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Checking the Path Towards Recovery from the COVID-19 Isolation Response*

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Abstract

This paper examines the impact of the behavioral changes and governments' responses to the spread of the COVID-19 pandemic using a unique dataset of daily private forecasters' expectations on a sample of 32 emerging and advanced economies from January 1 till April 13, 2020. We document three important lessons from the data: First, there is evidence of a relation between the stringency of the policy interventions and the health outcomes consistent with slowing down the spread of the pandemic. Second, we find robust evidence that private forecasters have come to anticipate a sizeable contraction in economic activity followed by a check mark recovery as a result of the governments' increasingly stringent response. The evidence suggests also that workplace restrictions have further contributed to the downturn and to the subsequent sluggish recovery—opening up the question about the costs of tighter work restrictions. Finally, we argue inflation expectations have not changed significantly so far. Through the lens of the neoclassical growth model, these changes in macro expectations can result from the resulting work disruptions and the potential productivity slowdown from the gradual de-escalation of the confinement.

JEL Classification: I18, F62, E30, C23, C83

Keywords: COVID-19, Macro Expectations, Flattening the Curve, Policy Response Stringency, Google Mobility.

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1 Introduction

Governments' awareness about the coronavirus (COVID-19) outbreak in Wuhan, China, in the fourth quarter 2019 has grown since news of the outbreak became public in early January 2020. In response to the rapid spread of COVID-19, governments around the world have taken a wide and increasingly stringent range of measures directed at containing, mitigating, and ultimately suppressing the pandemic (government responses thoroughly detailed, among others, in Hale et al. (2020)). In the early stages when the novel coronavirus was mostly imported, governments' deployed a mixture of containment policies aimed at tracing and isolating those infected with some targeted travel bans. Mitigation policies aimed at slowing down the spread became the dominant response generally after the novel coronavirus started to circulate locally (community transmission) making it more difficult to control the infectious disease.

Most governments endorsed preventive hygiene measures early on like hand washing, surface cleaning, and even the use of face masks. Lacking herd immunity or a vaccine for COVID-19 to achieve it, self-isolation at home for at-risk individuals and physical distancing measures such as avoiding crowded areas, encouraging work-from-home, and physically distancing themselves from others by at least 2 meters, became commonplace mitigation strategies to slowdown the spread of the pandemic.[1] Eventually, many governments ended up recommending even more extreme suppression measures of confinement or self-quarantine and border closures. Large-scale lockdowns for entire populations living in affected regions and countries with internal travel limited to essential activities has been in effect as well. Such extraordinary suppression interventions were ultimately aimed at reducing the spread of the pandemic by lowering the basic reproduction rate or expected number of cases directly transmitted by one infected case, denoted R_0, to less than 1.

The stated objective of the mitigation and suppression policies enacted is to delay the peak and reduce the burden on healthcare systems, lessening overall cases and spreading them over time (what is often referred as the *flattening the curve*).[2] Governments recognized the importance of quickly expanding testing as well as healthcare capacity (by increasing bed count, equipment, and whenever possible even personnel) to meet the increased demand.

[1] Herd immunity is an epidemiological concept that can be defined as the state of a population that became sufficiently immune to an infectious disease that such a disease will not spread at an R_0 higher than 1 (absent the type of restrictive policies of physical distancing that have been deployed during the current pandemic).

[2] The interested reader can explore the rationale of classical infectious disease model with an epidemic calculator, e.g., Goh (2020). For an overview of COVID-19 forecasting efforts around the world, see, e.g., Luo (2020) and the references therein.

The efficacy of adopting self-isolation, physical distancing, and confinement measures and the best manner of relaxing such policies remains uncertain, as conditions vary significantly around the world. Another potentially complicating factor is that the novel coronavirus itself mutates as it spreads (as can be seen in Hadfield et al. (2018)).

Flaxman et al. (2020) argue that the drastic policy interventions put in place appear to have had a significant impact in reducing the observed infection fatality rates and in saving lives among countries with more advanced epidemic profiles. Similarly, the evidence of Yilmazkuday (2020) examining the real-time impact of behavioral changes with a broad panel of mobility measures over time and across different locations from Google LLC (2020) community mobility reports suggests that less time spent in more crowded spaces is indeed working towards the goal of bending the curve. However, behavioral changes related to physical distancing and the concomitant government policies are also understood to have large economic and social costs as collateral damage, restraining economic activity severely in almost all cases. Research on the economic impact of infectious diseases and pandemics continues to evolve quite rapidly building on the existing bridges between mathematical and applied epidemiology on the one hand and health economics on the other hand (for a recent overview, see Hauck (2018)).

Yet, the COVID-19 pandemic poses a once-in-a-century challenge for the global economy. The 1918 pandemic (H1N1 influenza) caused another global pandemic estimated to have infected one-third of the world's population causing millions of deaths worldwide (Taubenberger and Morens (2006), CDC (2019)). While much has changed, countries across the world face with COVID-19 a challenge unlike any other seen since then. In this scenario, economic scholars must also consider the aggregate effects caused by such a global heath crisis, the propagation mechanisms and global spillovers of the shock through behavioral or policy-induced physical distancing, and also the short-term and potential long-term implications that all of this may have for the global economy. Not surprisingly, much current research in macroeconomics, albeit still at a preliminary stage, is focused on those questions and on advising policymakers on the efficacy of fiscal and monetary policy actions aimed at supporting the economic recovery and propping up long-term growth.[3]

Much of the debate has centered on the consequences of a global pandemic—specifically around what impact the stringent government response and behavioral changes are having on the size of the COVID-19-related economic contraction and on how the global recovery will shape up after that. It is too early to judge the broad macroeconomic consequences

[3] For a brief survey of the current work related to the COVID-19 pandemic, see Ingholt (2020). For a detailed list of current fiscal and monetary policy actions around the world, see IMF (2020).

of the pandemic on the global economy, but much of it—and even the efficacy of fiscal and monetary policies being currently deployed—hinges on how private agents' expectations about the future evolve. That is what we examine in this paper taking advantage of a unique dataset that allows us to observe updates on private forecasters' own assessment of the outlook at a daily frequency from Consensus Economics Inc. (2020). That gives us a window into how expectations for quarterly real GDP growth and headline CPI inflation have been re-shaped in real-time as more and more countries started to recognize the health risks of COVID-19 and began to articulate their own response to the pandemic.

We investigate empirically the shift of the expected path for real GDP and headline CPI over the period from first quarter 2020 till fourth quarter 2021 for a sample of 32 countries (a subset of the countries in the Grossman et al. (2014) database) with daily forecasts from Consensus Economics Inc. (2020) for each business day between January 1 and April 13, 2020. For that same group of countries, we exploit as predictors all daily data available on behavioral changes related to mobility from Google LLC (2020) community mobility reports. We also include in this longitudinal panel the measures of stringency in the governments' policy responses aimed at inducing or imposing physical distancing from Hale et al. (2020) and the number of recorded deaths from Roser et al. (2020). To analyze the data, we propose (a fairly novel application to international macro of) the linear mixed effects or multilevel model framework. This methodology allows us to incorporate both fixed and random effects.

First, consistent with the evidence elsewhere, we find that more stringent reactions imposing physical distancing correlate with a slower growth rate in recorded deaths attributed to COVID-19. In our sample, these effects become statistically significant after two weeks. Adding Google LLC (2020) community mobility data to the empirical model does not improve much the estimation results. Yet, preventive hygiene measures and other factors—including other omitted non-pharmaceutical interventions—could still be playing an important role that researchers must continue to explore. More research is also needed to disentangle the efficacy of the different measures governments' put in place.

Second, we show that private forecasters' expectations for near-term global growth have worsened dramatically since the beginning of March, 2020, in part a reflection of personal behavioral changes, stringent physical distancing policies, and attendant costs of responding to the spread of the pandemic. By our own estimation, these factors explain much of the shift in the expected path of real GDP over the next two years for the global economy. Moreover, our findings also suggest that private forecasters expect a check mark-shaped recovery when coming out from this global pandemic. Moreover, our data indicates that private forecasters expect the level of global output to stay beneath its pre-crisis path even by end of 2021.

Third, we show that the expected path of global headline CPI implied by private forecasters' expectations hardly changed during this period, with inflation expected to quickly get back to its anticipated pre-crisis rate. The evidence shows that while behavioral changes and policy response stringency have some effect, their common impact on the expected path for the price level over the next two years is otherwise marginal. Our forecasting evidence shows that, for private forecasters, the behavioral changes and government responses to the novel coronavirus have led to a significant reassessment of the outlook for economic activity but had little effect on their views about the expected path of the price level.

What guides their interpretation of the shock caused by the global pandemic is difficult to ascertain. We advance the idea, however, that such expectations are consistent with the standard neoclassical growth model (Backus et al. (1992)) and with established international business cycle facts (Kydland and Prescott (1990) and Martínez-García (2018)). Within the neoclassical framework, two key forces are at play.

First, individuals allocate a fraction of their discretionary time to income-earning activities in the private sector and the remaining goes to nonmarket activities (household production) and leisure. Labor supply has been severely constrained either by choice or required by government policy in response to the pandemic with a direct impact on economic activity. While the limitations on work are generally thought as only temporary, resuming economic activity gradually looks increasingly likely as loosening controls prematurely may allow the virus to stage a comeback and necessitate the reintroduction of restrictions. A gradual unwinding of the stringent policy restrictions will slow the recovery.

Second, economic outcomes depend on exogenous labor-augmenting technological changes, tax changes and even terms-of-trade shocks, which can vary both over time and across countries. The rate of technological change in particular is, as explained in Kydland and Prescott (1990), inherently related to "the arrangements and institutions that a society uses and, more important, to the arrangements and institutions that people expect will be used in the future. (...) And when a society's institutions change, there are changes in the productivity growth of that society's labor and capital." A number of factors can contribute to a slowdown in productivity along these lines and, therefore, a weaker recovery such as the one private forecasters' have come to expect from this global pandemic: from a loss of human capital (*know-how*) and slower productivity to behavioral changes affecting working conditions and relationships (work-from-home and on-line shopping becoming more prominent), or value-chain disruptions through increased protectionism, or deteriorating public finances with government debt buildup (pushing taxes higher, fears of sovereign crises), or disruptions in credit markets (fintech and shadow banking expanding, weakening of credit relationships, financial stress). In fact, some of these changes may simply accelerate patterns that predate the recession itself.

