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Macroeconomic Outcomes and COVID-19: A Progress Report

ABSTRACT This paper combines data on GDP and unemployment and from Google's COVID-19 Community Mobility Reports with data on deaths from COVID-19 to study the macroeconomic outcomes of the pandemic. We present results from an international perspective using data at the country level as well as results for individual US states and key cities throughout the world. The data from these different levels of geographic aggregation offer a remarkably similar view of the pandemic despite the substantial heterogeneity in outcomes. Countries like South Korea, Japan, Germany, and Norway and cities such as Tokyo and Seoul have comparatively few deaths and low macroeconomic losses. At the other extreme, New York City, Lombardy, the United Kingdom, and Madrid have many deaths and large macroeconomic losses. There are fewer locations that seem to succeed on one dimension but suffer on the other, but these include California and Sweden. The variety of cases potentially offers useful policy lessons regarding how to use non-pharmaceutical interventions to support good economic and health outcomes.

This paper combines data on GDP and unemployment and from Google's COVID-19 Community Mobility Reports with data on deaths from COVID-19 to study the macroeconomic outcomes of the pandemic and suggest tentative policy lessons. We present results from an international perspective using data at the country level as well as results for individual US states and key cities throughout the world.

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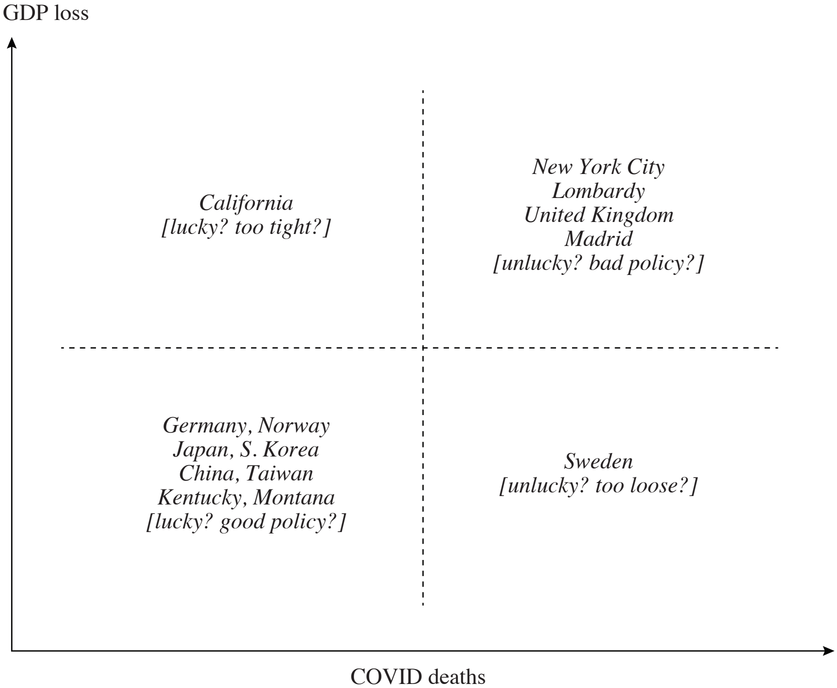
Figure 1. Summary of the Trade-Off Evidence



Source: Authors' construction.

The evidence to date can be summarized in a stylized way as shown in figure 1. On the horizontal axis is the number of deaths (per million population) from COVID-19. The vertical axis shows a cumulative measure of the macroeconomic losses apart from the value of the loss in life; for simplicity, here we call this the GDP loss. Throughout the paper, we will show data for various countries, US states, and global cities to fill in this graph quantitatively. We will also show the dynamics of how countries traverse this space over time. For now, though, we summarize in a stylized way our main findings.

One can divide the graph into four quadrants, based on many versus few deaths from COVID-19 and on large versus small losses in GDP. Our first significant finding is that there are communities in all four quadrants.

In the lower left corner of the diagram—the quadrant with the best outcomes—are Germany, Norway, China, Japan, South Korea, and Taiwan as well as US states such as Kentucky and Montana. Some combination of good luck and good policy means that these locations have experienced comparatively few COVID-19 deaths as a fraction of their populations while simultaneously keeping economic activity losses relatively low.

In the upper right quadrant—the one with the worst outcomes—New York City, Lombardy, the United Kingdom, and Madrid are emblematic of places that have had comparatively high death rates and large macroeconomic losses. Some combination of bad luck and policy mistakes is likely responsible for the poor performance on both dimensions. These locations were unlucky to be hit relatively early in the pandemic, perhaps by a strain of the virus that was more contagious than the one prevalent in other locations. Being hit early also meant that medical protocols at hospitals were less well developed and communities often did not take appropriate measures in nursing homes and care facilities to ensure that the most susceptible were adequately protected.

The other two quadrants of the chart stand out in interesting ways, having good performance on one dimension and poor performance on the other. Compared to New York City, Lombardy, Madrid, and the United Kingdom, Sweden and Stockholm had comparable death rates with much smaller losses in economic activity. But of course, that is not the only comparison. Relative to Norway and Germany, Sweden had many more deaths and comparable losses in economic activity. Relative to the worst outcomes in the upper right quadrant, Sweden is a success. But relative to what was possible—as illustrated by Germany and Norway—Sweden could have done better.

California, in the upper left quadrant opposite Sweden, also makes for a fruitful comparison. Relative to New York City, California had similarly large losses in economic activity, but far fewer deaths. At the start of the summer, both states had unemployment rates on the order of 15 percent. But New York City had 1,700 deaths per million residents, while California had just 300. From New York City's perspective, California looks enviable. On the other hand, California looks less successful when compared to Germany, Norway, Japan, and South Korea. These places had similarly low deaths but much smaller losses in economic activity. Once again, relative to what was possible—as illustrated by the best-performing places in the world—California could have done better.

One essential caveat in this analysis is that the pandemic continues. This chart and the graphs below may very well look quite different six months from September 2020. One of the most critical dimensions of luck is related to whether a location was hit early by the pandemic or had not yet been severely affected at the time of writing. Will a vaccine or cheap, widespread testing end the pandemic before these places are affected?

Still, with this caveat in mind, probably the most important lesson of the paper is that there are many observations that can be made based on the lower left quadrant of the graph: good outcomes on both the GDP and COVID-19 mortality are possible.

GOOD POLICY CAN SUPPORT BETTER OUTCOME We read our findings as suggestive (although not conclusive) evidence of the importance of good policies. Places like China, Germany, Japan, Norway, South Korea, and Taiwan are heterogeneous along various dimensions. The set includes large, dense cities such as Seoul and Tokyo. The set contains nations that were forewarned by experiences with SARS and MERS and countries like Germany and Norway that did not have this direct experience. There are places that were hit early, like China and South Korea, and places that were hit later, like Germany and Norway.

At the same time, our paper does not highlight precisely what these countries did to get these good outcomes. Such a task is next to impossible using aggregate data and requires the use of micro data analysis that exploits local variation (as in the many papers we cite below).

However, our findings suggest where to look for these more in-depth lessons. For example, China, Taiwan, and South Korea focused early on non-pharmaceutical interventions (NPIs) such as widespread use of masks, protection of the elderly, better indoor ventilation, limited indoor contact, and widespread testing and quarantine. In the case of Taiwan, Wang, Ng, and Brook (2020) report how the aggressive use of IT and big data supported the successful application of NPIs, a model copied to a large extent by China and South Korea.

Conversely, countries such as Spain and Italy, which suffered a harsh first wave but did not improve enough in terms of using analytics to track the epidemic, are again in a tight spot regarding number of cases, hospital occupancy, and deaths. As we move through the second wave of COVID-19 cases in the United States and Western Europe, the lessons regarding NPIs can improve both economic activity and death rate outcomes.

GOVERNMENT-MANDATED POLICY VERSUS SELF-PROTECTING BEHAVIOR By good policy, we do not just mean government-mandated actions but also all self-protecting voluntary changes in private behavior (perhaps induced by government information campaigns). Think about the case of the airline industry. Flight occupancy can fall because of government-imposed mandates such as international travel quarantines but also through the widespread voluntary cancellation of travel.

A growing consensus suggests that voluntary changes have played a crucial role. For instance, Arnon, Ricco, and Smetters (2020), using an integrated epidemiological-econometric model and county-level data, argue that the bulk of reductions in US contact rates and employment came from voluntary changes in behavior. However, the authors show that government-mandated NPIs reduced COVID-19 deaths by 30 percent during the first three months of the pandemic.

Goolsbee and Syverson (2020) compare consumer behavior within the same commuting zones but across boundaries with different policy regimes to conclude that legal restrictions account only for 7 percentage points of the overall reduction of more than 60 percentage points in consumer traffic. Nonetheless, the authors document that NPIs shift consumer activity across different industries (e.g., from restaurants into groceries).

Equivalent results to Arnon, Ricco, and Smetters (2020) and Goolsbee and Syverson (2020) are reported by Gupta and others (2020) using smartphone data and by Forsythe and others (2020) using unemployment insurance claims and vacancy posting. Similar findings regarding the preponderance of voluntary changes in behavior are reported for Europe by Chen and others (2020), for South Korea by Aum, Lee, and Shin (2020), and for Japan by Watanabe and Yabu (2020).

At a more aggregate level, Atkeson, Kopecky, and Zha (2020), using a range of epidemiological models, highlight that a relatively small impact of government mandates is the only way to reconcile the observed data on the progression of COVID-19 across a wide cross-section of countries with quantitative theory.

Notice that even if most of the reduction in mobility comes from voluntary decisions, we might still be far from a social optimum as agents do not fully account for the contagion externalities they create. Importantly, government information surely plays a key role in shaping agents' beliefs about the state of the epidemic and therefore influences voluntary behavior.

LITERATURE REVIEW Over the last few months, a gigantic body of literature on COVID-19 and economics has appeared. It is beyond our scope to review such literature, which touches on multiple questions, from the design of optimal mitigation policies (Acemoglu and others 2020) to COVID-19's impact on gender equality (Alon and others 2020). Instead, we highlight three sets of papers that have explored the interaction between COVID-19, the policy responses to it, and economic outcomes.

The first set of papers has extended standard economic models to incorporate an epidemiological block. Among those, early efforts include Alvarez, Argente, and Lippi (2020), Eichenbaum, Rebelo, and Trabandt (2020), Glover and others (2020), and Farboodi, Jarosch, and Shimer (2020). In this tradition, the contributions of models with many different sectors by Baqaee and Farhi (2020a, 2020b) and Baqaee and others (2020) are particularly interesting for the goal of merging micro data with aggregate outcomes and the design of optimal reopening policies. These models will also serve, in the future, as potential laboratories to measure the role of luck versus policy that we discussed above.

A second set of papers has attempted to measure the effects of lockdown policies. The results using Chinese data in Fang, Wang, and Yang (2020) indicate that early and aggressive lockdowns can have large effects in controlling the epidemic, and findings using German data (Mitze and others 2020) and Canadian data (Karaivanov and others 2020) point to the effectiveness of face masks in slowing contagion growth. Amuedo-Dorantes, Kaushal, and Muchow (2020) study US county-level data to argue that NPIs have a significant impact on mortality and infections.

A subset of these papers has dealt with Sweden, a country that implemented a much more lenient lockdown policy than its northern European neighbors. Among the papers that offer a more favorable assessment of the Swedish experience, Juranek and others (2020) have gathered administrative data on weekly new unemployment and furlough spells from all fifty-six regions of Sweden, Denmark, Finland, and Norway. Using an event-study difference-in-differences design, the authors conclude that Sweden's lighter approach to lockdowns saved between 9,000 and 32,000 seasonally and regionally adjusted cumulative unemployment/furlough spells per million population by week 21 of the pandemic. If we compare, for example, Sweden with Norway, these numbers suggest a crude trade-off (without controlling for any other variable) of around sixty-one jobs lost per life saved.[1] On the negative side, Born, Dietrich, and Müller (2020) and Cho (2020), using a synthetic control approach, find that stricter lockdown measures would have been associated with lower excess mortality in Sweden by between a quarter and a third.

The third set of papers has studied how to monitor the economy in real time (Cajner and others 2020; Stock 2020), how the sectoral composition of each country matters for the reported output and employment losses (Gottlieb and others 2020), and the impact of concrete policy measures. Among the latter, Chetty and others (2020) argue that stimulating aggregate demand or providing liquidity to businesses might have limited effects when the main constraint is the unwillingness of households to consume

1. Among many other elements, this computation does not control for the possibility that Sweden, by getting closer to herd immunity, might have saved future deaths or, conversely, that higher death rates today might have long-run scarring effects on the Swedish GDP and labor market.

due to health risks and that social insurance programs can be a superior mitigation tool. Goldberg and Reed (2020) extend the analysis of current economic conditions related to COVID-19 to emerging market and developing economies.

STRUCTURE OF THE PAPER In the remainder of the paper, we present the detailed evidence that underlies this stylized summary. Section I lays out a basic framework for thinking about figure 1. Section II presents evidence for countries using data on GDP from the first and second quarters of 2020 to measure the macroeconomic outcomes. It also shows evidence for US states, using monthly unemployment rates. Section III then turns to a complementary source of data on economic activity, the Google COVID-19 Community Mobility Reports.[2] We show that these economic activity measures are highly correlated with GDP and unemployment rates. The Google measures have additional advantages, however. In particular, they are available for a large number of locations at varying geographic levels of aggregation and are reported at the daily frequency and with a lag of only just a few days, an important feature given the natural lags in National Income and Product Accounts (NIPA) reporting. We reproduce our earlier findings using the Google data and produce new charts for key cities worldwide. The city-level data are important because of concerns about aggregating to, say, the national level across regions of varying densities. Section IV shows the dynamic version of our graphs at the monthly frequency using the Google data, so we can see how different locations are evolving. Finally, section V offers some closing thoughts.

I. Framework

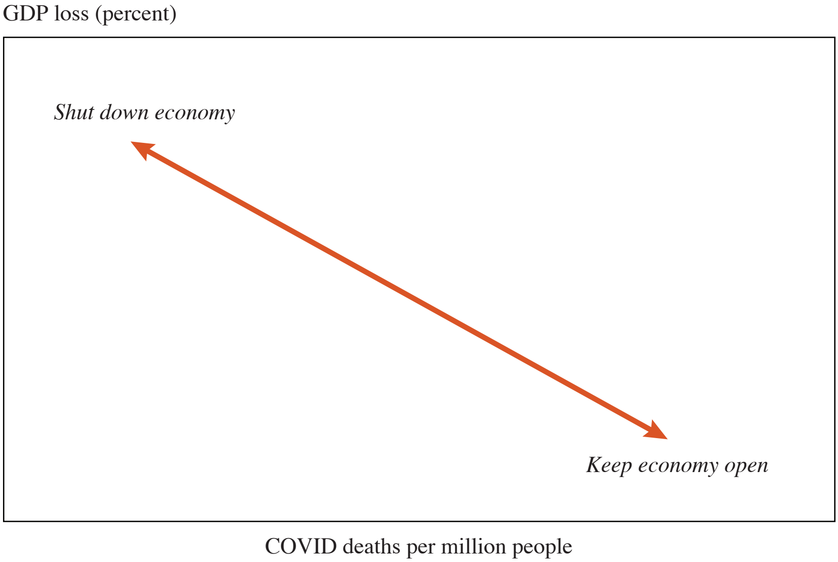
We focus on two outcomes in this paper: the loss in economic activity, as captured by reduced GDP or increased unemployment, and the number of deaths from COVID-19 per million people.[3] Even with just these simple outcome measures, it is easy to illustrate the subtle interactions that occur in the pandemic.

