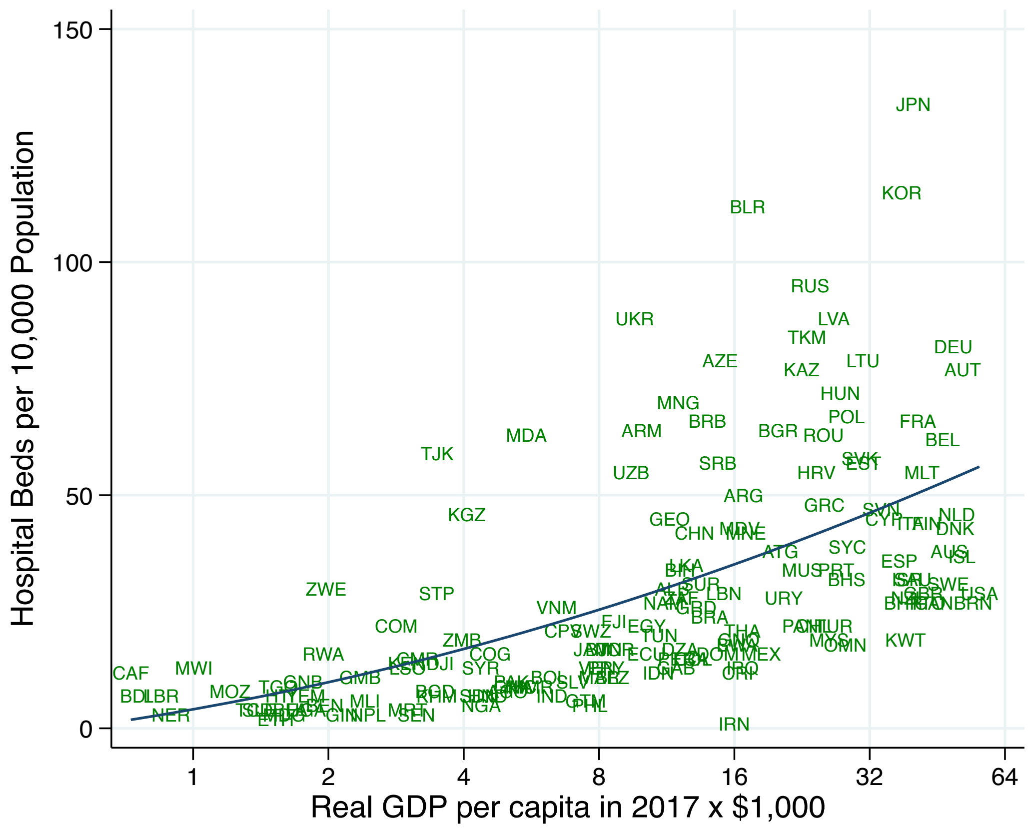
Note: Oxford Coronavirus Government Response Tracker's *Economic Support Index*.

Figure A.10: Fraction of the Population Older than Age 65



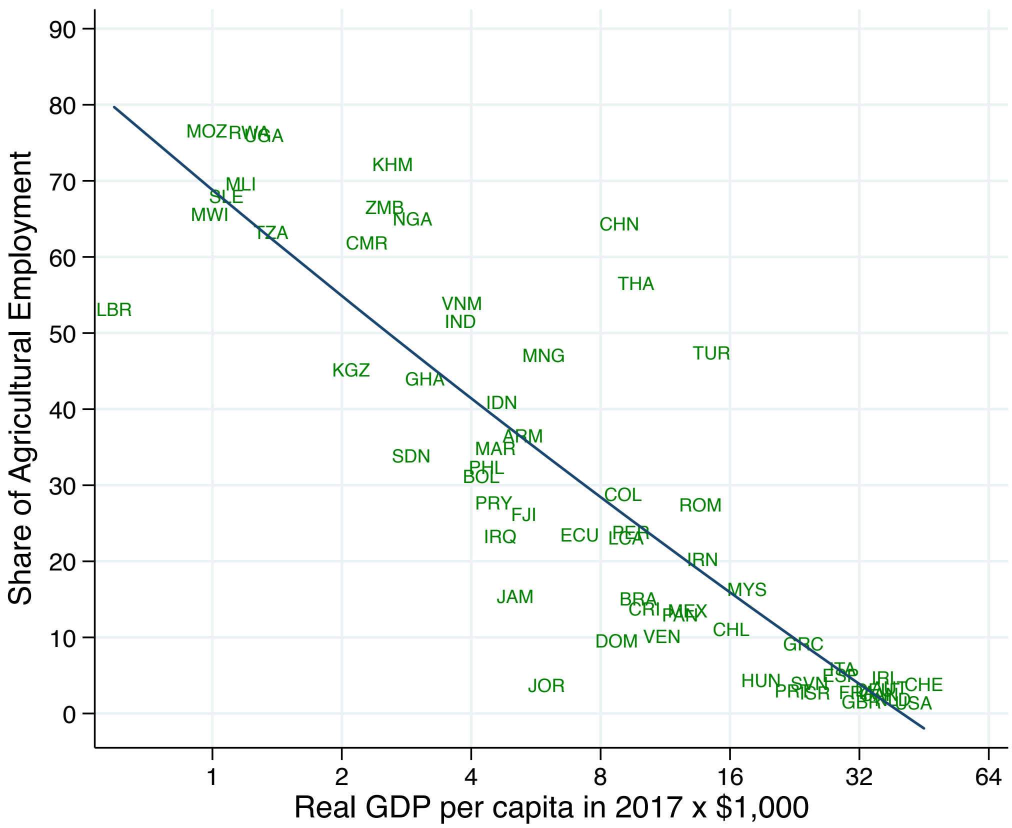
Note: This figure plots the proportion of population ages over 65 and above as a percentage of total population across 162 countries. GDP per capita is from Penn World Table 9.1 (Feenstra et al., 2015). Population data is World Bank staff estimates using the World Bank's total population and age/sex distributions of the United Nations Population Division's World Population Prospects: 2019 Revision.