At the end of the day, economic outcomes must reflect the individuals' ability (and willingness) to substitute between consumption and leisure at a given point in time and between consumption at different points in time. If the perceptions of private forecasters that we document here are in fact guided by this logic, then policymakers would do well to design macro policies that help ease the path towards economic recovery limiting the distortions faced by households and firms and facilitating the optimal allocation of resources. The success or lack thereof of such macro policies will depend on the ability of policymakers to act along those margins to prop up long-term economic growth and, if credible, will shape up the private agents' expectations going forward towards a more benign path with a lower output loss. The remainder of the paper goes as follows: In Section 2 we describe the data in detail and discuss our linear mixed effects estimation strategy. In Section 3 we introduce our results on the impact of mobility measures and policy stringency on the health outcomes in terms of the growth rate in reported deaths. In Section 4 we present our main findings regarding the impact that those same predictors have on the expected path for output and the price level globally, while in Section 5 we briefly conclude.

2 Methodological Approach

2.1 Data

The longitudinal panel we construct is based on a subset of 32 of the countries tracked in Grossman et al. (2014) which includes the United States and 31 of the major world economies with historically strong trade ties with the U.S.[4] These 32 countries accounted for an estimated 81.1 percent of world output in 2019 in purchasing power parity (PPP) terms, according to the annual shares of world GDP for each country projected (before the pandemic erupted into an economic crisis) by IMF WEO (2019).

The Oxford COVID-19 Government Response Tracker (OxCGRT) from Hale et al. (2020) produces a numerical daily indicator that tracks in real-time the extent and depth of the governments' policy reactions to the novel coronavirus outbreak worldwide. OxCGRT collects publicly available information on 13 indicators, 9 of which take account of a key govern-

[4] The countries included are Argentina, Australia, Brazil, Bulgaria, Canada, Chile, China, Colombia, Czech Republic, France, Germany, Hungary, India, Indonesia, Italy, Japan, Malaysia, Mexico, Netherlands, Peru, Philippines, Poland, Russia, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, the United Kingdom, the United States, and Venezuela.

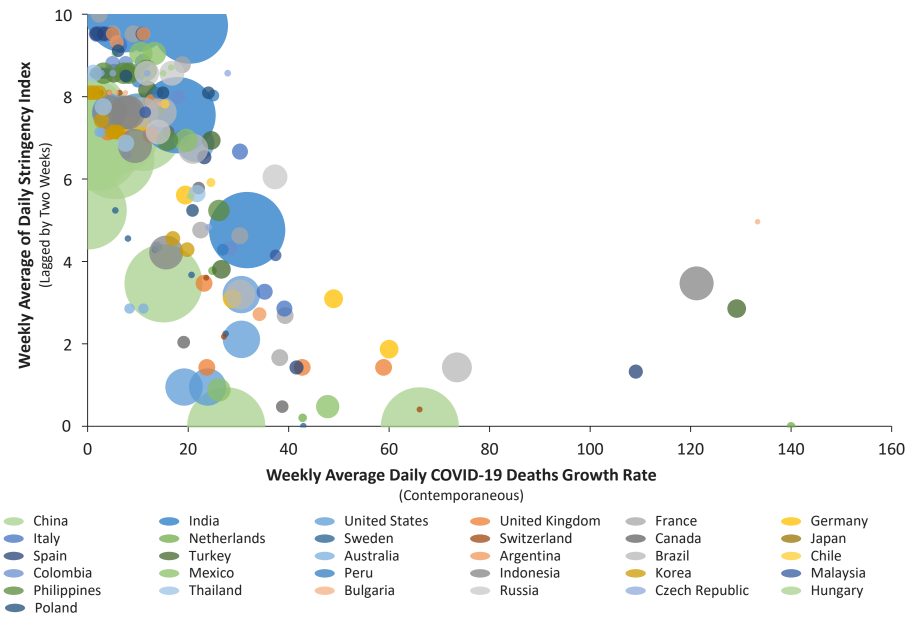
ment policy responses (school closing, workplace closing, cancel public events, close public transport, public information campaigns, restrictions on internal movement, international travel controls, testing policy, contact tracing). These 9 policy responses are recorded on an ordinal scale and aggregated into a common 'stringency index'. We include in our dataset the daily observations of the OxCGRT stringency index re-scaled to lie between 0 and 10 as a predictor to capture the wide range of measures that have been implemented in response to the COVID-19 outbreak by each one of the countries in our sample from January 1 through April 13, 2020.

We also include in the dataset the Google LLC (2020) community mobility reports as another predictor to help us gain further insight into the behavioral changes related to physical distancing aimed at combating COVID-19. The data is reported as a percent change in visits to different places within a geographic area compared to a baseline—the place categories included are grocery and pharmacy, parks, transit stations, retail and recreation, residential, and workplaces.[5] The baseline is the median value, for the corresponding day of the week, during the 5-week period from January 3 till February 6, 2020. The data shared by Google LLC (2020) starts in February 15, 2020, and went up to April 11, 2020 at the time we accessed it for our analysis—all countries have complete time series of these mobility measures, except for China and Russia for which there was no data available.

The Google LLC (2020) mobility series describe patterns of behavior for the place categories deemed by Google most useful to assess physical distancing efforts and are calculated based on their own data from users who have opted-in to Location History on their Google Account. The Google user sample may vary across time and countries depends on user settings, connectivity, and whether it meets the Google's privacy rules. In spite of the potential sample selection issues, these daily mobility series offer us a unique window into patterns of behavior across a number of place categories in real-time and allow us to assess physical distancing efforts in practice beyond what is captured by the OxCGRT stringency index.

[5] Grocery and pharmacy: Mobility trends for places like grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies. Parks: Mobility trends for places like local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens. Transit stations: Mobility trends for places like public transport hubs such as subway, bus, and train stations. Retail and recreation: Mobility trends for places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters. Residential: Mobility trends for places of residence. Workplaces: Mobility trends for places of work.

Figure 1. Scatter Plot of Health Outcomes (Growth Rate of Reported Deaths) and Government Response Stringency by Country



NOTE: The growth in recorded number of deaths (after the sixth reported death) for the 32 countries from DGEI is calculated as percent change from previous day from the daily tally in OxCGRT and One World in Data from January 1 till April 26, 2020. OxCGRT's stringency is also from January 1 till April 26, 2020 and scaled to 10. The size of each data point represents the relative population size in 2019 of each country. Each observation corresponds to a daily average of the daily values for each week starting from the week of January 20-January 26 and ending on the week of April 20-April 26. The stringency indicator is lagged two weeks on account of the incubation period of the coronavirus. Taiwan is the only country not plotted in the chart because during the sample period under consideration it has had six or less reported deaths due to COVID-19. All data as reported on April 27, 2020.
SOURCES: Database of Global Economic Indicators (DGEI) (Grossman et al. (2014)), Oxford University's Coronavirus Government Response Tracker (OxCGRT) and One World in Data, and author's calculations.

To assess the evolution of the disease infection caused by the pandemic, discerning a real-time signal from the reported cases can be very difficult in part because the reported numbers are dependent on each government's testing policy, on its scope, and on how this policy changes over time. Moreover, when an epidemic gets in full swing, the testing data is only showing the tip of the iceberg. Instead, the reported deaths attributed to COVID-19 give a somewhat more precise (albeit surely lagged) signal about the actual impact of the pandemic, as indicated by Flaxman et al. (2020). We obtain the number of daily officially recorded deaths for each one of 32 countries in the dataset over the period between January 1 and April 27, 2020 from Roser et al. (2020).[6] We then compute the daily growth rate in number of deaths attributed to the COVID-19 from the day before, after the sixth death, which is going to be one of our outcome variables (the health outcome variable).[7]

The second derivative here is key because, to have the intended effect of slowing down the spread of the novel coronavirus, behavioral changes and other policy interventions targeting the eventual suppression of the pandemic would need to result in statistically significant declines in the daily growth rate. Indeed, we illustrate such a negative relation in Figure 1 plotting, for each country, the weekly average of our health outcome variable and the weekly average of the stringency index lagged by two weeks. In this plot, the corresponding bubble size of a country is adjusted to reflect the country's population size in 2019 population.

The other outcome variables included in our dataset are the high frequency Consensus Economics Inc. (2020) continuous economic survey data on quarterly real GDP growth and quarterly headline CPI inflation. This forecast data is collected for the 32 countries in our dataset over the 6 forecasting quarters starting in first quarter 2020 for each business day from January 1 through April 13, 2020. Since February 17, 2020, the forecasting horizon gets expanded to include all 8 quarters starting in first quarter 2020 and ending in fourth quarter 2021. These Consensus Economics Inc. (2020) series are constructed as moving average of the latest 8+ qualified changed forecasts from their panel of forecasters. We use the observed data available up to fourth quarter 2019 in the Grossman et al. (2014) database and these Consensus Economics Inc. (2020) forecasts to construct an index for output and the price

[6] For additional information and detailed data tracking the real-time health outcomes of the pandemic, see e.g. Dong et al. (2020), Roser et al. (2020), and Worldometer (2020).

[7] We have considered also different cutoffs like, for instance, computing growth rates starting after the tenth death or twelfth death instead of after the sixth death. We find little difference in the results if we do this. We chose to report our results based on growth rates after the sixth death because that is the smallest cutoff in our country sample that rules out isolated cases or country experiences whenever wide community circulation of the novel coronavirus appears unlikely. For instance, this excludes Taiwan which has been remarkably successful with, as of April 28, 2020, just six recorded deaths. It also excludes imported cases that may precede a country's outbreak by several weeks (such as in the case of France).

level (indexed at $2019Q4 = 100$) for each workday update in our sample. We then take the log-deviation of the predicted level for both series in units relative to fourth quarter 2019 (that is, relative to $2019Q4 = 1$) times 100 as our two other outcome variables (the macro expectations variables).