To begin, figure 2 illustrates a simple trade-off between economic activity and deaths from the pandemic. In the short term, economic policy can shut the economy down sharply, which increases the economic losses

2. Google COVID-19 Community Mobility Reports, accessed October 9, 2020, https://www.google.com/covid19/mobility/.

3. There is a growing concern about the long-run health consequences for individuals who survived a COVID-19 infection. However, it is too early for any systematic international comparison of those long-run effects.

Figure 2. Economic Policy Trade-Off, Holding Health Policy and Luck Constant



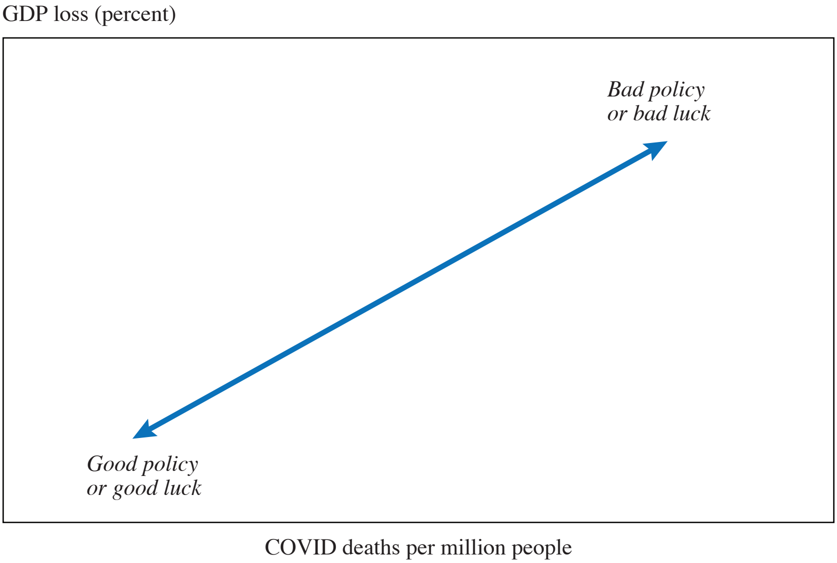
Source: Authors' construction.
Note: Holding health policy and luck constant, economic policy implies a trade-off between economic activity and deaths from COVID-19.

on the vertical axis but saves lives on the horizontal axis. Alternatively, policy could focus on keeping the economy active to minimize the loss in GDP at the expense of more deaths from the pandemic.

Figure 3 shows that the story is more complicated when health policy and luck are brought under consideration. There can be a positive correlation between economic losses and COVID-19 deaths. Good NPIs—for example, widespread use of masks, better indoor ventilation, protecting nursing homes, and targeted reductions in super-spreader events such as choirs, bars, nightclubs, and parties—can reduce the number of deaths with a limited impact on production. Furthermore, by reducing the death rate, such policies encourage economic activity by allowing people to return safely to work and the marketplace.

Similarly, luck plays an important but not yet fully understood role. Where does the coronavirus strike early versus late? Perhaps a country is in the lower-left corner in September 2020 with low deaths and little loss in GDP, but only because it has been lucky to avoid a severe outbreak. By early 2021, things may look different. Alternatively, was a region hit by a less infectious and deadly virus strain (see our next subsection)?

Figure 3. Health Policy Decisions and Luck Can Shift the Trade-Off



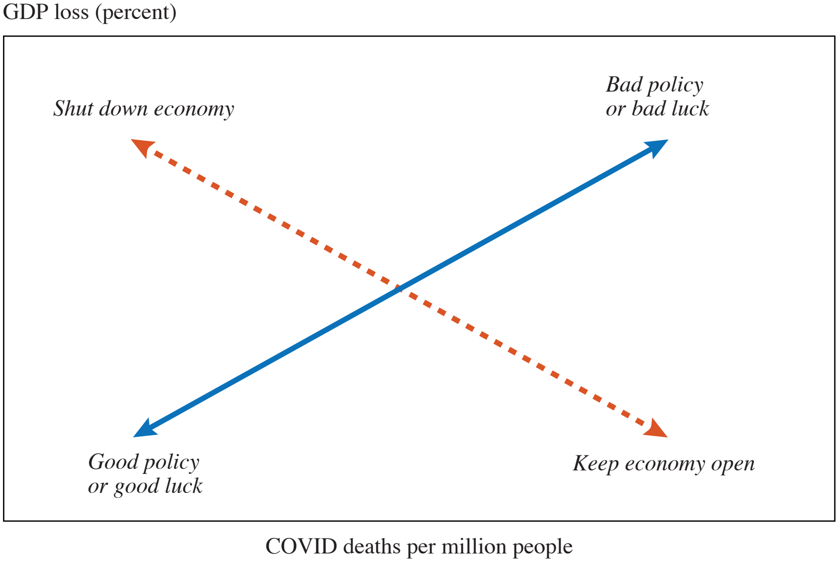
Source: Authors' construction.
Note: Health policy and luck can shift the trade-off between economic activity and deaths from COVID-19.

Given the steep age pattern of COVID-19 mortality rates, basic demographic differences influence the trade-off between deaths and GDP losses. This is another dimension of what we can call luck. COVID-19 has a steep age and obesity gradient. Younger and less-obese countries, many of them emerging market and developing economies, have experienced much better outcomes than one would have expected (Goldberg and Reed 2020).

To complicate matters, all of these forces play out over time, which gives rise to important dynamic considerations. For example, a community may keep the economy open in the short term, which may lead to a wave of deaths, and then be compelled to shut the economy down to prevent even more deaths. Two communities can end up with large economic losses, but very different mortality outcomes, because of these timing considerations. This can be thought of as being embodied in figure 3.

Figure 4 puts these mechanisms together in a single chart. It reveals that the correlation between economic losses and COVID-19 deaths that we see in the data is governed by a sophisticated collection of forces, both static and dynamic. When we see a cloud of data points in the empirical versions of this graph, we can think about how these various forces are playing out.

Figure 4. Economic Activity, COVID-19 Deaths, Health Policy, and Luck



Source: Authors' construction.
Note: Putting the two lines on the same chart explains why the data can be difficult to interpret.

I.A. Evidence on the Role of Mutation

We have mentioned that a simple mechanism behind luck is the strain of the virus that attacked a given location. From March to May 2020, a SARS-CoV-2 variant carrying the spike protein G614 which likely appeared in some moment in February replaced D614 as the dominant form of the virus globally (Korber and others 2020).

While the global transition to the G614 variant is a well-established fact, its practical consequences are still debated. Korber and others (2020) present experimental evidence that the G614 variant is associated with greater infectivity and clinical evidence that the new variant is linked with higher viral loads, although not with greater disease severity. Hu and others (2020), Ozono and others (2020), and Zhang and others (2020) report similar findings. However, these latter results regarding greater infectivity and higher viral load are not yet the consensus among scientists (Grubaugh, Hanage, and Rasmussen 2020).

In other words, there is some evidence—although far from conclusive—that the pandemic's timing may have played a role in determining the quadrant where each location falls in figure 1. If indeed the original D614 variant is less infectious, Asian countries (who were exposed more to this earlier form of the virus) faced a more straightforward trade-off between containing the epidemic and sustaining economic activity. Even within the United States, California, likely due to its closer ties to Asia, experienced a higher prevalence of lineages of D614 at the start of the health crisis than New York City, closer to Europe, and thus it had better initial outcomes regardless of the policies adopted.

II. Cumulative Deaths and Cumulative Economic Loss

This section shows the empirical versions of the trade-off graphs for various countries and US states using GDP and unemployment as measures of the economic outcomes.

II.A. International Evidence

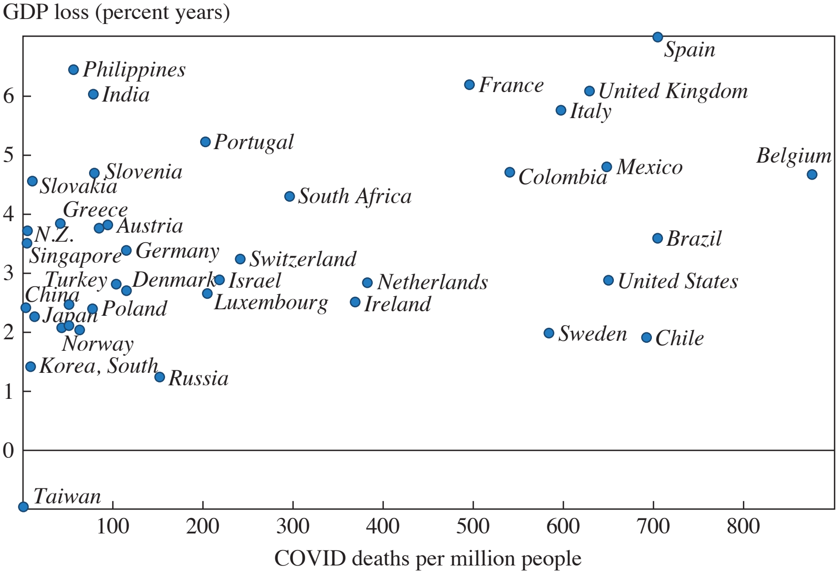
We use GDP data from the OECD and death data from Johns Hopkins University Center for Systems Science and Engineering (CSSE) to study the international evidence on COVID-19 deaths and GDP.[4] Figure 5 plots the COVID-19 deaths per million population as of October 9 against the loss in GDP. GDP loss is the cumulative loss in GDP since the start of 2020 (data from Q1 and Q2) and is annualized. For example, a value of 6 means that the loss since the start of 2020 is equivalent to a 6 percent loss in annual GDP.

Before discussing our findings, some warnings are appropriate. First, we only have observations up to 2020:Q2. Second, the numbers released so far are likely to be revised substantially. Even in normal times, the revisions of GDP early releases are considerable (Aruoba 2008). The difficulties in data collection during the pandemic suggest that the revisions for 2020 are bound to be even larger.[5] Third, GDP is only an imperfect measure of

4. OECD, Quarterly GDP, accessed October 1, 2020, https://data.oecd.org/gdp/quarterly-gdp.htm; Johns Hopkins University Center for Systems Science and Engineering, "2019 Novel Coronavirus COVID-19 (2019-nCoV) Data Repository," accessed October 9, 2020, https://github.com/CSSEGISandData/COVID-19/.

5. Recall, for example, the note on the Coronavirus (COVID-19) Impact on June 2020 Establishment and Household Survey Data: "The collection rate for the establishment survey in June was 63 percent. This is lower than the average for the 12 months ending in February 2020, before data collection was impacted by the pandemic, and lower than May (69 percent). This rate was also lower than that for June 2019 (71 percent)." https://www.bls.gov/cps/employment-situation-covid19-faq-june-2020.pdf. A similar issue relates to the state unemployment rates that we will use later. These rates are a combination of survey measurement on small state-level samples and a pooled time series model run by the Bureau of Labor Statistics. During the last months, we have seen large revisions in these rates.

Figure 5. International COVID-19 Deaths and Lost GDP



Sources: Johns Hopkins University CSSE, OECD, and authors' calculations.

Note: "GDP loss" is the cumulative loss in GDP in the first two quarters of 2020 and is annualized. For example, a value of 6 means that the loss is as if the economy lost 6 percent of its annual GDP.

economic activity. There are reasons to believe that those imperfections are even more acute in 2020.

For instance, consider government consumption. This item is measured by the sum of employee compensation, consumption of fixed capital, and intermediate goods and services purchased. Many government services, from the local DMV to public schools, were not offered (or only offered under a very limited schedule) during the lockdowns. However, most government employees were still paid (furloughs were rare in OECD countries), and the consumption of fixed capital is imputed according to fixed depreciation tables. Thus, except for some reduction of intermediate goods and services purchased, government consumption remained unchanged from the perspective of GDP. Indeed, in the United States, real government consumption increased .6 percent in 2020:Q2 with respect to 2020:Q1 while GDP dropped 9.0 percent. While part of the increase can be attributed to the fiscal stimulus and the fight against COVID-19, a substantial part of government consumption operated well below normal levels during that quarter with little impact on measured GDP.

With these considerations in mind, figure 5 suggests that there has not been a simple trade-off between deaths and GDP. Rather, countries can be seen to fall into several groups.

First, we have countries with low deaths and moderate GDP losses: Taiwan (with positive GDP growth!), South Korea, Indonesia, Norway, Japan, China, and Germany. Such countries illustrate an important lesson from the crisis: it was possible to emerge with relatively good performance on both dimensions. Importantly, this group is heterogeneous. It includes countries in both Asia and Europe. It includes countries with large, densely populated cities. And it includes countries that are globally highly connected to the rest of the world, including Germany and China, the two major export powerhouses of the world economy. Other countries nearby in the diagram include Poland, Greece, and Estonia.

Presumably, both good policy and good luck play important roles here. For example, Greece, a dense country with a poor track record in terms of economic governance and a public health system starved of resources after a decade of budget cuts, has performed so far surprisingly well. Greece's government approved restrictive measures when the number of cases was minimal and directed a well-coordinated health strategy. At the same time, Greece is less well connected with the rest of the European Union and has a fragmented geography, which has slowed down the virus's spread. Uncovering the explanation for Greece's success could yield important lessons.

Next, in the graph's upper-right part, we have countries with high death rates and large GDP losses: France, Spain, Italy, the United Kingdom, and Belgium. Some combination of bad luck and imperfect policy led these countries to suffer on both dimensions during the pandemic. The United Kingdom, as an example, suffered from more than 600 deaths per million people and lost the equivalent of 6 percent of a year's GDP. Also, high COVID-19 incidence might trigger nonlinear effects on mortality. There is evidence that the Italian and Spanish health systems were overwhelmed in March 2020, leading to many deaths that could have been avoided. Ciminelli and Garcia-Mandicó (2020) show that mortality in those Italian municipalities that were far from an ICU was up to 50 percent higher, which they argue was due to the congestion of the emergency care system during those crucial weeks.

A few countries in figure 5 are harder to classify. India and the Philippines have experienced a considerable reduction in GDP but comparatively few deaths per million people. As we will see later, however, the situation in India is still evolving. The United States and Sweden also stand out, with many COVID-19 deaths but smaller reductions in GDP than France, Italy, or Spain. As with India, however, the dynamic graphs we show later suggest that the position of the United States is still in flux.

The case of Sweden is particularly interesting because its government defied the consensus among other advanced economies and imposed much milder restrictions, explicitly aiming for herd immunity. Compared to the United Kingdom, Spain, or Italy, Sweden looks like a success story: it has a comparable number of deaths when normalized by population, but a significantly smaller loss in GDP. The shutdown in the United Kingdom, Spain, and Italy has already cost these economies the equivalent of 6 percent of their annual GDP, while the loss in Sweden has been just 2 percent of GDP.

On the other hand, with an alternative comparison, Sweden looks worse. In terms of deaths, Sweden has had around 575 deaths per million population vs. 50 in Norway, 60 in Finland, 115 in Denmark, and 115 in Germany. The other Nordic countries are a natural comparison group in terms of socioeconomic conditions, although differences in population distribution and mobility within this group should not be underestimated. Regarding economic outcomes, Norway and Sweden both report GDP losses of around 2 percent, while Denmark, Germany, and Austria are only slightly larger.