Figure A.11: Hospital Beds per 10,000 People



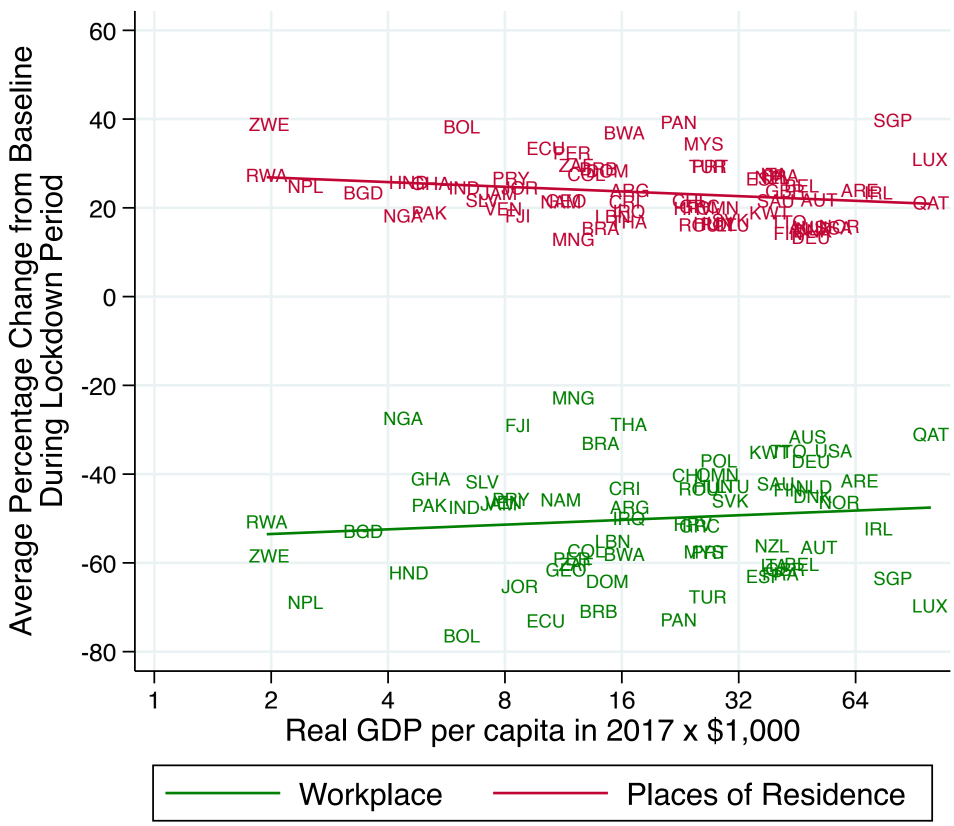
Note: This figure plots the number of hospital beds available per 10,000 inhabitants in 153 countries. GDP per capita is at PPP and taken from the Penn World Table 9.1 (Feenstra et al., 2015). The hospital bed data are from the World Health Organization's Global Health Observatory.