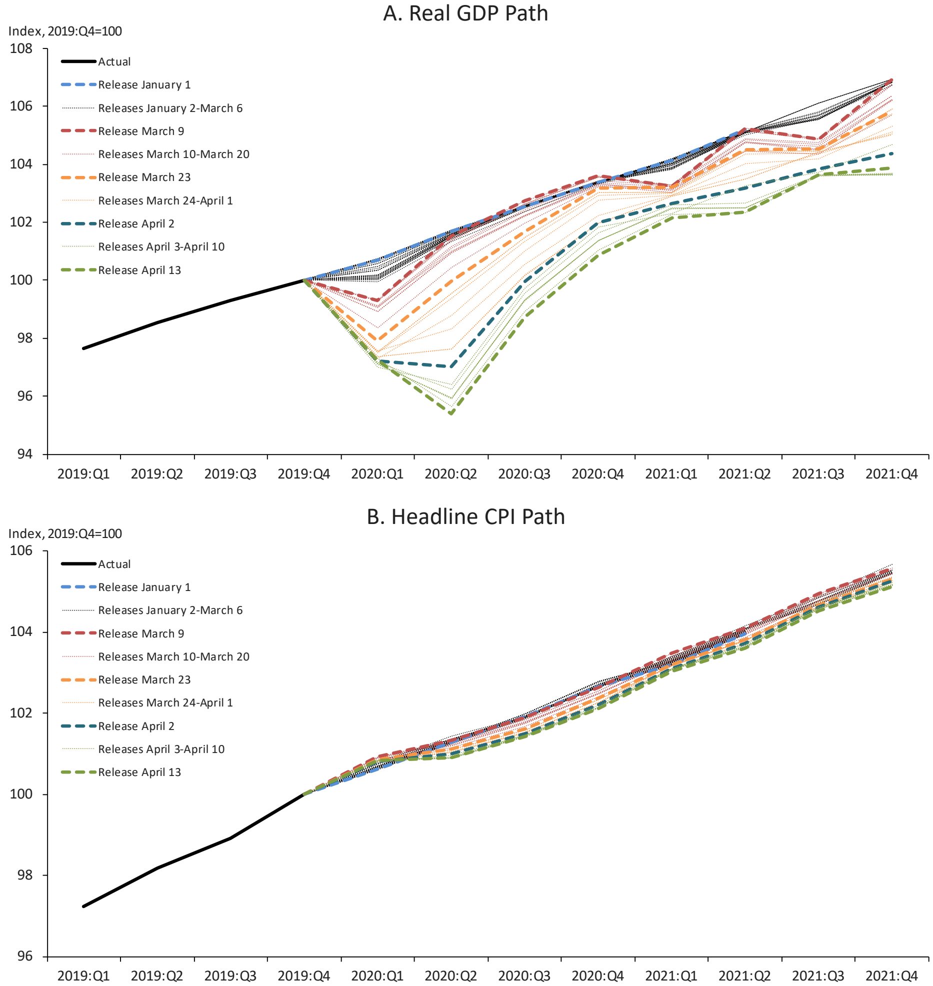
With this forecast data, we can illustrate the implied global path for real GDP and headline CPI up to 8 quarters ahead by aggregating the individual country series for each business day release of Consensus Economics Inc. (2020) forecasts. We use the same weighting scheme described in the methodology of Grossman et al. (2014) and the time-varying annual shares of PPP-adjusted world GDP for each country as projected in IMF WEO (2019).

Private forecasters' expectations offer a unique and dramatic perspective on the near-term global outlook. Global policy has evolved with awareness following the novel coronavirus outbreak in China. The first phase policy response largely centered on containment, with most restrictions aimed at preventing the migration of COVID-19 outside China and controlling community transmission once the virus had already made its way to a given country. As seen in Figure 2, the expected firming of global growth heading into 2021 predicted on January 1, 2020, remained largely unchanged during this first phase of containment. After another major outbreak hitting Italy by mid-February, more stringent policy responses gradually came to be adopted.

It was not until March 9, 2020, when Italy's Prime Minister Giuseppe Conte imposed a lockdown for the entire population of Italy restricting movement except for narrow work or health reasons, that more stringent policies aimed at mitigating and suppressing the pandemic became the new norm. Government policy responses in this second phase have had a major macroeconomic impact on the global economy, as evidenced by a rapid and dramatic worsening of the private forecasters' outlook in Figure 2. By March 9, private forecasters had already come to expect a global contraction in first quarter 2020 but still expected a strong bounce-back in second quarter 2020 and a return to the global output path expected at the beginning of 2020 by 2021.

However, by March 23, 2020, the more optimistic view of a V-shaped global recovery was already being abandoned and increasingly started to look like a check mark-shaped recovery instead. Since April 2, 2020, private forecasters' have been anticipating two consecutive quarters of negative growth—based on the aggregate of the 32 countries in our dataset—pointing to a global recession the likes of which we have not seen in peacetime (as discussed in Martínez-García (2020)). Still, the fear that loosening controls prematurely may allow the novel coronavirus to stage a comeback in the fall resulting in a W-shaped recovery as restrictions are re-introduced and uncertainty reignites, a possibility suggested by Ferguson et al. (2020), has not yet gained widespread credence among private forecasters.

Figure 2. Change in Private Forecasters' Macroeconomic Expectations



NOTE: The aggregate includes 32 of the countries in DGEI and is weighted with time varying PPP-adjusted GDP weights from the IMF. The path of global growth and global headline CPI inflation is calculated from continuous country forecasts from Consensus Economics Inc. on each business day from January 1 till April 13, 2020, as a moving average of the latest 8+ qualified changed forecasts. Forecasts for the second half of 2021 are only available since February 17, 2020. All data as reported on April 14, 2020.
SOURCES: Database of Global Economic Indicators (DGEI) (Grossman et al. (2014)), International Monetary Fund (IMF), Consensus Economics Inc., author's calculations.

In any event, the current expectations for a global recession are much more broad-based across sectors and industries than other recent recessions which, unlike this one, could be partly cushioned by a resilient service sector (as seen in Martínez-García et al. (2015) and Martínez-García (2018)). Moreover, private forecasters would put global economic activity well below the levels predicted at the beginning of the year over the entire forecasting horizon up to fourth quarter 2021. In contrast, the expected path of the aggregate price level shown in Figure 2 remained fairly unchanged, registering only, as of April 14, 2020, a modest step down shift during first half of 2020. Private forecasters' appear to retain confidence that inflation will afterwards quickly return to a rate similar to that which had been projected at the beginning of 2020 letting, in effect, bygones be bygones.[8]

2.2 Methodology

There are multiple ways to deal with hierarchical or multilevel data, one of which is simply to aggregate the data in a meaningful way along a particular dimension, as we do for health outcomes in Figure 1 and for macro expectations in Figure 2. However, analyzing aggregates does not really take advantage of all the detailed longitudinal panel data we have available for this period of time. To do so more fully, we must recognize first that country level observations are not necessarily independent, as within-country observations tend to be more correlated with each other over time than with observations from other countries at any given point in time. Partly this is the case because every country in our database was not hit at the same time by the spread of the pandemic. Moreover, we are also mindful that the relationship between predictors and outcomes across countries may differ from the relationship that exists within countries (or along the forecasting horizon for our macro expectations data). For those reasons, we adopt the linear mixed effects or multilevel framework that incorporates fixed and random effects to better capture the cross-sectional and longitudinal variation apparent in our dataset controlling for country-specific (and forecasting-horizon-specific) unobserved characteristics.

We follow the linear mixed effects methodology approach of Bates et al. (2015).[9] We fit a hierarchical linear model to the outcome vector, $Y_{t,j} = \{y_{t,jh}\}_{h=1}^{h}$, where the subscripts j and h denote the country and horizon of the each score recorded in the outcome vector, respectively and the subscript t indicates the day at which the outcomes and predictors are being sampled in our database. As noted before, there are 32 countries in our panel such

[8]This feature of letting bygones be bygones can partly reflect that many countries in our sample had become, either *de iure* or *de facto*, inflation targeters (Hammond (2012)).

[9]We implement this methodology using the R package **lmer** developed by Bates et al. (2015).

that $j \in \{1, ..., 32\}$ and the data is recorded at a daily frequency with the full sample starting on January 1, 2020, and ending on April 13, 2020. Our outcome variables include: (a) the observed daily growth rate of reported deaths, which we take as our indicator of health outcomes; and (b) the log-change in the private forecasters' expected path for real GDP and for headline CPI relative to the baseline of $2019Q4 = 1$, expressed in percent, which are our macro expectations outcomes. Based on current information from the CDC (2020), the incubation period for COVID-19 may range from $2 - 14$ days. Hence, informed by this, we take the daily growth rate two weeks from now as our preferred health outcomes measure (and $h = 1$).[10] The vector of macro expectation outcomes has up to 8 different forecasting horizons ($h = 8$) from first quarter 2020 till fourth quarter 2021 that we choose to model jointly.

We frame our hierarchical model for health outcomes with a two level-style equation:

First, at the within-country level, we have the regression of the outcome variable for country j, $y_{t,j}^{health}$, on the country-level predictors which include an intercept term and the indicator that captures the stringency of the government response to the pandemic, $stringency_{t,j}$. We entertained the idea of augmenting the specification with the Google LLC (2020) data on mobility, $mobility_{t,j}^{i}$, for any of the $i \in \{1, ..., 6\}$ different locations for which data is provided but we decided to retain the more parsimonious representation laid out here after careful exploration of the mobility data, as the Google series appear to have quite marginal effects on the model performance.

Second, at the between-country level, we allow the intercept to vary across countries by introducing a random effect term while keeping the slope on $stringency_{t,j}$ constant across countries.