In the case of the United States, the current high levels of infection and deaths mean that the country is still moving to the right in figure 5. The rise in cases in Western Europe in August and September 2020 is at such an early stage that it is impossible to gauge whether these countries will also witness significant levels of additional deaths.

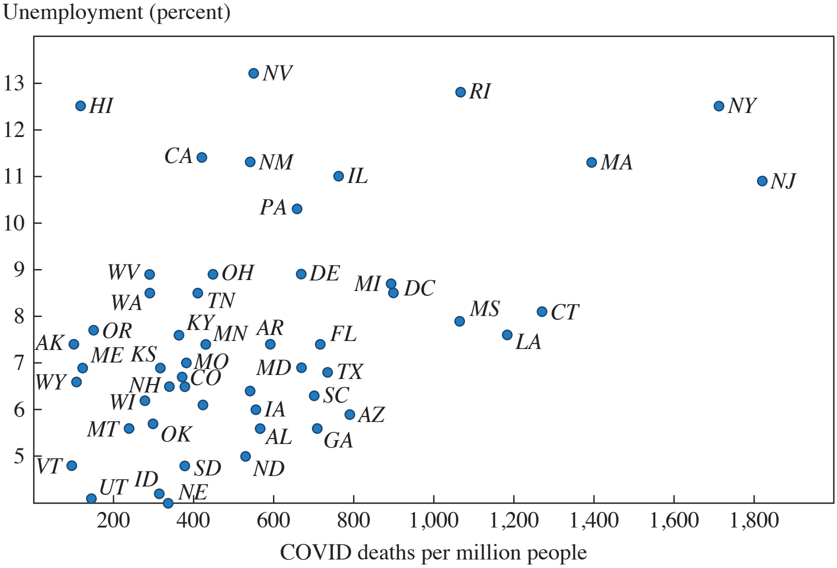
Finally, notice that figure 5 correlates COVID-19 deaths and GDP losses without controlling for additional variables (initial income per capita, industrial sectoral composition, density, demographics, etc.). We checked for the effects of possible controls, and we did not find any systematic pattern worth reporting.

II.B. US States and Unemployment

We now consider economic outcomes and deaths from COVID-19 across US states. In this case, our measure of economic activity is the unemployment rate. Figure 6 shows the unemployment rate for US states from August 2020 plotted against the number of deaths per million people as of October 9.

The heterogeneity in both the unemployment rate and in COVID-19 deaths is remarkable. States like New York, Massachusetts, and New Jersey have more than 1,200 deaths per million residents as well as unemployment

Figure 6. US States: COVID-19 Deaths and the Unemployment Rate



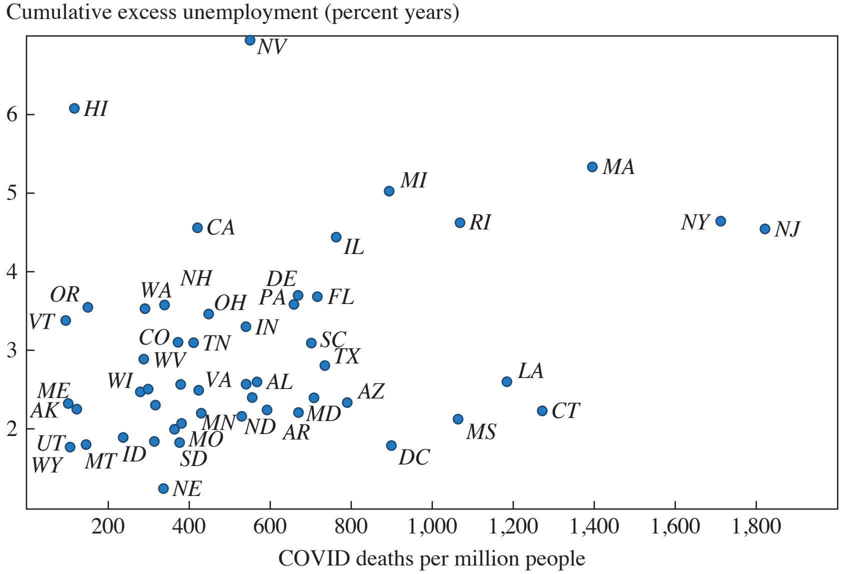
Sources: Johns Hopkins University CSSE, Bureau of Labor Statistics, and authors' calculations.
Note: The unemployment rate is from August 2020.

rates that, even after several months of recovery, exceed 10 percent. In contrast, states like Utah, Idaho, Montana, and Wyoming have very few deaths and unemployment rates between 4 and 7 percent.

Figure 7 cumulates the unemployment losses since February to create a more informative measure of the macroeconomic cost of the pandemic. In particular, we measure cumulative excess unemployment by summing the deviations from each state's February 2020 rate for each month and then dividing by twelve to annualize. In other words, a number like 6 in the graph implies that the loss to date is equivalent to having the unemployment rate be elevated by 6 percentage points for an entire year.

In this figure, it is interesting to compare New York, California, and Washington, DC. Both New York and California have had large declines in economic activity, the equivalent of having the unemployment rate be elevated by about 5 percentage points for an entire year. However, the number of deaths is very different in these two states. New York had around 1,700 deaths per million people, while California had around 400 as of October 9. What combination of luck and policy explains this outcome? Both states got hit relatively early by the coronavirus. Was California lucky

Figure 7. US States: COVID-19 Deaths and Cumulative Excess Unemployment



Sources: Johns Hopkins University CSSE, Bureau of Labor Statistics, and authors' calculations.

Note: Cumulative excess unemployment adds the deviations from each state's February 2020 rate for each month and then divides by 12 to annualize. In other words the loss to date is equivalent to having the unemployment rate be higher by a certain percentage for an entire year.

to get a strain from Asia that was less contagious and less deadly while New York got a strain from Europe that was more contagious and more deadly? Or did the policy differences between New York and California have enormous effects?

When compared to New York, California looks like a resounding success. On the other hand, one can also compare California to states like Washington and Minnesota, not to mention Montana and Nebraska. All of these other states had similar death rates but smaller employment losses. Did California shut down too much? Or were Nebraska and Minnesota lucky? Or did population density play an important role?

Finally, Washington, DC, stands out as a locale with relatively small employment losses—equivalent to an unemployment rate that is elevated by just 2 percentage points for a year—but substantial deaths. Washington, DC, looks somewhat like Sweden in this graph, but when we turn to the Google activity data below, the story will be a bit different: the prevalence of government jobs with stable employment may have limited the rise in the DC unemployment rate.

II.C. International Comparisons of Unemployment

Given our previous analysis, it would seem natural to compare the evolution of unemployment rates among the advanced economies. However, such a comparison is not especially informative in gauging the effects of COVID-19.

Many countries have passed generous government programs to induce firms to keep workers on the payroll even during lockdowns, count workers on furloughs with reduced pay as being employed, or classify workers who lost their jobs as out of the labor force if they are not searching for a new job due to the stay-at-home orders. Furthermore, severance costs make firing workers after a relatively transitory shock unattractive: firms might end up paying more in severance packages than the cost of just keeping their workers at home with pay for a few months. That means that the measured unemployment rate in some of the most severely hit countries has only increased by a few percentage points (from 13.6 percent in February 2020 to 15.6 percent in June 2020 in Spain) or even fallen (from 9.1 percent in February 2020 to 8.8 percent in June 2020 in Italy).[6]

The main exception is the United States, which features substantially different labor market regulations: unemployment jumped from 4.4 percent in March 2020 to 14.8 percent in April 2020 but then declined to 7.8 percent in September 2020.

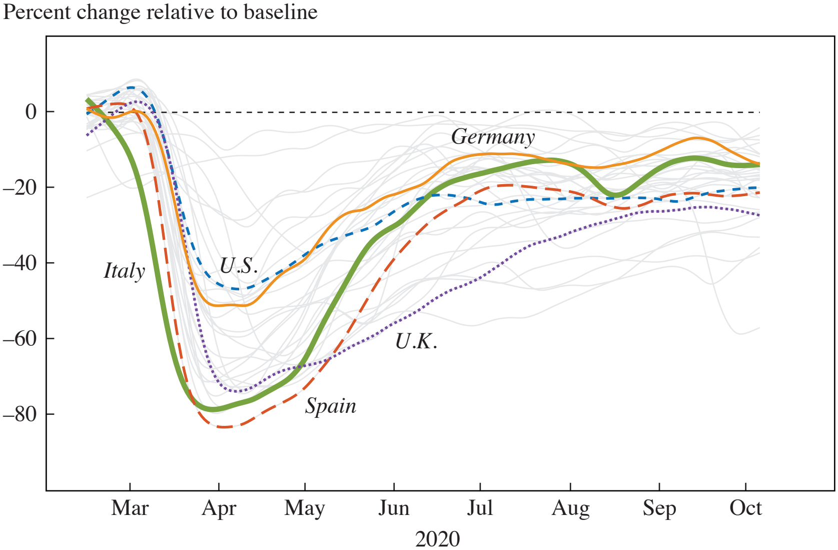
III. Activity from the Google Mobility Report Data

GDP and unemployment rates are standard macroeconomic indicators that are extremely useful. However, they also suffer from some limitations related to frequency and availability. In this section, we turn to another source of evidence: the COVID-19 Community Mobility Report data from Google for 2020. For shorthand, we will refer to this as the Google activity measure. These data show how daily location activity changes over time in a large number of countries and regions. The outcomes are grouped according to several destinations: retail and recreation, grocery and pharmacy, parks, transit stations, workplaces, and residences.

The Google activity measure has several key advantages relative to GDP or unemployment. First, it is available at a daily frequency, rather than quarterly or monthly. Second, it is reported with a very short lag of just a

6. Similar arguments would apply to a comparison of employment rates. The number of hours worked is reported by the OECD only at an annual frequency.

Figure 8. Google Activity: International Evidence



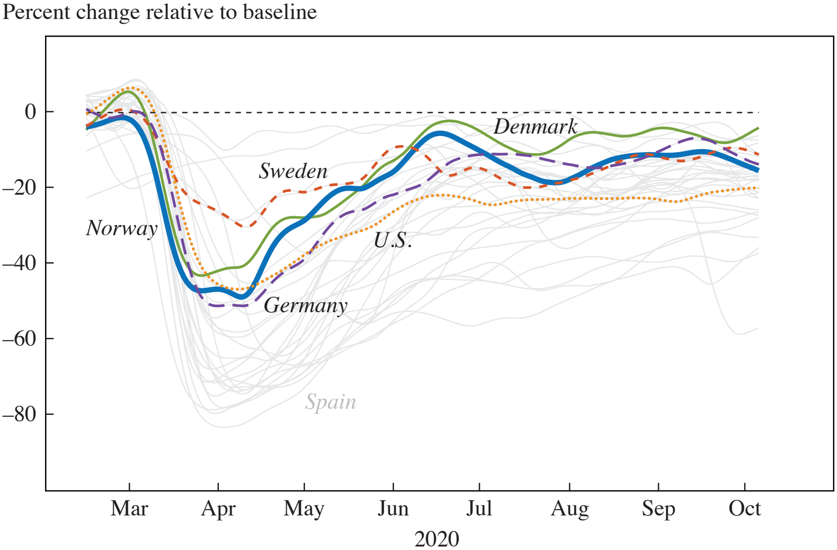
Sources: Google COVID-19 Community Mobility Reports and authors' calculations.
Note: Google activity is the equally weighted average of the retail and entertainment and workplace categories. The data are smoothed with an HP filter with smoothing parameter 400.

few days. By comparison, we only have 2020:Q2 GDP data for a handful of countries, and our latest unemployment rate data for US states are from September 2020. Finally, the Google data are also available at a very disaggregated geographic level, allowing us to look at cities as well as states and countries. In what follows, we focus on Google activity, defined as the equally weighted average of the retail and entertainment and workplace categories.

III.A. Google Activity over Time

Figure 8 shows the (smoothed) Google activity data over time for a large number of countries, highlighting a few. Italy and Spain show very sharp declines in activity starting quite early compared to the declines in the United States, the United Kingdom, and Germany. Activity recovers somewhat in May in Italy and Spain but only gradually in the United Kingdom. This appears to be a case of the United Kingdom being slow to get the pandemic under control, suffering from more deaths as a result, and being forced to keep its economy shut down for longer.

Figure 9. Google Activity: Northern Europe



Sources: Google COVID-19 Community Mobility Reports and authors' calculations.
Note: Google activity is the equally weighted average of the retail and entertainment and workplace categories. The data are smoothed with an HP filter with smoothing parameter 400.

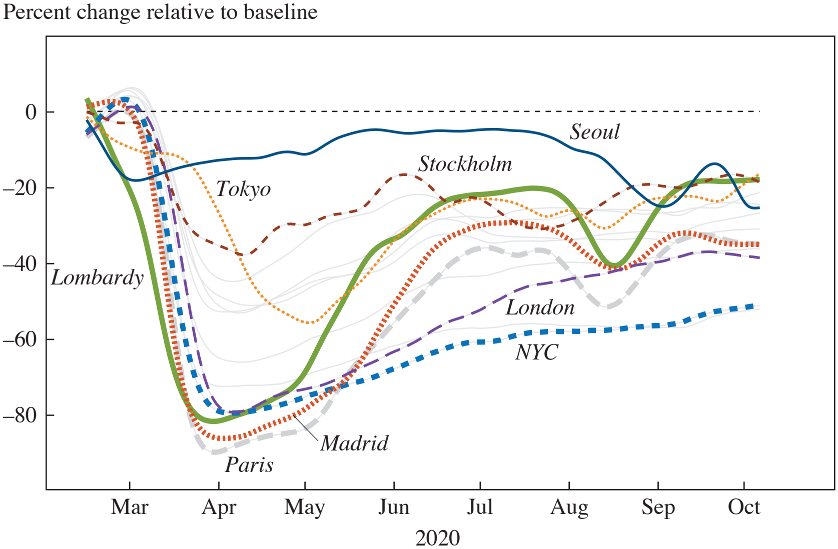
The United States and Germany are also interesting, in comparison. They have somewhat similar changes in activity but, as we've seen, very different COVID-19 outcomes. Among the highlighted countries, Germany had the smallest loss in economic activity and the fewest deaths.

Next, consider figure 9 which highlights the Scandinavian countries. These countries have even milder shutdowns than Germany and the United States. Sweden's shutdown is initially the mildest but by June it looks similar to Germany, Denmark, and Norway.

GLOBAL CITIES Figure 10 shows the Google activity measure for fourteen key international cities or regions. Lombardy and Seoul have very early shutdowns with 20 percent declines in activity by the first of March. Madrid and Paris and then New York City and finally London follow them down, with all four seeing activity down by around 80 percent as of April 1. Seoul recovers very quickly, while Tokyo sees a slow decline. Stockholm also has mild losses according to the Google activity measure.