Figure A.12: Size of the Agricultural Sector



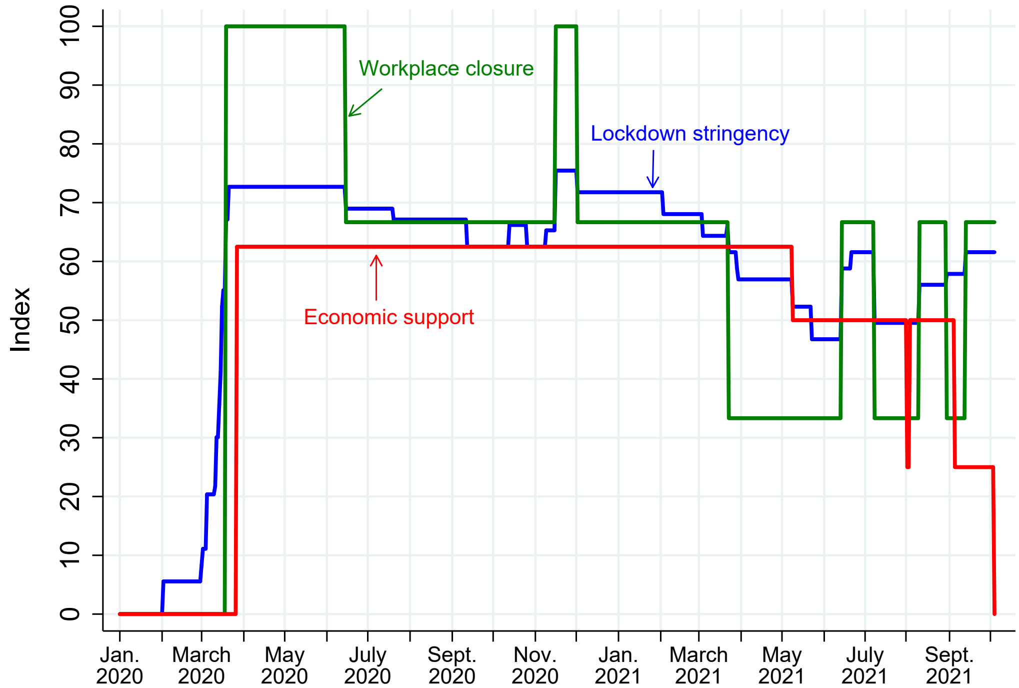
Note: Agriculture employment data is taken from the IPUMS database. GDP per capita is expressed at PPP and is taken from the Penn World Table 9.1 (Feenstra et al., 2015).

Figure A.13: Changes in Mobility Across Countries During Lockdown Periods



Note: This figure plots the average percentage changes of the mobility metric in the 'Places of Residence' and 'Workplace' categories in the Google Community Mobility Report (Aktay et al., 2020), during the lockdown periods for the 65 countries which had implemented or are implementing lockdown. GDP per capita is from Penn World Table 9.1 (Feenstra et al., 2015). The average across all 65 countries is 23.44 percent. The slope of the fitted line is 1.52, with p-value of 0.354 for the 'Workplace' category. For the 'Places of Residence' category, the slope of the fitted line is -1.52, with p-value of 0.083.

Figure A.14: Time-Series of Lockdown Policies and Economic Support in the United States



Note: This figure displays the time-series of Oxford Lockdown Stringency Index, Economic Support Index, and Workplace Closures for the United States.

B. Appendix Tables

Table B.1: ICU Bed Availability Across Countries

Country	ICU beds per 100,000 population	Per capita healthcare cost
United States	20.0-31.7	$7,164
Canada	13.5	$3,867
Denmark	6.7-8.9	$3,814
Australia	8.0-8.9	$3,365
South Africa	8.9	$843
Sweden	5.8-8.7	$3,622
Spain	8.2-9.7	$2,941
Japan	7.9	$2,817
UK	3.5-7.4	$3,222
New Zealand	4.8-5.5	$2,655
China	2.8-4.6	$265
Trinidad and Tobago	2.1	$1,237
Sri Lanka	1.6	$187
Zambia	0	$80

Source: Table 1 in Prin and Wunsch (2012). Healthcare cost includes all public and private expenditures.

Table B.2: Internally Calibrated Parameters and Model Fit

	Data	Model	Parameters	Description
U.S. GDP Decline, '19-'20	-4.10%	-4.01%	$A(P)$	Pandemic TFP
U.S. Employment Decline, '19-'20	-6.40%	-6.36%	ϕ_s	Productivity of remote work, social sector
Fraction Remote Workers pre COVID	8.20%	8.14%	σ_g	Variance of remote work taste shock

Table B.3: Multiple Correlates of GDP per Capita Change from 2019 to 2020

	Dependent variable: GDP per capita change from 2019 to 2020				
Independent variables	(1)	(2)	(3)	(4)	(5)
GDP per capita in 2019	-0.10**	0.037	-0.052	-0.027	-0.052
	(0.046)	(0.068)	(0.096)	(0.096)	(0.11)
GDP per capita in 2019^2	0.0014**	0.00021	0.00095	0.00066	0.00084
	(0.00066)	(0.00071)	(0.00098)	(0.00096)	(0.0011)
Agriculture emp. share		0.076***	0.083***	0.065**	0.062**
		(0.027)	(0.029)	(0.029)	(0.030)
Median age			0.12	0.080	0.074
			(0.082)	(0.082)	(0.082)
Lockdown stringency				-0.12***	-0.13**
				(0.043)	(0.053)
Economic support					0.024
					(0.038)
Constant	-4.21***	-8.03***	-10.6***	-3.09	-2.97
	(0.60)	(1.66)	(2.53)	(3.22)	(3.34)
Observations	144	144	144	140	140
R^2	0.031	0.071	0.084	0.157	0.163

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1