Hence, the model can be characterized as:

$$
\begin{aligned}
& L1 \ \ (within\ country): \\
& \quad y_{t,j}^{health} = \gamma_{0,j} + \gamma_{1,j} stringency_{t,j} + \varepsilon_{t,j}, \ \ \varepsilon_{t,j} \sim \mathcal{N}\left(0, \sigma_{\varepsilon}^{2}\right), \\
& L2 \ \ (between\ country): \\
& \quad \gamma_{0,j} = \beta_0 + u_{0,j}, \ \ \gamma_{1,j} = \beta_1, \ \ u_{0,j} \sim \mathcal{N}\left(0, \sigma_{u_0}^{2}\right).
\end{aligned} \tag{1}
$$

Substituting the level 2 equation into level 1, yields the following linear mixed model speci-

[10] We drop the subscript h because for health outcomes we have only one measurable outcome per period and per country. We have also implemented a more complex specification that includes three measurable outcomes per period and per country for the contemporaneous observation, the observation one week ahead, and the observation two weeks ahead with similar findings. Those additional results are omitted here, but available upon request.

fication for health outcomes:

$$y_{t,j}^{health} = (\beta_0 + u_{0,j}) + \beta_1 stringency_{t,j} + \varepsilon_{t,j},\ \varepsilon_{t,j} \sim \mathcal{N}\left(0, \sigma_\varepsilon^2\right),\ u_{0,j} \sim \mathcal{N}\left(0, \sigma_{u_0}^2\right). \tag{2}$$

This combined equation shows how the fixed and random intercept parameters together give the estimated intercept for a particular country.

Similarly, we model macro expectations as an outcome within a multilevel framework:

First, at the forecast horizon level within-country, we have the regression of the expectations outcome variable for country j and horizon h, $y_{t,jh}^{macro}$, on the within-country predictors. The predictors here include an intercept together with the country-specific government response stringency indicator, $stringency_{t,j}$. For the subsample that begins on February 15, 2020, for which there is Google LLC (2020) data on mobility, $mobility_{t,j}^{i}$, we augment the specification with the most informative country-specific mobility indicator among the 6 measures available while also permitting the mobility measure to interact with $stringency_{t,j}$. In this particular model, we allow the intercept $\beta_{0,jh}$ and the slope on the stringency variable $\beta_{1,jh}$ to have a random effect component allowing them to vary across forecasting horizons within a country.

Second, at the between-country level, we allow the intercept and slope on $stringency_{t,j}$ to vary across countries as their respective equations each include a random effect term. Moreover, we also allow the other coefficients ($\delta_{0,h}$, $\delta_{1,h}$, $\delta_{2,h}$, and $\delta_{3,h}$) to depend on h implying that stringency and mobility indicators as well as their interactions can vary across forecasting horizons.

Hence, the resulting model can be written down as:

$$\begin{aligned}
&L1\ (by\ forecast\ horizon,\ within\ country):\\
&\quad y_{t,jh}^{macro} = \gamma_{0,jh} + \gamma_{1,jh} stringency_{t,j} + \gamma_{2,jh} mobility_{t,j}^{i} + \gamma_{3,jh} stringency_{t,j} \times mobility_{t,j}^{i} + \varepsilon_{t,jh},\\
&\quad \gamma_{0,jh} = \delta_{0,jh} + u_{0,jh},\ \gamma_{1,jh} = \delta_{1,jh} + u_{1,jh},\ \gamma_{2,jh} = \delta_{2,jh},\ \gamma_{3,jh} = \delta_{3,jh},\\
&\quad \varepsilon_{t,jh} \sim \mathcal{N}\left(0, \sigma_\varepsilon^2\right),\\
&\quad \begin{pmatrix} u_{0,jh} \\ u_{1,jh} \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{u_{0,h}}^2 & \sigma_{u_{0,h},u_{1,h}} \\ \sigma_{u_{0,h},u_{1,h}} & \sigma_{u_{1,h}}^2 \end{pmatrix}\right),\\
&L2\ (between\ country):\\
&\quad \delta_{0,jh} = \beta_{0,h} + u_{0,j},\ \delta_{1,jh} = \beta_{1,h} + u_{1,j},\ \delta_{2,jh} = \beta_{2,h},\ \delta_{3,jh} = \beta_{3,h},\\
&\quad \begin{pmatrix} u_{0,j} \\ u_{1,j} \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{u_0}^2 & \sigma_{u_0,u_1} \\ \sigma_{u_0,u_1} & \sigma_{u_1}^2 \end{pmatrix}\right).
\end{aligned} \tag{3}$$

Substituting the level 2 equation into level 1, we can re-express the linear mixed model specification for the expectations outcomes as follows:

$$
\begin{aligned}
&y^{macro}_{t,jh} = (\beta_{0,h} + u_{0,j} + u_{0,jh}) + (\beta_{1,h} + u_{1,j} + u_{1,jh})\, stringency_{t,j} + \beta_{2,h} mobility^i_{t,j} + ...\\
&\quad \beta_{3,h} stringency_{t,j} \times mobility^i_{t,j} + \varepsilon_{t,jh},\\
&\begin{pmatrix} u_{0,jh} \\ u_{1,jh} \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2_{u_{0,h}} & \sigma_{u_{0,h},u_{1,h}} \\ \sigma_{u_{0,h},u_{1,h}} & \sigma^2_{u_{1,h}} \end{pmatrix}\right), \quad \begin{pmatrix} u_{0,j} \\ u_{1,j} \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2_{u_0} & \sigma_{u_0,u_1} \\ \sigma_{u_0,u_1} & \sigma^2_{u_1} \end{pmatrix}\right),\\
&\varepsilon_{t,jh} \sim \mathcal{N}\left(0, \sigma^2_{\varepsilon}\right).
\end{aligned} \tag{4}
$$

This equation shows how the model intercept and the slope on policy stringency are characterized by a common effect for each quarter, but can vary across countries and within a country across forecast horizons due to the assumed random effects structure.

A linear mixed effects model like our reference specifications in (2) and (4) can be cast in matrix form as follows:

$$y = X\beta + Zu + \varepsilon, \tag{5}$$

In (2), y refers to the $N \times 1$ column-vector of the outcome variable with N being the number of observations. The number of observations N equals the sample size T times the number of groups in the model g—that is, the number of countries ($g = 32$) in the health outcome regression and the number of countries times the number of forecasting horizons ($g = 32 \times 8$) for the macro expectations regression. X is an $N \times p$ matrix that contains all the p predictor variables and β is a $p \times 1$ column-vector of the corresponding regression coefficients. Z is the $N \times q$ matrix of the q random effects (the random complement to some of the predictors in X) where q equals the number of predictors with random effects times the number of groups in the model (g) and u is a $q \times 1$ vector of random effects coefficients (the random complement to some of the coefficients β). Finally, ε is the $N \times 1$ column-vector of the residuals of the model.

There are many reasons why allowing for that random variation could be useful, among others, because it allows us to take account of country-characteristics that are not modelled explicitly. Therefore, in doing so, these random effects help us extract a cleaner signal about the aggregate effects from behavioral changes and mandatory restrictions imposed by governments in response to the pandemic. However, it can be computationally complex to add random effects to a model, particularly when the specification has a lot of groups to begin with. Here, however, the random effects coefficients, u, are assumed to follow a multivariate normal distribution with mean zero and a $q \times q$ variance-covariance matrix, G, i.e.,

$$u \sim \mathcal{N}(0, G). \tag{6}$$

The random effect coefficients, u, are modeled as deviations from the coefficients, β, so they have mean zero. In other words, the random effects are just deviations around the mean value which is β.

Hence, under these assumptions, what we end up estimating for the random effects coefficients is their variance-covariance matrix G. As with any variance-covariance matrix, G is square, symmetric, and positive semidefinite. We know that a $q \times q$ variance-covariance matrix has redundant elements, that is, only $\frac{q(q+1)}{2}$ elements are unique. To simplify computation further while ensuring the resulting estimates imply that the variance-covariance matrix remains positive definite, G is transformed such that it depends on the component parameters, θ. In other words, G is a function of θ.

As in Bates et al. (2015), we express the variance covariance matrix G in terms of a relative covariance factor, Λ_θ, which is a $q \times q$ matrix that depends on θ and generates the following family of symmetric and positive definite matrices,

$$G_\theta = \sigma(\theta) = \sigma_u^2 \Lambda_\theta \Lambda_\theta^T, \tag{7}$$

where $\sigma_u^2 > 0$ is a scaling factor.[11] This is designed not just to estimate solely the (transformed) $\frac{q(q+1)}{2}$ non redundant elements but also to parameterize them in a way that yields more stable estimates for the variance-covariance unique elements (such as taking the natural logarithm to ensure that the variances are always positive).

The final piece of the linear mixed effects model is the variance-covariance matrix of the residuals, ε, in (5). The most general residual covariance structure is:

$$R = \sigma_\varepsilon^2 W, \tag{8}$$

where W is an $N \times N$ variance-covariance matrix with correlated (conditional) residuals and (conditionally) non-homogeneous variances, scaled by the parameter $\sigma_\varepsilon^2 > 0$. However, a common specification of R is simply $R = \sigma_\varepsilon^2 I^{-1}$, where I is the identity matrix. Starting from the more general setup presented in (8), the model in (5) can be converted into this simpler model with independent errors and equal variance (see, e.g., Heisterkamp et al. (2017) on the de-correlation of the linear mixed effects model).

Given the added assumption that residuals, ε, are normally distributed with mean zero

[11] Often the transformation can be achieved by means of a triangular Cholesky factorization $G = LDL^T$.

and variance-covariance, R, the conditional distribution of the outcomes from the linear mixed effects model can be described as:

$$y|X\beta + Zu \sim \mathcal{N}(0, R), \tag{9}$$

where the parameters to be estimated are β, θ, σ_u^2, and σ_ε^2 together with W when the residual variance matrix incorporates some form of heteroskedasticity and/or autocorrelation in the residuals. Equations (5) − (8) describe the general class of linear mixed models (the multilevel or hierarchical framework) that we use to analyze the data which can be estimated with standard maximum likelihood methods following—as we do here—the strategy of Bates et al. (2015).