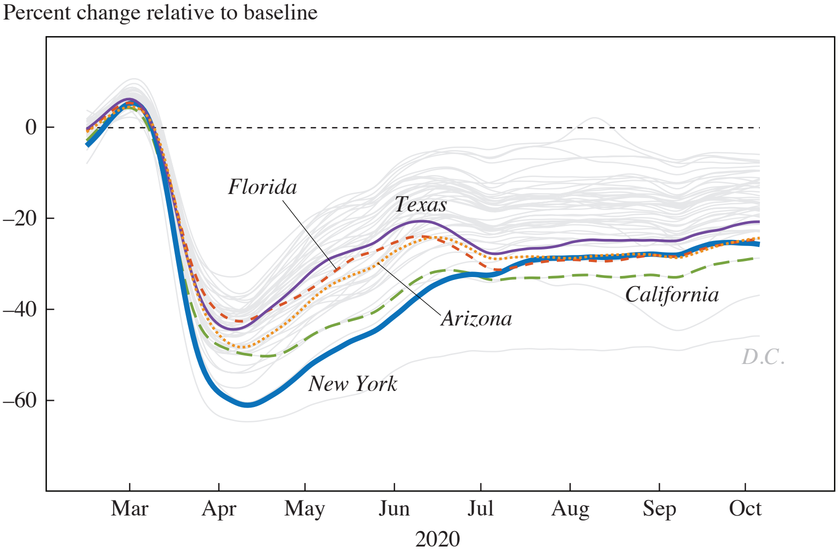
US STATES Figure 11 shows the Google activity data for US states. The heterogeneity of experience stands out, with some states close to normal by

Figure 10. Google Activity for Key Global Cities



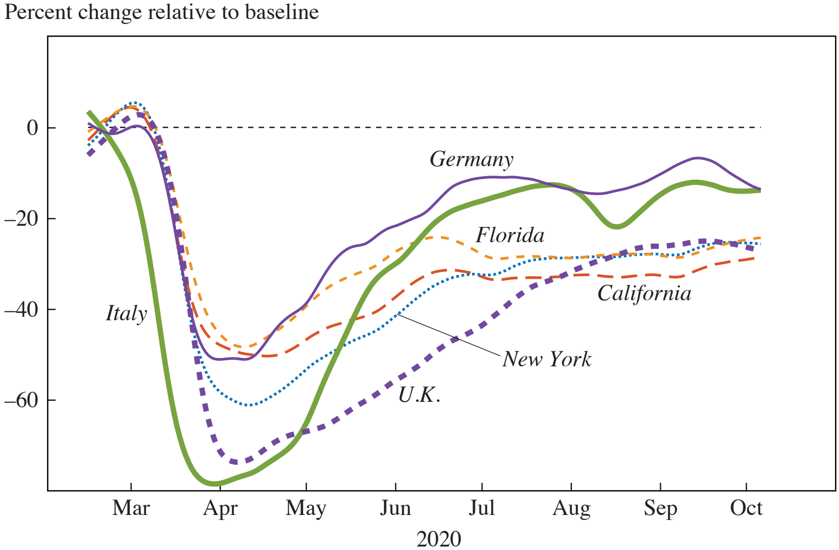
Sources: Google COVID-19 Community Mobility Reports and authors' calculations.
Note: Google activity is the equally weighted average of the retail and entertainment and workplace categories. The data are smoothed with an HP filter with smoothing parameter 400.

Figure 11. Google Activity for Key US States



Sources: Google COVID-19 Community Mobility Reports and authors' calculations.
Note: Google activity is the equally weighted average of the retail and entertainment and workplace categories. The data are smoothed with an HP filter with smoothing parameter 400.

Figure 12. Google Activity for Key US States and Countries

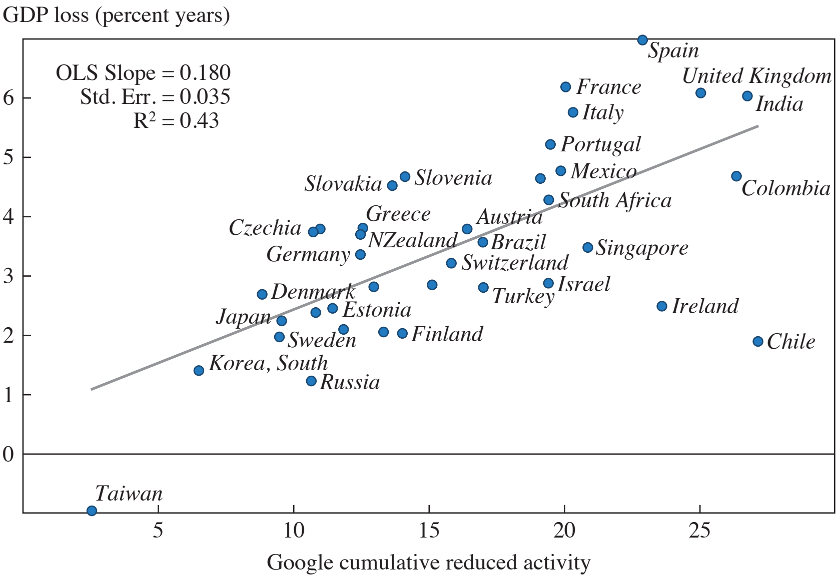


Sources: Google COVID-19 Community Mobility Reports and authors' calculations.
Note: Google activity is the equally weighted average of the retail and entertainment and workplace categories. The data are smoothed with an HP filter with smoothing parameter 400.

the summer while others remain 30 to 40 percent below baseline. Interestingly, Washington, DC, stands out: it has the largest decline of any state at virtually all dates, with activity more than 50 percent below baseline throughout the summer. Recall the contrast with the unemployment data shown earlier in figures 6 and 7. As the nation's capital, Washington, DC, is a special place: a large fraction of jobs are in the government sector and so therefore experienced small declines, while many employees are highly mobile, both nationally and internationally, resulting in large losses in Google activity.

Finally, figure 12 combines some of the key states and countries into a single graph for ease of comparison. The declines in Google activity in Italy and the United Kingdom are substantially larger than the declines in New York State and California, while Germany stands out as having even milder declines in activity than Florida. While the United Kingdom was slower than Italy (and slower than Spain and Germany—see figure 8) to shut down, it was as fast as New York and contracted economic activity more severely. New York had much worse outcomes in terms of deaths (1,700 versus 600), and this is true even if we compare New York City (2,800) versus London (650).

Figure 13. Cumulative Google Activity and Lost GDP



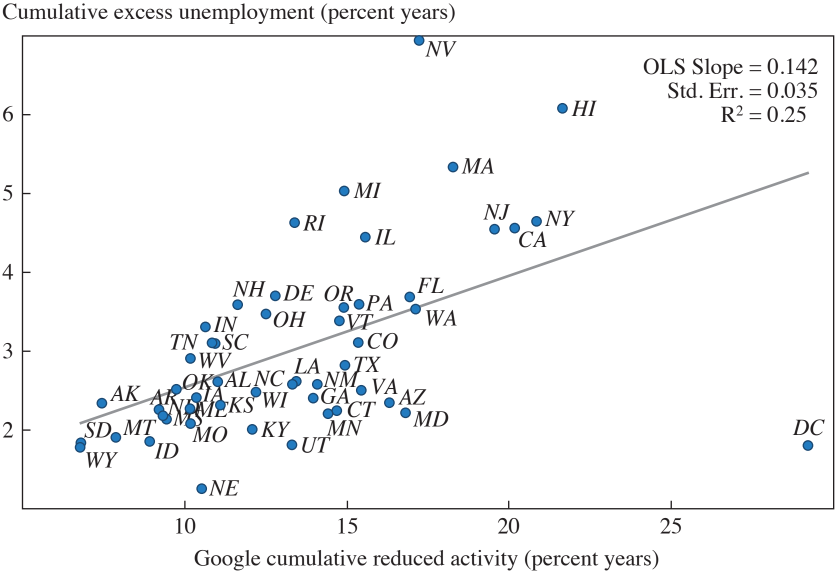
Sources: OECD, Google COVID-19 Community Mobility Reports, and authors' calculations.
Note: "GDP loss" reports the cumulative loss in GDP since the start of 2020 as a percentage of annual GDP. "Google cumulative reduced activity" measures the total amount of lost Google activity at an annual rate. The correlation in the graph is .65.

III.B. Correlating Economic Activity and Google Mobility

Before showing the trade-off graphs with the Google activity measure, we first demonstrate that this measure is correlated with the GDP loss and cumulative excess unemployment. The correlation with the GDP loss is shown in figure 13. Here and in what follows, we add up the areas in the Google activity graphs shown above to get a cumulative loss in Google activity. In particular, Google cumulative reduced activity measures the total amount of lost Google activity at an annual rate. A value of 20 indicates that, relative to baseline, it is as if activity at retail, entertainment, and workplace locations was reduced by 20 percent for an entire year. For example, a 40 percent reduction in activity each month for six months would deliver this value.

Figure 13 illustrates that the Google activity measure is a useful proxy for economic activity. The correlation between the loss in GDP and the cumulative reduction in activity is .65 (the square root of .43).

Figure 14. Cumulative Google Activity and Cumulative Excess Unemployment



Sources: Google COVID-19 Community Mobility Reports, Bureau of Labor Statistics, and authors' calculations.

Note: The correlation is 0.50; it rises to 0.69 if Washington, DC, is dropped.

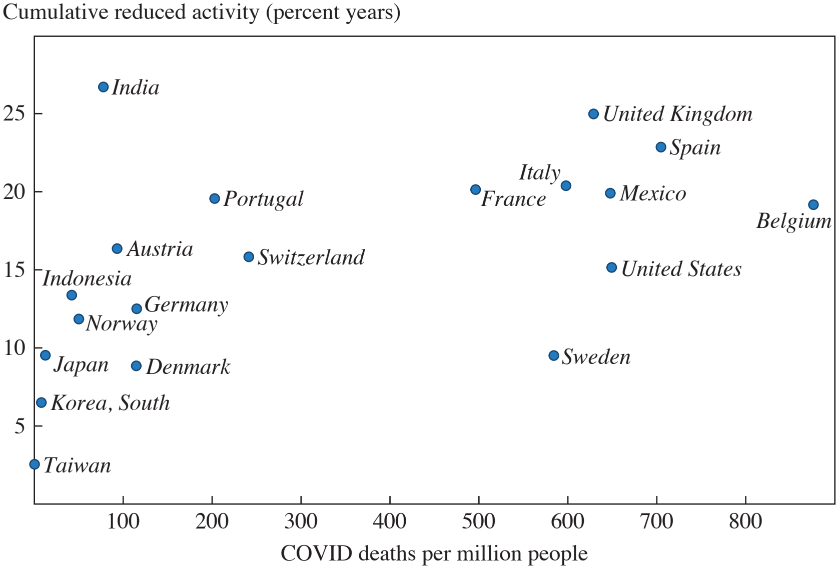
Figure 14 shows this same kind of evidence for US states, only this time for cumulative excess unemployment. The correlation with Google activity is .50 if Washington, DC, is included, but the District of Columbia is an outlier, as has already been mentioned; the correlation rises to .69 if this outlier is dropped.

III.C. Cumulative Results

COUNTRIES Figure 15 shows the cumulative lost activity according to the Google mobility data as of October 9. The first thing to appreciate is that the graph looks very similar to the GDP loss graph in figure 5. This is of course just another way of saying that the GDP data and Google data are highly correlated.

The key takeaways from this figure are therefore also similar. Belgium, the United Kingdom, Spain, and Italy have both very high deaths and very large losses in macroeconomic activity. Taiwan, South Korea, and Japan, as well as Denmark, Norway, and Germany are in the lower left of the graph,

Figure 15. COVID-19 Deaths (Latest) and Cumulative Google Activity (September)



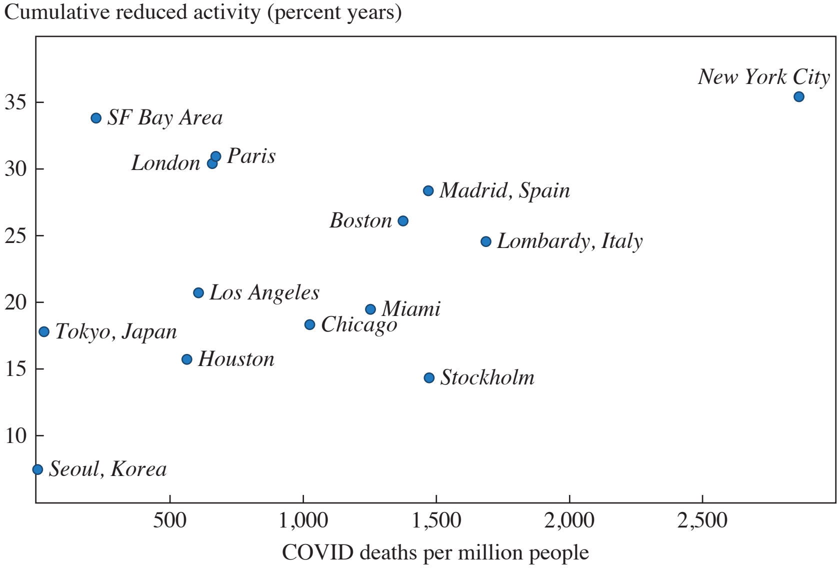
Sources: Google COVID-19 Community Mobility Reports, Johns Hopkins University CSSE, and authors' calculations.

Note: Google activity is the equally weighted average of the retail and entertainment and workplace categories. "Cumulative" refers to the fact that we add up the losses for every month between February and September 2020.

with good performance on both dimensions. Sweden stands out. It looks successful compared to countries like the United Kingdom, Spain, and Italy, with similar deaths but much smaller losses in GDP. On the other hand, compared to Norway and Germany, Sweden looks much less successful, with similar losses in economic activity but far more deaths. The United States is a similar case in that it has fewer deaths and smaller losses in economic activity than the United Kingdom, Spain, and Italy, but it looks much worse than Norway and Germany. India stands out in the upper left quadrant of the graph, having large losses in economic activity with comparatively few deaths. The United States and India have the additional disadvantage that their situations were still rapidly evolving at the time of writing.

CITIES Figure 16 shows one of the advantages of the Google data by disaggregating to the city level for a collection of key cities around the world. Broadly speaking, we see the same types of outcomes for cities that we saw for countries and states using macroeconomic data. New York City has by far the highest death rate in the world at around 2,800 per million people.

Figure 16. Global Cities: COVID-19 Deaths and Cumulative Google Activity



Sources: Google COVID-19 Community Mobility Reports, Johns Hopkins University CSSE, and authors' calculations.

Interestingly, it also has the largest cumulative economic loss, equivalent to around 35 percent of a year's activity.

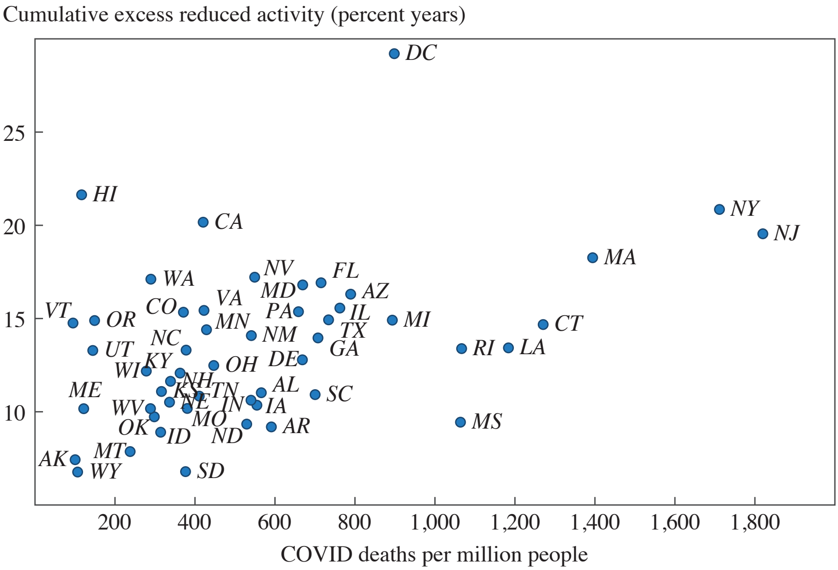
The economic loss is only slightly larger than losses in other cities such as London, Paris, and San Francisco. These cities have far fewer deaths than New York City, however, at around 650 per million for London and Paris and just 220 for the San Francisco Bay Area.