3 Are Government Interventions Working?

There is a great deal that we still do not understand about the nature of the pandemic, its origins, its evolution, the broad health risks it poses or its prognosis and likelihood of becoming endemic. There is also much debate about the best practices to tackle this novel coronavirus for which none of us has natural immunity and for which no vaccine yet exists.[12] The government responses across countries have been so far very varied, with notable differences having to do with the intensity and the timing of the interventions. A deeper exploration is underway to extract the lessons from the international experience which will equip us with an increasingly better understanding about the pandemic over time.

In this paper, we take on a much more narrowly defined question. We explore whether the policy response appears to have a discernible relation with the health outcomes as suggested by the scatterplot in Figure 1. As noted in Subsection 2.1, we focus for this purpose on the daily growth rate in the number of reported deaths for the countries in our sample as our indicator of health outcomes. We estimate the specification laid out in (2) at different leads between the outcome variable and the main predictor, the stringency indicator. We settle on a lead of two weeks which is consistent with the incubation range for the novel coronavirus as this provides us with a cleaner estimate of the relation within our available data sample.

We summarize the best specifications with and without predictors for model (2) in Table 1. It is worth recalling that augmenting the model with any of the Google LLC (2020) mobility data that we use in this paper does not appear to improve its performance in a

[12] For a cost-benefit analysis of pandemic mitigation through vaccination using an influenza pandemic as a case study, see CEA (2019).

meaningful way. This could reflect the fact that once the health risk is known, compliance with the government-imposed restrictions becomes largely voluntary for a large fraction of the population (at least for a limited period of time). Accordingly, the stringency indicator should suffice to describe the role that physical distancing is having helping contain the person-to-person transmission of the novel coronavirus.

The marginal effects of stringency from the preferred model with predictors are shown in Figure 3. While stringency explains only part of the variation we encounter in the data as can be seen by the modest R-squared for the fixed effects, the negative relation between health outcomes and the degree of stringency of the government response is consistent and statistically significant. The cross-sectional variation in the intercepts that we show in the random effects by country in Figure 3 suggests that country-characteristics that are not modelled explicitly (for example, differences in urban density, demographics, environmental and cultural factors, etc.) can be quite significant.

Moreover, the random effects also can capture differences in the timing of the outbreak in each country arising from the fact that the pandemic spread rapidly but not instantaneously across countries. For instance, countries where the pandemic hit later could learn from the experiences of the countries that had to deal with it before, something which seems to have been an important consideration particularly since Italy went into a nation-wide lockdown. The cross-sectional variation in the intercept can also reflect the differences in the timing at which countries decided to impose more stringent interventions—for example, Portugal acted sooner than Spain when active cases of community circulation were lower and avoided overwhelming its healthcare system and the steep cost in lives seen in Spain.[13]

Part of the challenge in modeling health outcomes and interpreting these results is that the data is still quite noisy. For instance, there is already growing awareness that there exists a gap that some have referred as the 'missing deaths' between the deaths attributed to the novel coronavirus and the difference between the total number of deaths and those that are usual during this period of the year. Moreover, while the model can account for the different *ex ante* characteristics of the countries (urban density, demographics, environmental, cultural, etc.), it does not capture a richer set of predictors (hygiene, etc.) nor reflects the efficacy of the different intervention measures put in place to achieve physical distancing.

Finally, as more countries get progressively involved in the response and we secure more

[13] See, e.g., IHME (2020) for an assessment of healthcare system capacity and needs and WHO (2020) for self-reporting country data related to legislation, coordination, surveillance, response, preparedness, human resources, risk communication and other capacities of the healthcare system prior to the onset of the COVID-19 pandemic.

up-to-date data, the results in Table 1 will surely be revised and expanded. Therefore, we must acknowledge that at this stage our health outcome results only confirm the negative relation between the stringency of the government response and the number of recorded deaths in Figure 1. What the data suggests is simply that these unprecedented government actions around the world, by limiting one-on-one contact, appear to have had some effect slowing down the course of the disease and limiting the worst outcomes, the fatality rate in the population.[14]

The slowdown in the growth rate in deaths itself does not imply a flatter peak, perhaps just a delayed one, nor does it rule out future waves of the virus. Much discussion will surely focus going forward on these issues as well as on some of the major unknowns: the degree of immunity already present in the population; how to de-escalate from the unprecedented measures put in place without causing a new wave of the pandemic; and how to protect the most vulnerable (while maintaining the ability of the health system to cope) as we progress towards a more stable scenario where either the virus goes away or—more likely—a large share of the population develops a degree of immunity (either with the help of a vaccine or through herd immunity) and may even become endemic.

Table 1. Growth Rate in Recorded Deaths from COVID-19: Intercept-Only Model and Model with Explanatory Variables

Model for Growth Recorded Deaths	M1: Intercept-only			M2: With Stringency as Predictor		
	Estimate	2.5% CI	97.5% CI	Estimate	2.5% CI	97.5% CI
Fixed Effects						
Intercept	17.4892	15.2102	19.7917	34.8904	30.7701	39.1582
Stringency				-2.7931	-3.3412	-2.2478
Random Effects						
$\sigma_{intercept}$	4.9797	3.3773	7.1730	5.7597	4.1085	8.0874
σ_{ε}	16.1422	15.2470	17.1281	14.7713	13.9503	15.6760
Intraclass Correlation Coefficient (ICC)	0.0869			0.1320		
Observations	594			594		
Pseudo-R^2 (fixed effects)	0.0000			0.1731		
Pseudo-R^2 (total)	0.0869			0.2822		
AIC	5026.98			4933.28		
BIC	5040.14			4950.82		

NOTE: Mixed effects linear regression model clustered by country. The outcome variable, the growth in recorded number of deaths (after the sixth reported death) for 32 of the countries in DGEI, is calculated as percent change from previous day based on the daily tally in OxCGRT from January 1 till April 13, 2020. The outcome variable corresponds to the daily growth rate two weeks from now. OxCGRT's stringency is also from January 1 till April 13, 2020 and scaled to 10.

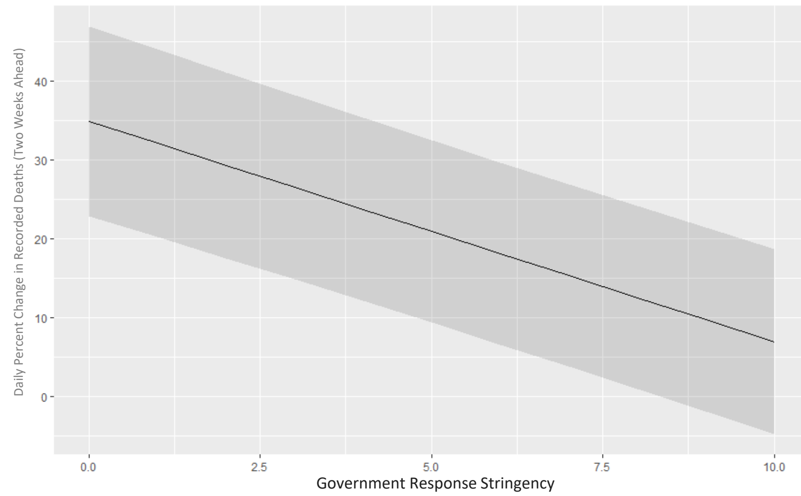
SOURCES: Database of Global Economic Indicators (DGEI) (Grossman et al. (2014)), Oxford University's Coronavirus Government Response Tracker (OxCGRT), and author's calculations.

[14] To be precise, what we show is evidence consistent with a slowing of the growth rate in reported deaths attributed to COVDI-19 in real-time. There is not necessarily the same as a reduction in the tranmission rate due to a number of conditional demographic and behavioral factors that are contributing to the result. For instance, we cannot be certain about the transmission rate within the population because the decline in the growth rate in reported deaths could be the result of reductions in the transmissions among the most vulnerable groups alone (the elderly, those with some pre-existing health conditions, etc.) due to the stringency measures of self-isolation on them while the overall transmission rate for the population as a whole may not have followed the same pattern.

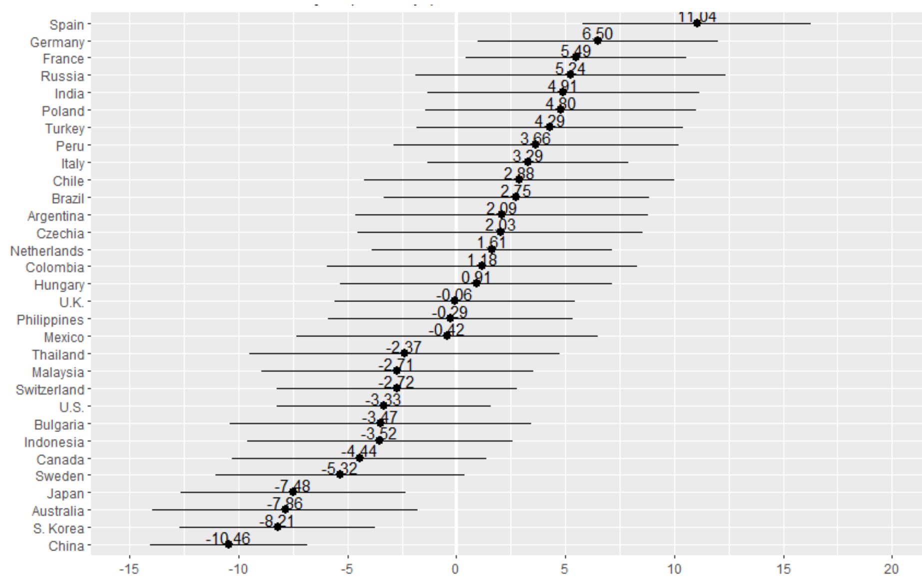
Figure 3. Marginal Effects of Predictor (Government Response Stringency) on Outcome Variable (Growth Rate in Recorded Deaths from COVID-19)

(Deaths: Model 2)

A. Marginal Effects



B. Random Effects by Country



NOTE: The growth in recorded number of deaths (after the sixth reported death) for the 32 countries in DGEI is calculated as percent change from previous day from the daily tally in OxCGRT and One World in Data from January 1 till April 13, 2020. OxCGRT's stringency is also from January 1 till April 13, 2020 and scaled to 10. For this exercise we use the same real-time sample we have available for macro expectation outcomes. All data as reported on April 14, 2020.
SOURCES: Database of Global Economic Indicators (DGEI) (Grossman et al. (2014)), Oxford University's Coronavirus Government Response Tracker (OxCGRT) and One World in Data, and author's calculations.

4 What Are the Expected Macro Effects?

The economic consequences of the lockdown that brought the economies of many countries around the world to a halt have been increasingly felt in the rapidly shifting (and dire) expectations of private forecasters. We analyze the evidence using the richer model presented in (4). What we obtain from this model is a cleaner signal of the significance of both the policy restrictions put in place to slow down the pandemic as well as the importance of the behavioral changes that have taken place nearly simultaneously. We summarize our evidence for the path of output in Table 2. We consider two models with predictors, both of which are superior to an alternative specification without them. While the sample is more restricted when we look at the statistical model with policy stringency but also with direct effects from mobility in the workplace and an interaction of the stringency and mobility indicators, this specification performs better than the more parsimonious model that has stringency as the sole predictor.

Overall, we find that the predictors in the model account for a significant part of the variability in the data (as can be judged, for instance, by the R-squared for the fixed effects). We interpret the evidence on mobility in the workplace in our preferred specification as indicative that, from the point of view of its economic impact, much depends (in the judgement of private forecasters) on whether and to what extent the businesses and workers are able to continue operations (through work-from-home or other arrangements).

In order to explore the impact on the outlook of both policy stringency and mobility, we plot the simple slopes of the model in Figure 4. The simple slopes depict the expected output path at each quarter from first quarter 2020 through fourth quarter 2021 if stringency is set one standard deviation below its mean (limited restrictions) vs. one standard deviation above (strong restrictions) when all other covariates are at their respective grand means. We perform the same exercise for the mobility in workplaces predictor where a one standard deviation below the mean refers to a situation with reduced operations in the usual workplace locations while one standard above the mean suggests workplace activity has seen only a limited decline.

We find that strong reductions in the footprint in workplaces has a major effect on the outlook for output and leads to a similar check mark recovery as the one we saw in Figure 2. The impacts are comparable in size to those that can be expected from the stringency of the policy restrictions themselves. From our preliminary exploration of health outcomes in Section 3, it is too early to judge whether stricter lockdowns that limit the ability to continue working (except for those activities deemed essential) have had a major effect in achieving the goal of flattening the curve or whether similar outcomes could have been attained with more targeted measures. However, it is apparent from the evidence that the clamp down on workplace activity has had a major effect on the perceptions about economic activity driving the shift in expectations among private forecasters. The evidence appears to suggest that the economic costs of disrupting business operations are an important factor behind the expected large declines in economic activity around the world and behind the view of a check mark-shaped recovery.

The differences in the ability to work from home can explain some of the cross-sectional variation that we see in the random effects aggregated to the country level that we show in Figure 4. Other differences in how the COVID-19 response policies where deployed across countries are also apparent in the variation shown in the random effects. At the end of the day, what the evidence suggests to us is two things:

First, that macro risk management (or lack thereof) is a very important aspect of the overall strategy in this pandemic.[15] And, at least from the point of view of private forecasters, the restrictions to work are having a major effect on economic activity above and beyond what else governments are throwing at us to bring the COVID-19 pandemic under control. By our estimates, lesser economic damage would be expected the more supportive of business continuity and continued working operations the government policies in effect are. Or, put in other words, private forecasters expect work disruptions to be specially damaging aggravating the recession and worsening the outlook for the recovery. Once the restrictions on labor are gradually lifted, the standard neoclassical growth model tells us that the recovery will also depend on whether (and to what extent) the lockdown causes a loss of human more than physical capital and a breakdown in arrangements that may lead to a slowdown in productivity (and loss of *know-how*).

[15] This is not by itself a surprising result. It stands to reason that if people cannot work at their normal places of work, output will of necessity decline, except for work that can done from home. Our findings show that private forecasters recognize that, but also indicate how quantitatively important those labor disruptions are in their overall assessment of the economic impact of the governments' responses to the pandemic.

Table 2. Expected Real GDP Path:
Intercept-Only Model and Model with Explanatory Variables

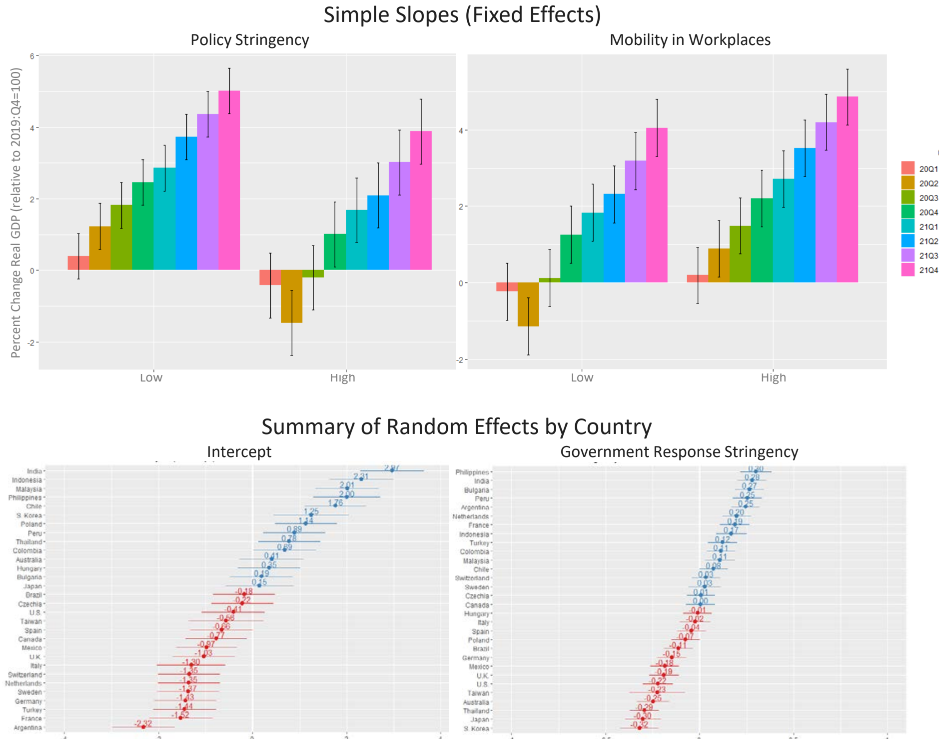
Model for Expected Real GDP Path	M1: Intercept-only			M2: With Stringency as Predictor			M3: With Stringency and Mobility as Predictors		
	Estimate	2.5% CI	97.5% CI	Estimate	2.5% CI	97.5% CI	Estimate	2.5% CI	97.5% CI
Fixed Effects[a]									
Intercept	-0.0166	-0.7197	0.6866	0.4858	-0.2577	1.2293	0.4248	-0.1996	1.0492
2020Q2	-0.0037	-0.5128	0.5054	1.2372	0.7172	1.7573	0.8541	0.3313	1.3773
2020Q3	1.0430	0.5339	1.5521	1.7416	1.2217	2.2617	1.5632	1.0407	2.0866
2020Q4	1.9230	1.4139	2.4322	2.2606	1.7407	2.7807	2.1370	1.6147	2.6607
2021Q1	2.4808	1.9717	2.9899	2.7237	2.2037	3.2438	2.5775	2.0551	3.1010
2021Q2	3.0647	2.5555	3.5738	3.6136	3.0936	4.1337	3.2932	2.7706	3.8169
2021Q3	3.4461	2.9340	3.9583	4.6653	4.1369	5.1940	4.0632	3.5408	4.5870
2021Q4	4.3069	3.7947	4.8190	5.2228	4.6945	5.7516	4.7096	4.1876	5.2339
Stringency				-0.1624	-0.1753	-0.1495	-0.0558	-0.1451	0.0334
Workplace Mobility							-0.0080	-0.0159	0.0000
2020Q2 X Stringency				-0.4010	-0.4193	-0.3828	-0.0699	-0.1463	0.0069
2020Q3 X Stringency				-0.2258	-0.2440	-0.2075	-0.0771	-0.1535	-0.0003
2020Q4 X Stringency				-0.1091	-0.1274	-0.0909	-0.0389	-0.1155	0.0378
2021Q1 X Stringency				-0.0785	-0.0967	-0.0602	-0.0238	-0.1003	0.0529
2021Q2 X Stringency				-0.1774	-0.1956	-0.1591	-0.0140	-0.0905	0.0629
2021Q3 X Stringency				-0.1746	-0.1973	-0.1518	-0.0270	-0.1035	0.0499
2021Q4 X Stringency				-0.1152	-0.1380	-0.0925	-0.0199	-0.0965	0.0570
2020Q2 X Workplaces							-0.0212	-0.0325	-0.0100
2020Q3 X Workplaces							-0.0079	-0.0191	0.0034
2020Q4 X Workplaces							-0.0040	-0.0153	0.0072
2021Q1 X Workplaces							0.0009	-0.0103	0.0121
2021Q2 X Workplaces							-0.0117	-0.0229	-0.0005
2021Q3 X Workplaces							-0.0022	-0.0134	0.0091
2021Q4 X Workplaces							0.0000	-0.0112	0.0112
Stringency X Workplaces							0.0031	0.0020	0.0041
2020Q2 X Stringency X Workplaces							0.0098	0.0083	0.0113
2020Q3 X Stringency X Workplaces							0.0048	0.0033	0.0063
2020Q4 X Stringency X Workplaces							0.0026	0.0011	0.0041
2021Q1 X Stringency X Workplaces							0.0014	-0.0001	0.0029
2021Q2 X Stringency X Workplaces							0.0050	0.0035	0.0065
2021Q3 X Stringency X Workplaces							0.0025	0.0010	0.0040
2021Q4 X Stringency X Workplaces							0.0013	-0.0002	0.0028
Random Effects									
By Forecast Quarter within Country									
$\sigma_{intercept}$	1.1087	0.9275	1.1248	1.0434	0.9520	1.1498	0.9596	0.8616	1.0730
$\rho_{intercept, stringency}$							-0.2470	-0.3878	-0.0936
$\sigma_{stringency}$							0.1066	0.0944	0.1206
By Country									
$\sigma_{intercept}$	1.7029	1.3395	2.2448	1.0821	1.4344	2.3982	1.3736	1.0649	1.8368
$\rho_{intercept, stringency}$							0.1270	-0.2513	0.4717
$\sigma_{stringency}$							0.1932	-0.2513	0.4717
σ_{ε}	1.5478	1.5313	1.5646	1.0537	1.0424	1.0651	0.8848	0.1502	0.2579
Intraclass Correlation Coefficient (ICC)									
By Forecast Quarter within Country	0.1639			0.1974			0.2564		
By Country	0.4579			0.6013			0.5255		
Observations	18944			18944			9608		
Pseudo-R^2 (fixed effects)	0.2389			0.3782			0.4907		
Pseudo-R^2 (total)	0.7121			0.8748			0.9263		
AIC	63452.98			50730.98			26513.02		
BIC	63538.02			50877.87			26792.66		