Madrid, Boston, and Lombardy stand out the way Spain and Italy did before, with a high death rate and large economic losses. In contrast, Seoul and Tokyo are much like South Korea and Japan. Stockholm also is positioned about the same as Sweden.

Finally, cities such as Los Angeles and Houston lie in the middle, with deaths somewhat similar to Paris and London, but with noticeably less cumulative loss in economic activity.

US STATES Figure 17 shows the Google activity data and deaths for US states. Apart from Washington, DC—where the large decline in activity contrasts with the small rise in the unemployment rate, as noted above—the pattern is quite similar to what we saw in the unemployment data in figure 7.

Figure 17. US States: COVID-19 Deaths and Cumulative Google Activity



Sources: Google COVID-19 Community Mobility Reports, Johns Hopkins University CSSE, and authors' calculations.

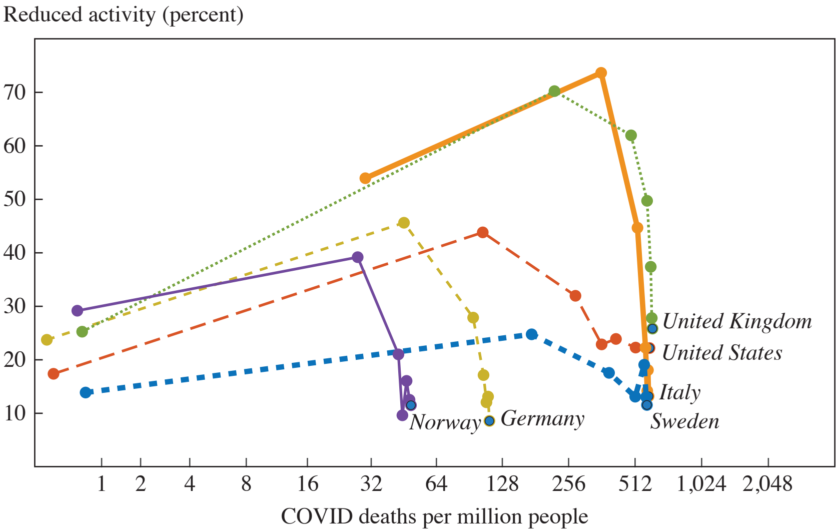
IV. Dynamic Versions of the Trade-Off Graphs

We now take advantage of the high-frequency nature of both the Google activity data and the COVID-19 data to examine the dynamic evolution of our outcomes. In what follows, we show outcomes at the monthly frequency, from March through September. Each dot on the graph is a monthly observation, connected in order, for selected locations identified at the most recent observation point. After experimenting with different ways of showing these data, we focus on plots for the current (flow) Google activity measure instead of the cumulative loss in economic activity.

IV.A. Countries

Figure 18 shows the dynamics for the flow of Google activity for a small set of countries, focused on the United States and some key European economies. The general pattern is that between March and April, countries move sharply up and to the right, as COVID-19 deaths explode and the countries severely restrict economic activity. After April, countries break in two directions. Italy, Germany, Norway, and the United Kingdom see COVID-19

Figure 18. Monthly Evolution from March to September, 2020, for Key Economies



Sources: Google COVID-19 Community Mobility Reports, Johns Hopkins University CSSE, and authors' calculations.

Note: The vertical axis is the current flow of Google activity, averaged for each month. The horizontal axis plots log(1 + deaths) where deaths are as of the 15th of each month.

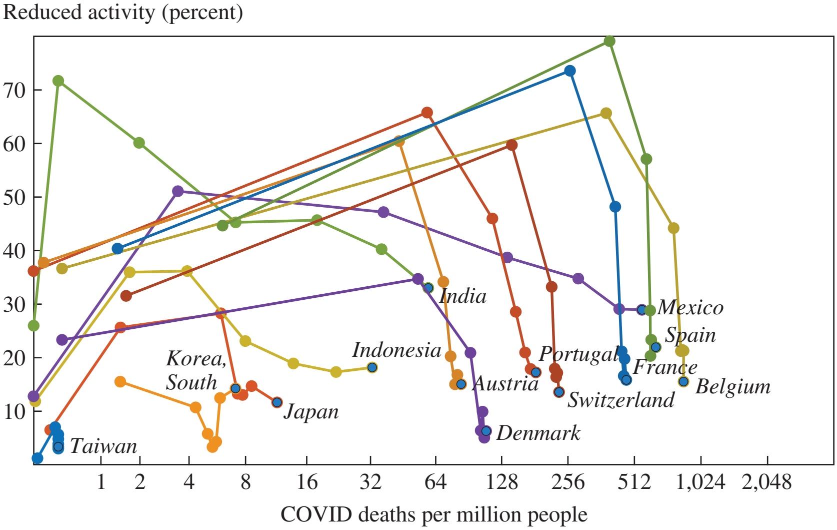
deaths stabilize by May or June, and economic activity starts to recover: the dynamics take the lines sharply downward. In Sweden and the United States, in contrast, deaths continue to increase and there is less economic recovery; the movement is more to the right instead of straight down.

Figure 19 shows this same kind of graph for an additional dozen countries, including Taiwan, South Korea, India, Japan, Mexico, France, and Spain. The same variation is seen among these countries. Most have a large sharp move up and to the right followed by a recovery in economic activity and a stabilization of deaths, illustrated by the vertical nature of the lines in the graph. In contrast, Mexico, India, and Indonesia experience a persistent move to the right as the pandemic continues and deaths have yet to stabilize.

IV.B. Global Cities

Figure 20 shows similar dynamics for key cities or regions around the world. New York City, Lombardy, Madrid, London, and Paris all move sharply up and to the right with the onset of the pandemic. By May, however, the stabilization of deaths and the gradual reopening of the economies is apparent in the vertical portion of the curve.

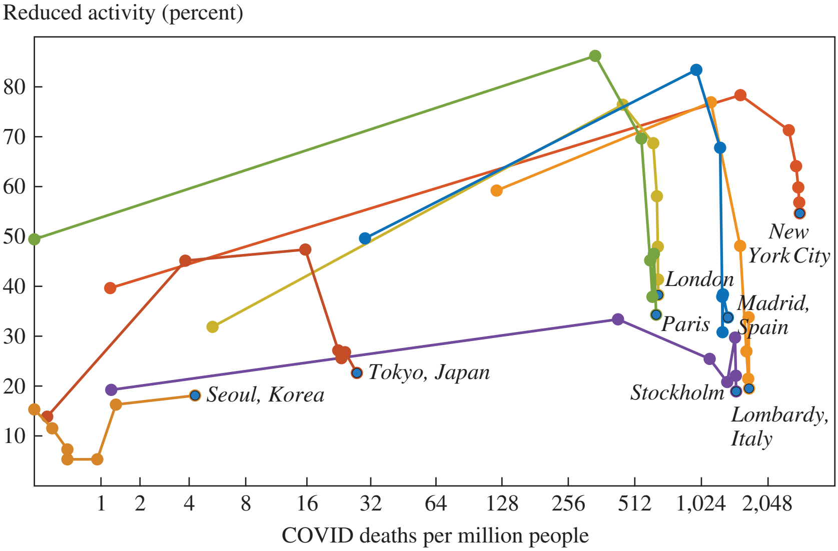
Figure 19. Monthly Evolution from March to September, 2020, for Additional Countries



Sources: Google COVID-19 Community Mobility Reports and authors' calculations.

Note: The vertical axis is the current flow of Google activity, averaged for each month. The horizontal axis plots log(1 + deaths) where deaths are as of the 15th of each month.

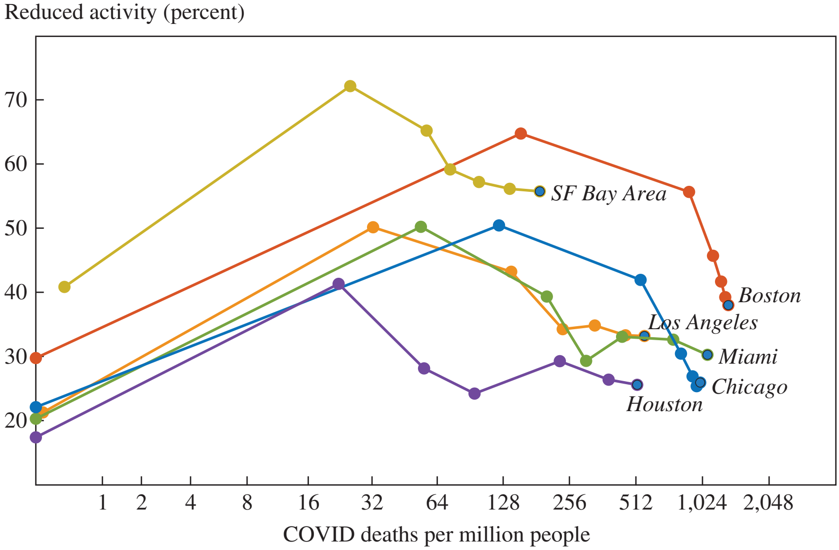
Figure 20. Global Cities: Monthly Evolution from March to September, 2020



Sources: Google COVID-19 Community Mobility Reports, Johns Hopkins University CSSE, and authors' calculations.

Note: The vertical axis is the current flow of Google activity, averaged for each month. The horizontal axis plots log(1 + deaths) where deaths are as of the 15th of each month.

Figure 21. US Cities: Monthly Evolution from March to September, 2020



Sources: Google COVID-19 Community Mobility Reports, Johns Hopkins University CSSE, and authors' calculations.

Note: The vertical axis is the current flow of Google activity, averaged for each month. The horizontal axis plots log(1 + deaths) where deaths are as of the 15th of each month.

Stockholm is an interesting contrast in that Google activity declines by only about 20 to 30 percent for the entire spring, far less than in many other cities. On the other hand, the rightward move continues for longer, resulting in appreciably more deaths.

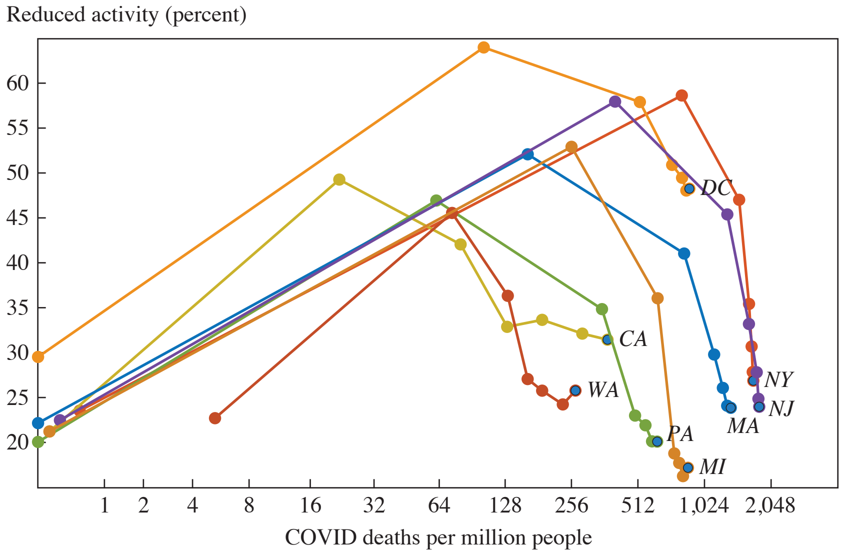
Finally, Tokyo and Seoul are interesting to compare. Tokyo had a much larger decline in economic activity peaking at around 45 percent in April and May. By comparison, Seoul saw reductions of 20 percent or less each month. While both cities end with enviably low deaths, the death rate in Seoul is about 4 per million versus six times larger at 24 per million in Tokyo.

Figure 21 shows a similar graph for cities in the United States. Here the continued rightward trends in Houston, Miami, Los Angeles, and San Francisco are evidence that the pandemic was not yet under control.

IV.C. US States

The next two figures show the dynamics for US states, confirming the two types of patterns we've seen in countries and cities. Figure 22 shows that in states like New York, New Jersey, Massachusetts, Michigan, and

Figure 22. US States: Monthly Evolution from March to September, 2020



Sources: Google COVID-19 Community Mobility Reports, Johns Hopkins University CSSE, and authors' calculations.

Note: The vertical axis is the current flow of Google activity, averaged for each month. The horizontal axis plots log(1 + deaths) where deaths are as of the 15th of each month.

Pennsylvania, deaths have stabilized. By contrast, figure 23 shows many states where this is not true. The continued movement to the right documents the continued rise in deaths from COVID-19.

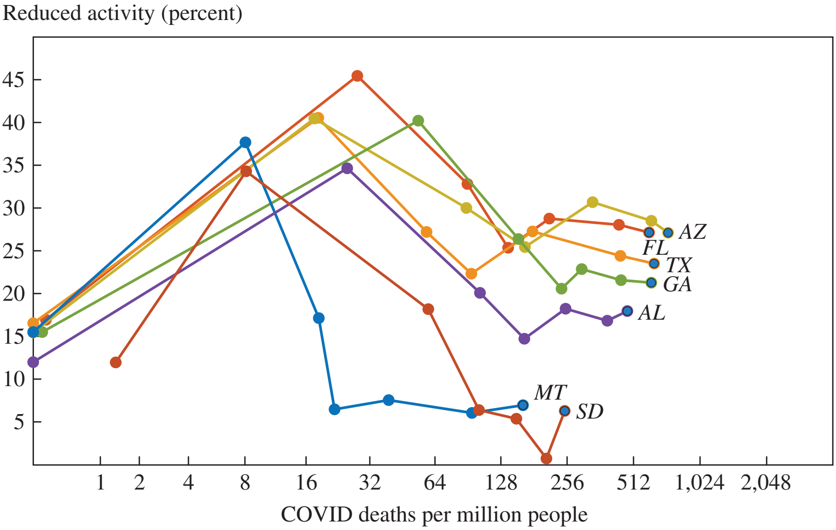
V. Conclusion

We have combined data on GDP, unemployment, and Google's COVID-19 Community Mobility Reports with data on deaths from COVID-19 to study the pandemic's macroeconomic outcomes.

Our main finding is that most countries, regions, or cities fall in either of two groups: large GDP losses and high fatality rates (New York City, Lombardy, United Kingdom) or low GDP losses and low fatality rates (Germany, Norway, Kentucky). Only a few exceptions, mainly California and Sweden, depart from this pattern.

This correlation has a simple explanation at a mechanical level. Through some combination of government mandates and voluntary changes in behavior, those areas that suffered high mortality reduced economic activity dramatically to lower social contacts and slow down the pandemic's spread.

Figure 23. Other US States: Monthly Evolution from March to September, 2020



Sources: Google COVID-19 Community Mobility Reports, Johns Hopkins University CSSE, and authors' calculations.

Note: The vertical axis is the current flow of Google activity, averaged for each month. The horizontal axis plots log(1 + deaths) where deaths are as of the 15th of each month.

In comparison, those locations that were able to control the virus from the beginning could maintain economic activity and suffer fewer deaths.