NOTE: Mixed effects linear regression model clustered in two levels by country and by forecasting quarter within a country (with up to 8 forecasting horizons from 2020Q1 till 2021Q4). The outcome variable, the expected real GDP for 32 of the countries in DGEI, is the projected path deviation relative to 2019:Q4=100. It is calculated from continuous country forecasts from Consensus Economics Inc. released each business day as a moving average of the latest 8+ qualified changed forecasts, from January 1 till April 13, 2020. The outcome variable is imputed at all every one of the forecasting horizons for which there is data (third and fourth quarter 2020 are missing until February 17, 2020). OxCGRT's stringency is from January 1 till April 13, 2020 and scaled to 10. The Google-provided data on mobility is available for all countries ex. Russia and China from February 15 till April 11, 2020.

SOURCES: Database of Global Economic Indicators (DGEI) (Grossman et al. (2014)), Oxford University's Coronavirus Government Response Tracker (OxCGRT), Google COVID-19 Community Mobility Reports, Consensus Economics Inc., and author's calculations.

Figure 4. Relation Between Predictors and Outcome Variable (Expected Real GDP Path) at Different Forecasting Horizons

(GDP: Model 3)



NOTE: The real GDP for the 32 countries in DGEI is the deviation of the projected path relative to 2019:Q4=100 calculated from continuous country forecasts from Consensus Economics Inc. on each business day from January 1 till April 13, 2020, as a moving average of the latest 8+ qualified changed forecasts. Forecasts for the second half of 2021 are only available since February 17, 2020. Stringency is from January 1 till April 13, 2020 and scaled to 10. The Google-provided data on mobility is available for all countries ex. Russia and China from February 15 till April 11, 2020. High and Low are set at +/- one standard deviation. All data as reported on April 14, 2020.
SOURCES: Database of Global Economic Indicators (DGEI) (Grossman et al. (2014)), Oxford University's Coronavirus Government Response Tracker (OxCGRT), Google COVID-19 Community Mobility Reports, Consensus Economics Inc., and author's calculations.

Second, the pace of the recovery is anticipated to be gradual and, as such, can be described as a check mark recovery consistent with pattern for the aggregate global outlook shown in Figure 2. A number of plausible scenarios could arise consistent with such a check mark-shaped recovery path. A more benign hypothesis would be that of a U-shaped recovery. The rationale for that envisions that COVID-19 may linger until the summer, with restrictions loosening gradually. It takes time to return to full capacity and repair the disrupted international trade and financial relationships. Thus, growth is not on a firmer footing until late 2021 or beyond. A less benign hypothesis would be that loosening controls prematurely may allow the novel coronavirus to stage a comeback in the fall, a possibility suggested early on by Ferguson et al. (2020). This may result in a W-shaped recovery, as restrictions are re-introduced and uncertainty reignites. The least benign scenario is that the recovery turns L-shaped—a result of a weakened medium-term outlook (arising from factors such as economic strains from COVID-19-related sovereign debt buildup, fears of a financial crunch and heightened uncertainty, protectionist and interventionist policies, etc.).[16]

Another piece of evidence that arises from our analysis of the private forecasters' expectations is about the path of inflation. Our findings suggest that the performance of predictors such as the stringency of policy or any changes in mobility has at best a marginal effect on the expected path of headline CPI. The estimates summarized in Table 2 suggest that these predictors explain little. This, in fact, perhaps is not that surprising after all, since we already noted in Figure 2 that the changes in the expected path of the price level have been very modest so far. It is interesting to note that mobility through transit stations is the only predictor that has a statistically significant effect in the regression, perhaps because some variation in expected inflation in the early part of 2020 could be attributed to supply disruptions and the limitations this low mobility in transit stations imposes on consumers trying to shop around at stores (perhaps only compensate by on-line shopping). Moreover, when we explore the corresponding simple slopes in Figure 5, we find that much tighter or looser mobility does not contribute much to change the outlook for inflation. The modest changes of the price level also seem consistent with a standard neoclassical interpretation of the impact of the unfolding global recession.

[16] On the significance of the credit and uncertainty linkages, see for example the work of Balke et al. (2017).

Table 3. Expected Headline CPI Path: Intercept-Only Model and Model with Explanatory Variables

Model for Expected Expected Headline CPI Path	M1: Intercept-only			M2: With Stringency as Predictor			M3: With Stringency and Mobility as Predictors		
	Estimate	2.5% CI	97.5% CI	Estimate	2.5% CI	97.5% CI	Estimate	2.5% CI	97.5% CI
Fixed Effects[a]									
Intercept	1.0135	-1.5415	3.5685	1.0153	-1.5407	3.5712	1.0425	-1.6910	3.7761
2020Q2	0.7101	-0.7918	2.2120	0.8511	-0.6514	2.3536	0.8079	-0.7874	2.4031
2020Q3	1.4593	-0.0426	2.9612	1.6142	0.1117	3.1167	1.5765	-0.0187	3.1717
2020Q4	2.2584	0.7565	3.7603	2.4064	0.9039	3.9089	2.3619	0.7666	3.9571
2021Q1	3.2360	1.7341	4.7379	3.3713	1.8688	4.8738	3.3320	1.7368	4.9272
2021Q2	3.9904	2.4886	5.4923	4.1327	2.6302	5.6352	4.0953	2.5000	5.6905
2021Q3	4.6619	3.1600	6.1638	4.9402	3.4376	6.4429	4.8689	3.2737	6.4641
2021Q4	5.4588	3.9568	6.9607	5.7075	4.2048	7.2101	5.6414	4.0462	7.2367
Stringency				-0.0006	-0.0036	0.0025	0.0094	-0.0010	0.0198
Mobility in Transit Stations							0.0009	-0.0016	0.0035
2020Q2 X Stringency				-0.0456	-0.0499	-0.0413	-0.0208	-0.0355	-0.0061
2020Q3 X Stringency				-0.0500	-0.0543	-0.0458	-0.0245	-0.0392	-0.0099
2020Q4 X Stringency				-0.0478	-0.0521	-0.0436	-0.0264	-0.0411	-0.0118
2021Q1 X Stringency				-0.0437	-0.0480	-0.0394	-0.0089	-0.0235	0.0058
2021Q2 X Stringency				-0.0460	-0.0503	-0.0417	-0.0095	-0.0242	0.0052
2021Q3 X Stringency				-0.0542	-0.0596	-0.0489	-0.0182	-0.0329	-0.0036
2021Q4 X Stringency				-0.0484	-0.0538	-0.0431	-0.0148	-0.0294	-0.0001
2020Q2 X Transit							-0.0040	-0.0076	-0.0004
2020Q3 X Transit							-0.0042	-0.0078	-0.0006
2020Q4 X Transit							-0.0029	-0.0065	0.0007
2021Q1 X Transit							0.0018	-0.0018	0.0054
2021Q2 X Transit							-0.0020	-0.0057	0.0016
2021Q3 X Transit							-0.0035	-0.0071	0.0001
2021Q4 X Transit							-0.0027	-0.0063	0.0010
Stringency X Transit							0.0001	-0.0002	0.0004
2020Q2 X Stringency X Transit							0.0009	0.0005	0.0013
2020Q3 X Stringency X Transit							0.0009	0.0005	0.0013
2020Q4 X Stringency X Transit							0.0007	0.0003	0.0011
2021Q1 X Stringency X Transit							0.0003	-0.0001	0.0007
2021Q2 X Stringency X Transit							0.0008	0.0004	0.0012
2021Q3 X Stringency X Transit							0.0008	0.0004	0.0012
2021Q4 X Stringency X Transit							0.0007	0.0003	0.0011
Random Effects									
By Forecast Quarter within Country									
$\sigma_{intercept}$	3.0518	2.7896	3.3579	3.0530	2.7907	3.3591	3.1367	2.8590	3.4625
By Country									
$\sigma_{intercept}$	6.5360	5.1701	8.5821	6.5385	5.1722	8.5854	6.7686	5.3166	8.9733
σ_{ε}	0.2875	0.2845	0.2907	0.2479	0.2453	0.2506	0.2339	0.2306	0.2373
Intraclass Correlation Coefficient (ICC)									
By Forecast Quarter within Country	0.1787			0.1788			0.1766		
By Country	0.8197			0.8200			0.8224		
Observations	18944			18944			9608		
Pseudo-R^2 (fixed effects)	0.0531			0.0534			0.0579		
Pseudo-R^2 (total)	0.9985			0.9989			0.9991		
AIC	8219.80			3324.22			1656.28		
BIC	8304.84			3471.11			1907.24		