This observation suggests that controlling the epidemic is vital to mitigating GDP losses. It is easy to be sympathetic with this view, as it avoids the classic trade-offs in economics between alternative ends. With COVID-19, the evidence suggests that it is possible to be successful on both dimensions, minimizing deaths as well as other economic losses.

Nonetheless, it is challenging given our current data to gauge the extent to which a low death toll was the product of good luck versus good policy. Taiwan, South Korea, and Germany have been praised for their early and aggressive testing programs and intensive use of contact tracing, and several papers have highlighted the effectiveness of non-pharmaceutical interventions. But Taiwan and South Korea might have been hit by a less contagious form of the virus and might have benefited from prior experience with SARS and MERS. More of the circulation of SARS-CoV-2 in Germany might have occurred among younger cohorts than in other European countries. Further research will be required to separate the roles of luck from policy and to determine which policies were especially effective.

These arguments also work in reverse when we analyze the two main outliers in our data set: California and Sweden. California seems to have lost too much GDP given the severity of the health crisis it faced. Sweden could have reduced its mortality without too much GDP loss, at least as suggested by its Nordic neighbors' performance. But again, California was hit early by the first form of virus, perhaps less contagious. From the perspective of California's policymakers, the decisions taken ex ante in March might be fully justified even if too tight ex post. Sweden might have suffered from higher density in Stockholm, worse demographics, and other social differences with its neighbors.

Finally, we should notice that COVID-19 has policy spillovers, both in terms of health and economic outcomes. Had Italy controlled its epidemic earlier, France and Germany might have suffered a milder crisis. And if China had not undertaken draconian measures in Wuhan, South Korea might look very different today. Before rushing to judgment regarding the effect of different policies, these spillover effects must be analyzed in more detail. Regarding economic outcomes, a fall in global economic activity has dire consequences even for countries that have been able to control the virus. For example, Goldberg and Reed (2020) document that emerging market and developing economies have suffered from massive capital outflows and large price declines for certain commodities, especially oil and nonprecious metals.

Our conclusions are subject to a fundamental consideration. Health professionals in China started to suspect the presence of a new respiratory disease in the last week of December 2019. The first public message regarding the pandemic occurred on December 31, 2019, and was reported as a minor news item by a few Western media outlets. Only ten months have passed since that news.

Furthermore, the pandemic continues. Even in the best-case scenario in which effective vaccines and rapid tests become widely available by early 2021, we will still face, at the very least, a difficult first two quarters of 2021. There are already some indications that an additional wave of the pandemic may crest in the autumn of 2020 and winter of 2021. All the graphs that we report may look quite different by mid-2021. By then, it may be much more apparent how much the divergence in outcomes is driven by luck and by policy.

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Comment and Discussion

COMMENT BY

ANDREW ATKESON The paper by Fernández-Villaverde and Jones is a useful summary of the patterns of lost economic activity and COVID-19 deaths that have been seen to date across a wide range of locations, both countries and states of the United States. This paper is part of a rapidly growing body of literature that looks to estimate the relationship between pandemic deaths and lost economic output, both in current data and in data from the 1918–1919 Spanish influenza.

My comment is focused on the question of how should we interpret empirical findings on the cross-country or cross-regional relationship between cumulative deaths and lost economic activity from COVID-19 or the Spanish influenza such as those presented in this paper. What should we expect to see in the cross-sectional relationship across countries or US states between cumulative deaths and cumulative lost activity from this pandemic? Should we expect to see higher cumulative deaths associated with higher cumulative lost activity as one might expect if some regions were simply more susceptible to the pandemic than others? Or should we expect the reverse: higher cumulative deaths associated with lower cumulative lost activity as one might expect if one envisioned a trade-off for behavior and policy between disease control and economic output? This question is central to our establishing an empirical framework to determine to what extent does this cross-sectional heterogeneity in activity and deaths result from inherent differences across countries and regions versus reflecting the impact of heterogeneous private and public policy responses to the pandemic.

In their paper, Fernández-Villaverde and Jones point to luck and policy as two factors that might vary across locations and thus play a role in shaping the observed differences in outcomes. In my comment, I take a small step toward giving the terms “luck” and “policy” structural interpretations within the context of a simple epidemiological model that incorporates in a very reduced-form way elements of an endogenous response of behavior, and hence economic activity, to the state of the disease in the population. I refer to this model as a behavioral SIR model.[1]

This behavioral SIR model extends the standard epidemiological SIR model with two equations. One equation relates the level of human activity to the transmission rate of the disease. The higher the level of human activity, the more frequently infected and susceptible people meet and transmit the disease from one to the other. The other equation relates the level of daily deaths to the level of human activity. The higher the level of deaths from the disease, the greater is the level of fear in the population and hence the lower is the level of human activity. In this model, with these two equations, I interpret luck as factors determined in advance of the pandemic that alter the rate of disease transmission in a given location, holding fixed the level of human activity in that location. These factors might include population density, average temperature and humidity, predetermined cultural differences regarding physical contact (kissing and shaking hands, etc.), and the demographic structure of households. I interpret policy as factors that alter the strength of the endogenous response of activity to the current state of the disease. These factors might include true policy differences regarding the speed and severity of lockdowns in response to rising deaths from COVID-19 as well as heterogeneity across locations in the semielasticity of the decentralized response of individuals in choosing to avoid contact with others based on the current state of the epidemic in their location.

My main finding with this simple behavioral SIR model is that the slope of the relationship in the cross section across regions between cumulative deaths and cumulative lost activity depends on whether it is differences in luck or policy that are driving the heterogeneity in outcomes across locations. I establish this finding with two illustrative numerical experiments solving for the equilibrium paths of activity and COVID-19 deaths implied by this model for locations that differ either in terms of their luck or their policy.

In the first experiment, regions differ in the level of disease transmission holding fixed activity but are identical in terms of the semielasticity of the relationship between agents’ choice of activity and the current level

1. The model is derived from one first presented by Gianluca Violante at the NBER Economic Fluctuations and Growth Summer 2020 meeting, July 11, on Zoom; slides available at http://conference.nber.org/confer/2020/EFGs20/Violante.pdf.

of daily deaths. This heterogeneity implies that regions with higher basic reproduction numbers (transmission rates at the start of the epidemic) experience both higher cumulative deaths and higher cumulative lost activity. As we shall see, the outcomes in the hypothetical regions considered in this model experiment resemble those shown in figure 3 of the paper by Fernández-Villaverde and Jones. Because these differences in disease transmission rates across regions are assumed to have been determined prior to the start of the pandemic, it would not be correct to interpret differences in outcomes across regions in this experiment as resulting from policy differences. Instead, it would seem reasonable to say that these differences across locations are driven by luck.

In the second experiment, regions differ in the semielasticity of agents' endogenous response of activity to daily deaths but are identical in terms of the level of transmission holding fixed activity. Equivalently, one can interpret the heterogeneity across locations in this experiment as being driven by differences in the semielasticity of policy-induced restrictions on human activity in response to rising daily deaths. In this experiment, in contrast to what we found in the first experiment, regions with agents (or policies) that are highly responsive in terms of reducing activity as daily deaths rise end up with lower cumulative deaths and higher cumulative lost activity. As we shall see, the outcomes in the hypothetical regions considered in the model experiment resemble those shown in figure 2 of the paper by Fernández-Villaverde and Jones. In this case, there appears to be a trade-off between economic outcomes and cumulative deaths from the disease, where this trade-off can be interpreted as a trade-off for policy between disease control and economic outcomes.

Finally, in a third experiment, I show how by allowing both for heterogeneity in the disease transmission rate given activity and in the semielasticity of the response of activity to the level of daily deaths, one might find a region in each quadrant of figure 1 in the paper. This experiment simply highlights that to interpret the cross-country and cross-state data on cumulative deaths and cumulative lost economic activity in this pandemic (or in 1918–1919) one must be careful to disentangle which sources of heterogeneity are driving the differing outcomes across regions.

The remainder of my comment is organized as follows. First I present the behavioral SIR model that I use in my experiments. Then I briefly discuss how this model is capable of reproducing salient features of the data on the transmission of COVID-19 seen across most countries and regions of the world. In this part of my discussion, I make reference to work I have done with Karen Kopecky and Tao Zha documenting four stylized facts about COVID-19 over the past six months (Atkeson, Kopecky, and Zha 2020). I then conduct my numerical experiments and conclude.

A BEHAVIORAL SIR MODEL Consider the following specification of a behavioral SIR model. I apply the model either to countries or to states of the United States. I normalize the population to one in each region that I consider. Thus, the model's implications for daily and cumulative deaths and activity in a region should be interpreted on a per capita basis.

At any point in time, the state vector for the model is the distribution of the individuals in the population across four compartments S, I, R, or D for susceptible, infected, recovered, or dead, respectively.

The dynamics of the population in region i across these disease compartments are given by the following equations:

$$\dot{S}_i(t) = -\beta_i(t) S_i(t) I_i(t), \tag{1}$$

$$\dot{I}_i(t) = [\beta_i(t) S_i(t) - \gamma] I_i(t), \tag{2}$$

$$\dot{R}_i(t) = \gamma(1 - \nu) I_i(t), \text{ and} \tag{3}$$

$$\dot{D}_i(t) = \gamma \nu I_i(t). \tag{4}$$

Here a dot over a variable (on the left side of these equations) indicates the time derivative of that variable.

Note that the parameter γ is the recovery rate from the disease, and the parameter ν is the fatality rate (the fraction of those that cease being infectious because they died). For simplicity, I assume that these parameters are common across regions and constant over time.[2]

I assume that the transmission rate of the disease at time t in region i, denoted by β_i (t), is a function of activity in the region $Y_i(t)$ at that date:

$$\beta_i(t) = \bar{\beta}_i Y_i(t)^{\alpha} \exp(\nu_i(t)). \tag{5}$$

2. Clearly, in a full empirical study one would want to consider the possibility that these parameters might vary across regions or over time. Variation across regions or over time in the parameter γ governing the length of time that an infected individual may meet and infect a susceptible individual may reflect different policies for identifying and isolating infected individuals. Variation in the fatality rate ν across regions over time may reflect different age compositions of the population getting infected or different regimes for treating those with infections.

Here activity $Y_i(t)$ is measured using cell phone or similar data or, alternatively, data on economic activity. The parameter $\bar{\beta}_i$ in equation (5) is a fixed coefficient that captures features of the population of region i determined prior to the epidemic that might have an impact on transmission. Factors considered in the literature include population density, modes of transportation (subway versus car, etc.), household and demographic structure, cultural norms (bowing versus shaking hands or kissing), temperature and humidity, and so on. This is the parameter that I interpret as corresponding to luck.

The parameter α captures the elasticity of transmission with respect to activity. For simplicity, we assume that this parameter is common across regions.

The parameter $v_i(t)$ represents a potentially time-varying shock to the region-specific relationship between activity and transmission that may represent the impact of policy or natural variation in the transmission of the virus over time. I normalize $v_i(0) = 0$. When interpreting variation in $v_i(t)$ as representing the impact of policies, here I am thinking about policies such as mask wearing, ventilation, physical distancing, redesign of work spaces, or other measures implemented after the start of the epidemic that reduce transmission given a fixed level of activity.

I normalize the level of activity at the start of the pandemic to $Y_i(0) = 1$. Given this normalization, the parameter $\bar{\beta}_i$ sets the transmission rate of the virus in region i at the start of the epidemic. Specifically, $\bar{\beta}_i/\gamma$ corresponds to the basic reproduction number of the epidemic in region i, denoted by $\mathcal{R}_i(0)$. For this reason, I identify variation in $\bar{\beta}_i$ across regions as predetermined, or luck, while variation over time in $v_i(t)$ would correspond to changes in policy or personal behavior made after the start of the epidemic.[3]

Next I introduce the behavioral component of the model. I assume that individuals' decisions to engage in activity in region i at time t, $Y_i(t)$, are a declining function of the time derivative of cumulative deaths, $\dot{D}_t(t)$, which I refer to as the current level of daily deaths. I specify this function describing behavior as

$$Y_i(t) = \exp\left(-\sigma_i \dot{D}_t(t) + u_i(t)\right). \tag{6}$$

3. Note that constant shifts in the level of $\exp(v_i(t))$ have an equivalent impact on the relationship between activity and disease transmission in equation (5) to changes in the parameter $\bar{\beta}_i$. Thus fixed differences in policies of this kind are not distinguishable from fixed differences in the basic reproduction number in terms of their impact on model outcomes.

Here, $\sigma_i > 0$ represents the semielasticity of activity $Y_i(t)$ with respect to daily deaths. Note that we allow the semielasticity σ_i to vary by region.

The variable $u_i(t)$ in equation (6) represents a time-varying shock to the region-specific relationship between deaths and activity. I interpret $u_i(t)$ as reflecting policies such as lockdowns or closures that would reduce activity below what agents might choose in a decentralized fashion. Note that if such policies are imposed conditional on the state of the disease, with restrictions on activity becoming more severe as the level of daily deaths rises—as in $u_i(t) = -\eta_i \dot{D}_i(t)$ with $\eta_i > 0$—then this dimension of policy heterogeneity across regions would also be a reason for why the semielasticity of activity with respect to daily deaths would vary across regions. Thus, I interpret differences in the semielasticity of activity with respect to daily deaths as due to either private behavior or public policy. Together I interpret these differences as policy.

I compute the cumulative loss in activity using the equation

$$\text{(7)} \qquad \dot{CY}_i(t) = 1 - Y_i(t),$$

with initial condition $CY_i(t) = 0$. Note that a large value of this variable corresponds to more lost cumulative activity relative to the prepandemic level of $Y_i(0) = 1$.

Observe that by substituting equation (6) into equation (5) we get a reduced-form relationship between the current level of daily deaths and the transmission rate given by

$$\text{(8)} \qquad \beta_i(t) = \bar{\beta}_i \exp\left(-\alpha\sigma_i \dot{D}_i(t) + \alpha u_i(t) + v_i(t)\right).$$

To solve this model for a particular region i, I specify initial conditions $S_i(0)$, $I_i(0)$, $R_i(0)$, $D_i(0)$, and $CY_i(0)$; parameters γ, ν, $\bar{\beta}_i$, α, and σ_i; and time paths for shocks $v_i(t)$ and $u_i(t)$. I solve for the implied evolution of the disease using equations (1) to (4) and the reduced form for transmission in equation (8). I then solve for activity from equation (6) and cumulative activity from equation (7).

Parameter Values. In what follows I perform several computational experiments with this model in which I examine the course of the epidemic and activity in hypothetical regions that differ in terms of their parameters $\bar{\beta}_i$ and σ_i.

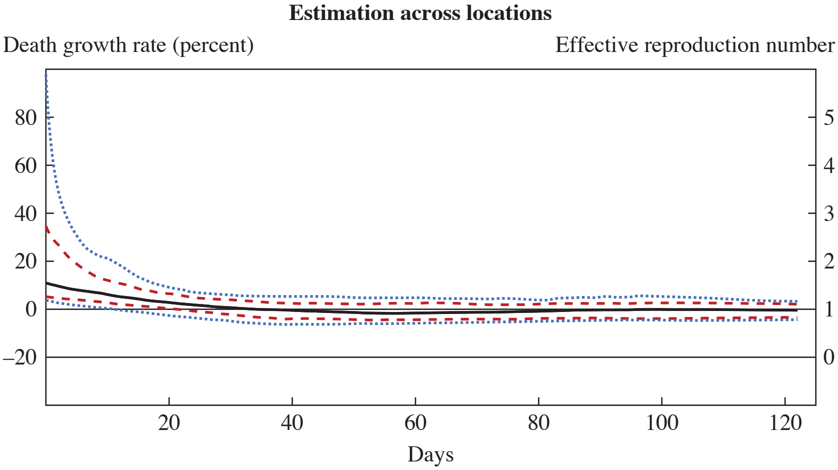
In all of the computational experiments, I solve the model for 180 days and I start from identical initial conditions of $R_i(0) = D_i(0)$, $I_i(0) = 0.0001$, $S_i(0) = 1 - I_i(0)$, and $CY_i(0) = 0$. I set $\gamma = 1/5$, $\nu = 0.005$, and $\alpha = 2$ in all experiments. (Note that some argue for $\alpha = 2$ on the grounds that an increase in activity by the representative agent results in an increase in meetings equal to the square of the increase in activity.) In these computational experiments, I set all shocks $u_i(t) = v_i(t) = 0$ for all t. I leave consideration of the impact of such shocks on model-implied outcomes to future research.

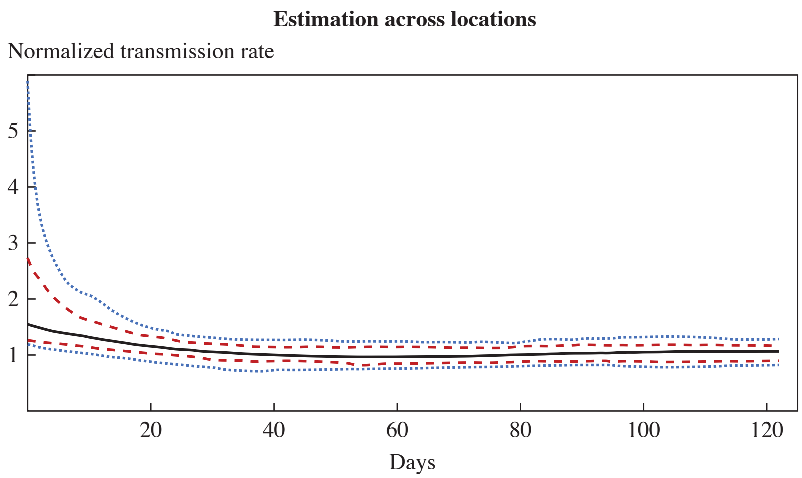
STYLIZED FACTS ON COVID-19 TRANSMISSION In this comment, I address this question regarding our expected cross-sectional relationship between cumulative activity and cumulative deaths using a simple behavioral SIR model of the first 180 days of the epidemic. I chose this model because of its ability to reproduce salient features of the data on the transmission of COVID-19 (as captured by the time path of the parameter $\beta_i(t)$ and the corresponding effective reproduction number $\mathcal{R}_i(t) \equiv \beta_i(t)S_i(t)/\gamma$ in the model above) seen across most countries and regions of the world. More specifically, in recent work with Kopecky and Zha (Atkeson, Kopecky, and Zha 2020), we document four salient facts about the dynamics of the COVID-19 epidemic observed so far. I show an updated presentation of these four facts using data through September 9 in figure 1 of this discussion. In this updated presentation, we estimate the dynamics of the COVID-19 epidemic in fifty-one countries and thirty-one states of the United States. We show the dynamics of the distribution of growth rates of daily deaths across these locations starting from the date at which cumulative deaths reached twenty-five in each location on the left axis of this figure. On the right axis of this figure, we show the dynamics of the distribution of effective reproduction numbers across these locations implied by our SIR model above.

The first three facts that we document in figure 1 are as follows: First, across all countries and US states that we have studied, the growth rates of daily deaths from COVID-19 fell from a wide range of initially high and highly dispersed levels to levels close to zero within twenty to thirty days after each region experienced twenty-five cumulative deaths. Second, after this initial period, growth rates of daily deaths have hovered around zero or below everywhere in the world. Third, the cross-sectional standard deviation of growth rates of daily deaths across locations fell very rapidly in the first ten days of the epidemic and has remained at a relatively low level since then.

These three facts can be seen in the first panel of figure 1. The left-hand scale in that plot shows the distribution of estimated growth rate of daily deaths across fifty-one countries and thirty-one US states, with the start of the data in each location taken from the first date at which cumulative

Figure 1. Dynamics of the Distribution of Growth Rates of Daily Deaths, Effective Reproduction Numbers, and Transmission Rates with Location and Sampling Uncertainty





Source: Author's calculations.

Notes: The solid line in both charts represents the median posterior estimate of these variables across fifty-one countries and thirty-one states of the United States. The two dashed lines in both charts contain two-thirds of the posterior probability at each point in time, and the two dotted lines .90 of the posterior probability. The growth rates of death are estimated according to the fitted mixture of modified log-logistic densities. Effective reproduction numbers and normalized transmission rates are based on the SIR model.

deaths reached twenty-five. The solid line is the median estimate of the growth rate. The dashed lines contain two-thirds of the posterior probabilities (considering both sampling and regional variation), and the dotted lines contain 90 percent of the posterior probabilities of estimated growth rates. In this figure, we see high and highly dispersed initial growth rates, with the distribution of growth rates of deaths falling to around zero with much less dispersion after twenty to thirty days. We see that this distribution of growth rates of daily deaths has stayed centered roughly around zero with a low cross-sectional variation relative to the cross-sectional variation observed in the initial phase of the epidemic.

The fourth fact we identify is as follows. When interpreted through a range of epidemiological models, these first three facts about the growth rate of COVID-19 deaths imply that both the effective reproduction numbers and transmission rates of COVID-19 fell from widely dispersed initial levels and the effective reproduction number has hovered around one after the first thirty days of the epidemic virtually everywhere in the world. This fact can be seen on the right-hand scale of the first panel of figure 1 and in the second panel of that figure, which shows the dynamics of the distribution of disease transmission rates across locations. Note that in a simple SIR model, the effective reproduction number is a linear transformation of the growth rate of daily deaths. Thus, the model-implied reproduction numbers ($\mathcal{R}_i(t) \equiv \beta_i(t)S_i(t)/\gamma$) for our locations can be read off the right-hand axis in the first panel of figure 1. We see, as with the growth rates of daily deaths, that the effective reproduction numbers across locations fell from high and highly dispersed initial levels close to one rather rapidly and have remained close to this level since. The transmission rates $\beta_i(t)/\gamma$ are calculated from the effective reproduction numbers after backing out an estimate of the pool of susceptible individuals $S_i\ (t)$ in each location.

The dynamics of the growth rates of deaths and the transmission rates of COVID-19 shown in figure 1 stand in sharp contrast to those patterns that would be predicted by a standard SIR model in which the transmission rate $\beta_i(t)$ is assumed to stay constant at a fixed value over time.[4] In such a model, absent policy intervention, the growth rates of daily deaths and the corresponding effective reproduction numbers of the disease would have remained high and highly dispersed for quite a long time.

Many economic models of the COVID-19 epidemic that build on a standard SIR model are based, at least qualitatively, on a structure that

4. Such a model is equivalent to one in which the semielasticity of activity with respect to daily deaths—σ_i in equation (6)—is equal to zero.

incorporates analogs of equations (5) and (6) resulting in a reduced-form relationship between the transmission rate and daily deaths shown in equation (8). As we shall see in the numerical experiments below, this simple behavioral SIR model implies an initial dispersion of growth rates of daily deaths (and effective reproduction numbers) across locations as determined by heterogeneity in the parameter $\overline{\beta}_i$ in equation (5) across locations. Likewise, we shall see that, for a wide range of parameters, the growth rate of daily deaths in each location falls rapidly toward zero, or more precisely, a bit below zero, with the speed of the decline determined by heterogeneity in the parameter σ_i in equation (6) across locations. Thus this simple model can produce a wide range of disease outcomes at least roughly consistent with the disease dynamics shown in figure 1. The corresponding implications of this model for activity are then derived from equations (6) and (7).

WHAT IS THE RELATIONSHIP BETWEEN DEATHS AND ACTIVITY? I now use computational experiments to make three points.

First, this model can reproduce qualitatively the dynamics of disease transmission and activity seen in many locations for a wide range of parameter values.

Second, in the cross section of locations, this model can generate a positive relationship between cumulative deaths and cumulative lost activity or a negative relationship between cumulative deaths and cumulative lost activity depending on whether it is the parameters $\overline{\beta}_i$ or elasticities σ_i that vary across locations.

Third, in the cross section of locations, if differences in both $\overline{\beta}_i$ and σ_i across locations are considered, the model can generate outcomes for cumulative deaths and cumulative lost activity located in all four quadrants of the diagram in figure 1 in the paper by Fernández-Villaverde and Jones.

Experiment 1: Differences in the basic reproduction number imply more cumulative deaths with more lost cumulative activity. In our first computational experiment, I consider three regions that differ in the parameter $\overline{\beta}_i$ having an impact on the level of the relationship between activity and transmission in equation (5). I interpret this experiment as showing the impact of predetermined features of the region that have an impact on the level of transmission given activity.

Recall that the ratio $\overline{\beta}_i/\gamma$ corresponds to the basic reproduction number of the disease in region i, that is, to the effective reproduction number of the disease at the beginning of the epidemic. Consistent with the range of estimates seen across regions in figure 1, I set this basic reproduction number to $\overline{\beta}_i/\gamma$ equal to 2.75, 2.25, and 1.75 in three locations. I assume that the semielasticities $\sigma_i = 125{,}000$ are the same in each region.

I show the results from this computational experiment in figure 2. Panel A shows the path of daily deaths per million residents in these three hypothetical locations. Panel B shows the time path of daily activity relative to the pre-epidemic level (normalized to one). Panel C shows the path of the effective reproduction number in each location. Panel D shows the cross-sectional relationship between cumulative deaths per million over a period of 180 days and the logarithm of cumulative lost activity over the same time period.

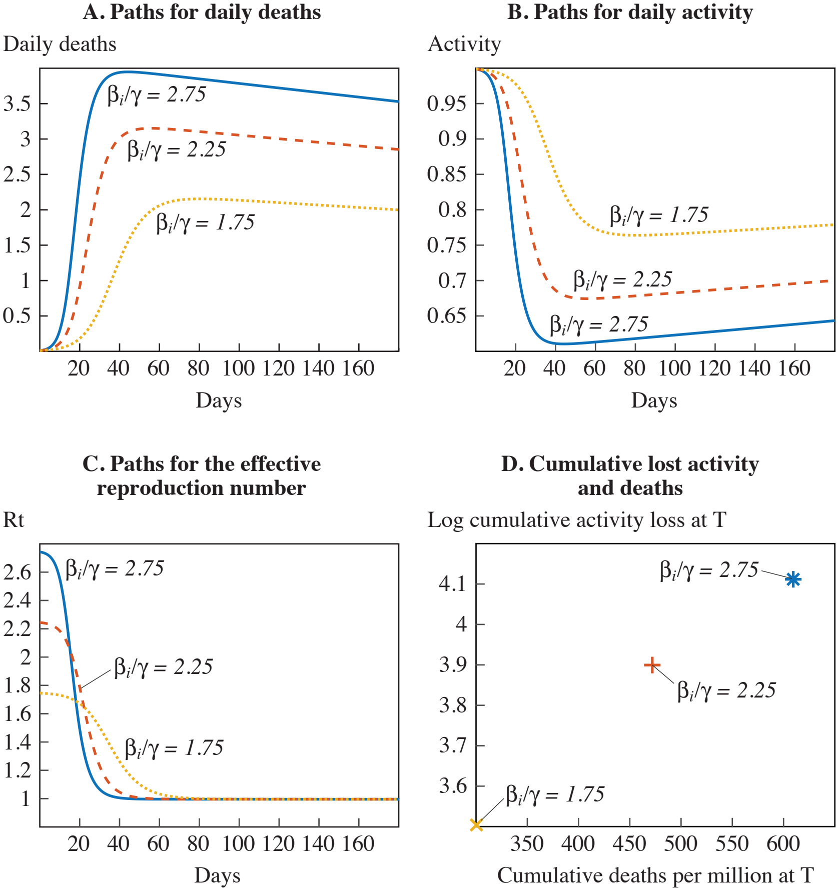
In this figure, we see a dramatic initial increase in daily deaths per million in each location, followed by a slow decline in the number of daily deaths. Activity declines abruptly, followed by a slow recovery. We see that the effective reproduction number in each location starts at initially dispersed levels and then falls relatively rapidly to slightly below one. This outcome is consistent with the data shown for a wide range of countries and US states in figure 1. Finally, in panel D, we see a positive slope in the relationship between cumulative deaths and the log cumulative lost activity—that is, more deaths are associated with more lost activity.

The intuition for this outcome is straightforward. These regions share the same parameters in equation (6) relating the level of daily deaths to current activity, but they differ in equation (5), relating the level of activity to transmission and, hence, the growth rate of daily deaths. Thus, we see that the region with the highest value of $\bar{\beta}_i$ has higher daily deaths, lower activity, and a higher effective reproduction number than the other regions, leading, after 180 days, to worse outcomes in terms of both cumulative deaths and lost economic activity. One might reasonably ascribe the difference in outcomes here to differences in luck.

Experiment 2: Differences in semielasticities of activity with respect to daily deaths imply more cumulative deaths with less lost cumulative activity. In our second computational experiment, I consider three regions that differ in the semielasticity σ_i governing the slope of the relationship between the level of daily deaths and activity in equation (6). I assume that these semielasticities are given by $\sigma_i = 40{,}000$, 80,000, and 160,000. I assume that the parameter $\bar{\beta}_i$ having an impact on the level of the relationship between activity and transmission in this case does not vary across regions. I set this basic reproduction number to $\bar{\beta}_i/\gamma$ equal to 2.25 in all three locations.

In figure 3, I show the results from this computational experiment. As before, panel A shows the path of daily deaths per million residents in these three hypothetical locations. Panel B shows the time path of daily activity relative to the pre-epidemic level. Panel C shows the path of the

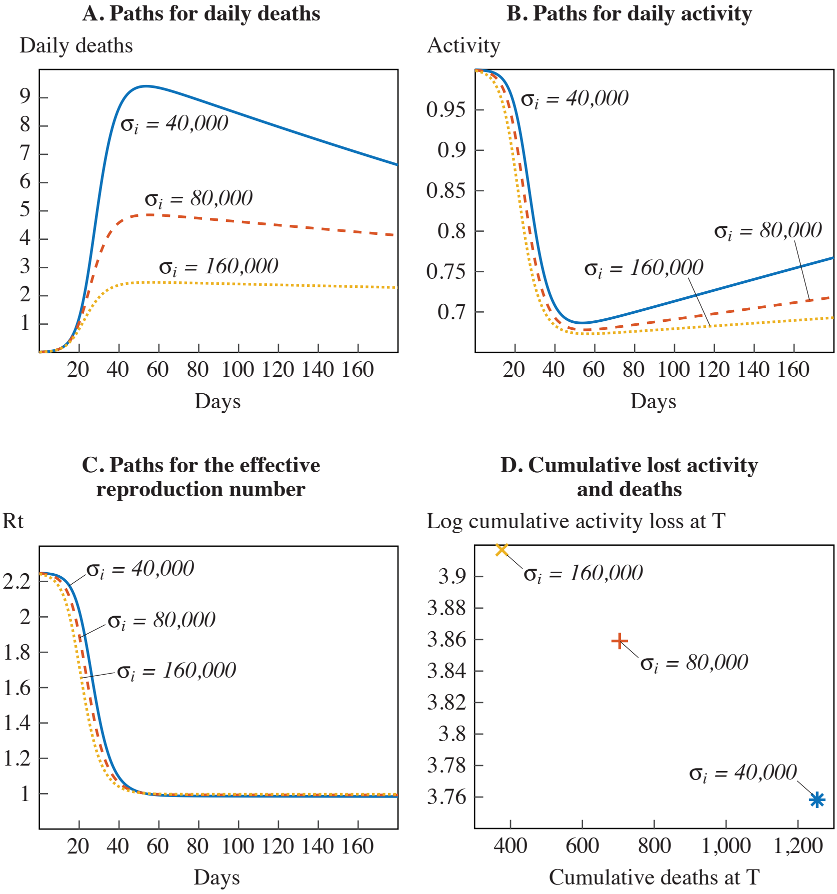
Figure 2. Implications of a Behavioral SIR Model corresponding to Alternative Values of the Basic Reproduction Number



Source: Author's calculations.

Notes: Experiment 1 addresses dynamics of the epidemic and activity in three regions that vary in the level of transmission given activity $\bar{\beta}_i$. In panel D this heterogeneity across regions leads to an upward-sloping relationship between cumulative deaths and cumulative lost activity.

Figure 3. Implications of a Behavioral SIR Model corresponding to Alternative Values of the Semielasticity of Activity with Respect to Daily Deaths



Source: Author's calculations.

Notes: Experiment 2 addresses dynamics of the epidemic and activity in three regions that vary in the semielasticity of activity with respect to daily deaths σ_i. In panel D this heterogeneity across regions leads to a downward-sloping relationship between cumulative deaths and cumulative lost activity.

effective reproduction number in each location. Panel D shows the cross-sectional relationship between cumulative deaths per million over a period of 180 days and the logarithm of cumulative lost activity over the same time period.

In terms of their rough shapes, the dynamics of daily deaths, activity, and the effective reproduction number shown in figure 3 are similar to those dynamics shown in figure 2. In figure 3, panel D, however, we see a negative slope in the relationship between the log of cumulative deaths and the log cumulative lost activity—that is, more deaths are associated with less lost activity.

The intuition for this result is straightforward. Because these three regions share the same parameter $\overline{\beta}_i$ in equation (5), they all have the same transmission rate of the epidemic holding fixed the level of activity. Region 3, however, has the highest semielasticity of activity with respect to daily deaths, and hence activity and the effective reproduction number both fall more rapidly as daily deaths begin to rise. This elastic response of activity to daily deaths then leads to an apparent trade-off between cumulative deaths and cumulative lost activity.

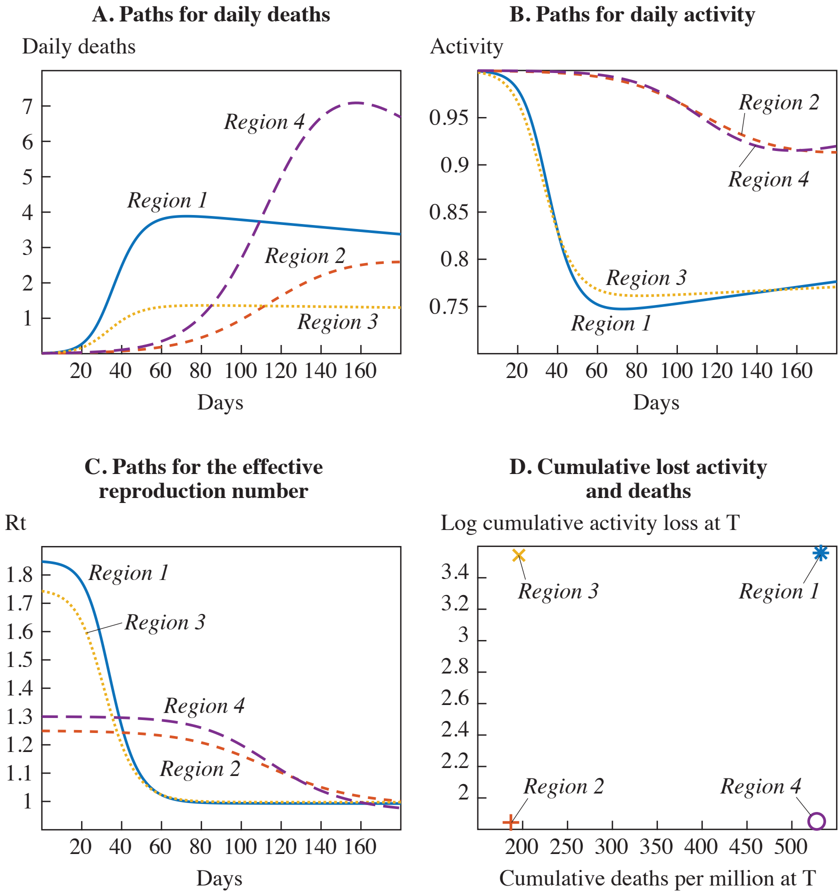
Experiment 3: Differences in both luck and policy lead to a cloud. In our third computational experiment, I consider four regions that differ both in the parameter $\overline{\beta}_i$ in equation (5) governing the transmission rate given the level of activity and in the semielasticity σ_i governing the slope of the relationship between the level of daily deaths and activity in equation (6). For the four regions that I consider, numbered 1, 2, 3, and 4 in figure 4, I set the basic reproduction numbers to $\overline{\beta}_i/\gamma = 1.85$, 1.25, 1.75, and 1.3 and the corresponding semielasticities to $\sigma_i = 75{,}000$, 35,000, 200,000, and 12,500, respectively.

In figure 4, I show the results from this computational experiment. As before, panel A shows the path of daily deaths per million residents in these four hypothetical locations. Panel B shows the time path of daily activity relative to the pre-epidemic level. Panel C shows the path of the effective reproduction number in each location. Panel D shows the cross-sectional relationship between cumulative deaths per million over a period of 180 days and the logarithm of cumulative lost activity over the same time period.

Note that in panel D this heterogeneity across regions leads to regions with cumulative deaths and cumulative lost activity in all four corners of figure 1 in the paper by Fernández-Villaverde and Jones.

These simple computational experiments illustrate that the interpretation of the cross-sectional relationship between cumulative deaths and cumulative

Figure 4. Dynamics of the COVID-19 Epidemic in Four Regions



Source: Author's calculations.

Notes: Experiment 3 addresses dynamics of the epidemic and activity in four regions that vary both in the transmission rate given the level of activity $\bar{\beta}_i$ and in the semielasticity of activity with respect to daily deaths σ_i. In panel D this heterogeneity across regions leads to regions with cumulative deaths and cumulative lost activity in all four corners of figure 1 in the paper by Fernández-Villaverde and Jones.

lost activity is dependent on which cross-sectional heterogeneity in regional characteristics is generating the cross-sectional variation in the data. Which type of heterogeneity is driving the data now (or was driving the data in 1918–1919) is unknown and should be a subject for future research.

REFERENCE FOR THE ATKESON COMMENT

Atkeson, Andrew, Karen Kopecky, and Tao Zha. 2020. "Four Stylized Facts about Covid-19." Working Paper 27719. Cambridge, Mass.: National Bureau of Economic Research. https://www.nber.org/papers/w27719.

GENERAL DISCUSSION Caroline Hoxby started the general discussion off by observing that the variation we see might be due to compliant versus noncompliant behavior. This is an important factor to economic activity because the variation in compliance will influence mobility and subsequent actions to reduce the spread of the virus. For example, Northern California (the San Francisco Bay area) and Southern California (Los Angeles) have the same level of regulations. "So what explains the difference?" she asked. It is most likely not attributable to density because San Francisco is denser than Los Angeles. But to her understanding, there is a difference in compliance between the two locations. Another example is Sweden versus the United States; Swedes are more likely to be compliant. She suggested finding data to use for this compliance measure, such as number of masks being purchased and other surveillance measures.

Martin Baily pointed out that the authors used the number of deaths as the outcome measure as opposed to deaths relative to the number of cases. Baily mentioned a recent study that found there were very wide cross-country differences in the ratio of deaths to confirmed cases.[1] This could be due to differences in reporting, but the gaps were large enough to suggest the findings reflect actual outcome differences. In the study, the United States had a very high number of cases per million persons, but the number of deaths per number of cases was much lower than most other OECD countries. France and the United Kingdom, for example, had many more deaths relative to the number of cases than did the United States. Fernández-

1. Ben Balmford, James D. Annan, Julia C. Hargreaves, Marina Altoè, and Ian J. Bateman, "Cross-Country Comparisons of Covid-19: Policy, Politics and the Price of Life," *Environmental and Resource Economics*, August 4, 2020, 1–27, https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7400753/.

Villaverde and Jones look at number of deaths, which reflects not only how many people catch the disease but also the deaths per number of cases, which is affected by the quality of treatment given to those who become ill.

Ken Rogoff questioned to what extent the outcomes are affected by the commonness of nursing homes and their protocols. Nursing home protocols, he stated, are a big contributor to the variation in the United States. In addition, nursing homes are less common in developing economies, which is one hypothesis for why COVID-19 hasn't spread as fast in those countries. Furthermore, Rogoff commented that looking at other outcomes of health such as life expectancy and morbidity, as opposed to deaths alone, will be of interest in a few years.

Mervyn King noted that data on COVID-19 deaths internationally are difficult to compare because the definition of a COVID-19 death varies from one location to another. Because of this, many have looked instead at monthly excess deaths relative to a five-year moving average. An advantage of this comparison is that it offers a view of the period before the pandemic. Countries with low excess deaths in 2019 had higher excess deaths in 2020, now attributable to COVID-19. This factor might explain the difference between Sweden and the United Kingdom, in addition to the nursing home factor mentioned by Rogoff. King adds that it is also relevant to the comparison between Sweden and Norway. In 2019, Norway had high number of excess deaths while Sweden had fewer. In 2020, Sweden caught up due to COVID-19.

King added that this is relevant to Andrew Atkeson's discussion of luck. King stated that luck can also refer to the starting point and the prevalence of countries in terms of their vulnerability to an epidemic of an infectious disease as opposed to just policy issues. He concluded by praising the presentation and discussion thus far.

Jason Furman believed he had an explanation for the lack of correlation based on two factors. One, the bigger the prevalence of the virus the worse for the economy. Second, if the country is more averse to the virus, it takes bigger steps for any amount of the virus, which is also worse for its economy. For example, New Zealand had a lower prevalence of the virus but with very few cases confirmed the government engaged in extensive shutdowns. This might also explain some of the summer trends in the United States. Although Arizona, California, and Florida had higher numbers of virus cases, economic activity in those states was the same as in Connecticut, Maine, and Vermont, which had lower numbers of cases but were more averse. Furman concluded his remarks with this question: Is there an underlying parameter, where some places do more or less in response to the same virus, that is inversely correlated with the virus? His hypothesis is this underlying parameter is why there isn't a strong correlation between the virus and economic activity.

Bob Hall pointed out the negative relationship between COVID-19 and tuberculosis. In countries like India, for example, tuberculosis is a pandemic but there are substantially lower COVID-19 death rates. There is some speculation that this is due to the treatment of and vaccinations for tuberculosis, which are widely practiced in third-world countries like India. This would indicate that those treatments have an effect against COVID-19.

Elaine Buckberg addressed the idea that trust in government has an effect on the results. She wonders if this question should be rephrased as rather a willingness to behave in the interest of the common good versus individualism. One way she suggested to measure this is by looking at fiscal variables such as the size of government budget or size of transfers. Although for some Asian countries, which have a historical behavior of wearing masks to protect others, it might not work well.

Tristan Reed recommended his paper with Pinelopi Goldberg presented at the Summer 2020 special edition of BPEA.[2] In this paper, the authors performed cross-country regressions and found a lot of explanatory power in health code variates, age distribution, obesity, and population density. He wondered how the addition of those variables would affect the analysis.

James Stock endorsed Reed's recommendation. He recognized that both this paper and the previous one focused on lost economic output versus lives in one way or another, either through mandated shutdowns or other outcomes as discussed here.[3] He believes this is a reasonable framing for what happened in March and in April. But starting in May and including the present (September 2020), we know that there's more going on. He related this to the point Rogoff made about nursing home protocols. We now know more about how limiting the spread of the virus and protections for the elderly can contain the virus.

Other ways of containing the virus while not affecting the economy are masks, testing, and quarantine mandates, Stock added. The key lessons from these papers for policies moving forward are about adhering to and

2. Pinelopi Koujianou Goldberg and Tristan Reed, "The Effects of the Coronavirus Pandemic in Emerging Market and Developing Economies: An Optimistic Preliminary Account," Brookings Papers on Economic Activity, Summer (2020), xx–xx.

3. Alexander Arnon, John Ricco, and Kent Smetters, "Epidemiological and Economic Effects of Lockdown," in the present volume of *Brookings Papers on Economic Activity*.

doing things that are good both for reducing deaths and preserving the economy. A common theme in the papers is that people would prefer to live than die and to work than not. The tragedy at the moment was that this is not the direction we had decided to go. He concluded that local officials have been given only one option, which is not a terrific option.

Jesús Fernández-Villaverde responded that if this presentation had been given two weeks earlier, he would have leaned toward luck. But given the second wave in Europe over the few weeks preceding the conference, he believes that policy makes a huge difference. One good example of this is Italy versus Spain. In Spain, ICU beds in Madrid were over 100 percent capacity on September 23. In Milan, Italy, they were not. He hypothesized that maybe the difference in some countries versus New York was due to luck in February. What was happening in Milan versus Madrid at that moment, he believes, was very clearly due to some policy decisions. In another six months or a year, these hypotheses and ideas would be much clearer.

Fernández-Villaverde continued by praising some of the suggested ideas thus far. In response to the comment made by King about using excess deaths, he responded that he and his coauthor have used this measurement in another paper that incorporates more econometrics. When using excess deaths, there is very little change in results. This is because there is an indication that countries with worse deaths scenarios, such as Spain or Italy, have also undercounted to a greater degree.

Fernández-Villaverde stated that it would be great to have good measures of compliance and social trust. Even within the United States there is variation across states, and states such as Vermont and Maine have done better than similar states. This could be attributable to differences in behavior and cultures of people across states. He hopes that in another year, there will be better measures and data on compliance. Currently there are some data on mask use, but it might not be credible. If we were in a totalitarian society like China, where everyone is recorded, we could actually check videos and take measurement of these topics.

Fernández-Villaverde concluded by stating he is in agreement with Stock and Rogoff about evaluating other outcomes and looking at long-term consequences. But it is difficult because at this time we do not have data. In five years, this will be an interesting topic to revisit.

Chad I. Jones added that there is luck involved with timing. If this paper had been written in May, for example, Arizona would have seemed great. Montana and South Dakota would have been seen as moving toward the right. There is luck involved in the timing and recording the analysis.

To echo Fernández-Villaverde's comments, in six months to a year we may see different outcomes on these graphs.

Andrew Atkeson concluded the discussion by responding to Furman's comments. He stated that the elasticity of the response of activity to infections is captured in New Zealand as they have responded aggressively to the disease. In the broader question of luck versus policy, an important case study comes from the Spanish flu. One of the biggest lessons from the Spanish flu is that some places were hit hard in the first wave while others were hit hard in the second wave. He notes that density is not a good proxy for luck and that something else is influencing how and when a location gets hit. The challenge is disentangling that factor from policy.