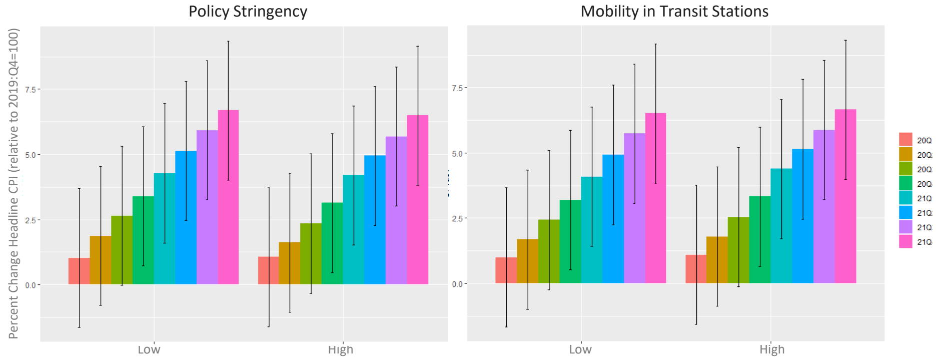
NOTE: Mixed effects linear regression model clustered in two levels by country and by forecasting quarter within a country (with up to 8 forecasting horizons from 2020Q1 till 2021Q4). The outcome variable, the expected headline CPI for 32 of the countries in DGEI, is the projected path deviation relative to 2019:Q4=100. It is calculated from continuous country forecasts from Consensus Economics Inc. released each business day as a moving average of the latest 8+ qualified changed forecasts, from January 1 till April 13, 2020. The outcome variable is imputed at all every one of the forecasting horizons for which there is data (third and fourth quarter 2020 are missing until February 17, 2020). OxCGRT's stringency is from January 1 till April 13, 2020 and scaled to 10. The Google-provided data on mobility is available for all countries ex. Russia and China from February 15 till April 11, 2020.

SOURCES: Database of Global Economic Indicators (DGEI) (Grossman et al. (2014)), Oxford University's Coronavirus Government Response Tracker (OxCGRT), Google COVID-19 Community Mobility Reports, Consensus Economics Inc., and author's calculations.

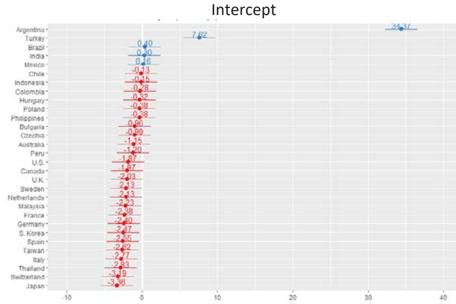
Figure 5. Relation Between Predictors and Outcome Variable (Expected Headline CPI Path) at Different Forecasting Horizons

(CPI: Model 3)

Simple Slopes (Fixed Effects)



Summary of Random Effects by Country



NOTE: The headline CPI for the 32 countries in DGEI is the deviation of the projected path relative to 2019:Q4=100 calculated from continuous country forecasts from Consensus Economics Inc. on each business day from January 1 till April 13, 2020, as a moving average of the latest 8+ qualified changed forecasts. Forecasts for the second half of 2021 are only available since February 17, 2020. Stringency is from January 1 till April 13, 2020 and scaled to 10. The Google-provided data on mobility is available for all countries ex. Russia and China from February 15 till April 11, 2020. High and Low are set at +/- one standard deviation. All data as reported on April 14, 2020.
SOURCES: Database of Global Economic Indicators (DGEI) (Grossman et al. (2014)), Oxford University's Coronavirus Government Response Tracker (OxCGRT), Google COVID-19 Community Mobility Reports, Consensus Economics Inc., and author's calculations.

The differences across countries that we observe in the random effects grouped by country in the same Figure 5 tend to show patterns that predate the current recession—low inflation among many advanced economies, and high inflation in some emerging economies.

5 Concluding Remarks

The costs of ignoring the challenges ahead of us are aptly noted by President Dwight D. Eisenhower when he stated that: "In preparing for battle I have always found that plans are useless, but planning is indispensable." With the analysis we do in this paper we are hoping to aid with the "planning" by providing some insight into the formation of private expectations at this critical time (at the onset of the COVID-19 pandemic). The period we explore from January 1 through April 13, 2020, has been characterized by strong goverment emphasis centered primarily on bending the curve and to a lesser extent on dealing with the economic consequences of such extraordinary interventions.

Our analysis of the underlying signals about the global outlook from a country panel of daily forecasts from Consensus Economics Inc. (2020) suggests that a check mark recovery has become the point of reference among private forecasters who anticipate a prolonged downward shift in the expected path of economic activity, but only a marginal impact on the expected path of the price level, as governments scramble to provide fiscal and monetary support with which to redress some of the macro consequences of the stringent policy interventions imposed to deal with the health consequences of the COVID-19 pandemic.

The path the global economy takes should become more apparent as new data becomes available. The path of the recovery will depend on how policymakers, households and firms respond to the impact of the spread of COVID-19 as efforts continue to curb risks to the global economy and prop up long-term growth prospects. The important lesson that we derive from this exercise is that, unusual as this episode is, the private forecasters' assessment of the current recession seems consistent with the basic predictions of the neoclassical growth model against which the efficacy of the macro policy actions that are being deployed or considered could be judged.

How do we get out of this? Any company depends, above all else, on its ability to innovate and compete. The productivity of a country is only that of all its companies added up. Let's think of a tapas bar... A tapas bar is no different than an engineering firm—it is another value chain. Instead of engineering, there is food and cooking involved. If due to the confinement the owner of the tapas bar is not able to pay the wages, ends up losing the expert cook and the friendly waiters, relations with vendors and suppliers break down, and when it finally reopens, customers also stop going, because it has lost much of the value added the tapas bar provided for them, then the business will not survive. The key is to retain the *know-how* and that also includes that of all the value chain (suppliers, etc.) as well as knowing your costumers who appreciate those tapas and pay for them. In other words, retaining the *know-how* also involves retaining the market "matches" that made the business successful in the first place.

The economic impact of this pandemic will depend greatly on whether, like the tapas bar, the economy maintains its human capital and those arrangements and *know-how* that determine its productivity: if the confinement does not destroy this, recovery will be faster; otherwise, it may take longer to rebuild the economy. In other words, disruptions of supply chains and the destruction of organizational capital due to firm liquidations, low physical and human capital investment from strained balance sheets, education and training deficiencies could end up lowering labor productivity and total factor productivity (TFP), thereby slowing the recovery. Hence, to help sustain and even strengthen the recovery it is important that the lockdown is not so long that the country loses those productive skills (*know-how*) and that liquidity measures have been sufficient to allow the innovation capacity and human capital of the country to remain largely intact.

Still, at this point some impact may simply be unavoidable due to the severity of the disruption in many countries and on international trade and financial relationships, as well as from changes in consumer behavior that may predate the recession but could accelerate during the crisis becoming largely permanent afterwards (such as on-line shopping, fintech solutions to facilitate business to consumer transactions (B2C), etc.), deteriorating public finances with government debt buildup, etc.

References

Backus, D. K., P. J. Kehoe, and F. Kydland (1992). International Real Business Cycles. *Journal of Political Economy 100*(4), 745–755. https://doi.org/10.1086/261838.

Balke, N., E. Martínez-García, and Z. Zeng (2017). Understanding the Aggregate Effects of Credit Frictions and Uncertainty. *Federal Reserve Bank of Dallas Globalization and Monetary Policy Institute Working Paper No. 317*. June 2017 (Revised: October 2019). https://doi.org/10.24149/gwp317r1.

Bates, D., M. Mächler, B. Bolker, and S. Walker (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software 67*(1), 1–48. https://doi.org/10.18637/jss.v067.i01.

CDC (2019). 1918 Pandemic (H1N1 Virus). *Centers for Disease Control and Prevention - On-line Resources*. https://www.cdc.gov/flu/pandemic-resources/1918-pandemic-h1n1.html.

CDC (2020). Coronavirus (COVID-19). *Centers for Disease Control and Prevention - On-line Resources*. https://www.cdc.gov/coronavirus/2019-ncov/index.html.

CEA (2019). Mitigating the Impact of Pandemic Influenza through Vaccine Innovation. *Council of Economic Advisors of*. Executive Office of the President of the United States. https://bit.ly/3c845fz.

Consensus Economics Inc. (2020). Consensus Economics Daily GDP and Inflation Forecasts. *Macroeconomic Survey Firm*. https://www.consensuseconomics.com/.

Dong, E., H. Du, and L. Gardner (2020). An Interactive Web-Based Dashboard to Track COVID-19 in Real Time. *Lancet Infectious Diseases*. Available at: https://doi.org/10.1016/S1473-3099(20)30120-1. Data repository: https://github.com/CSSEGISandData/COVID-19. Accessed on: April 15, 2020.

Ferguson, N. M., D. Laydon, G. Nedjati-Gilani, and et. al. (2020). Report 9: Impact of Non-pharmaceutical Interventions (NPIs) to Reduce COVID-19 Mortality and Healthcare Demand. Technical report, Imperial College London & Abdul Latif Jameel Institute for Disease and Emergency Analytics (J-IDEA), COVID-19 Response Team. https://doi.org/10.25561/77482.

Flaxman, S., S. Mishra, A. Gandy, and et al. (2020). Report 13: Estimating the Number of Infections and the Impact of Non-pharmaceutical Interventions on COVID-19 in 11 European Countries. Technical report, Imperial College London & Abdul Latif Jameel

Institute for Disease and Emergency Analytics (J-IDEA), COVID-19 Response Team. https://doi.org/10.25561/77731.

Goh, G. (2020). Epidemic Calculator. *Web-based tool*. http://gabgoh.github.io/COVID/index.html.

Google LLC (2020). COVID-19 Community Mobility Reports. *Data use policy: Creative Commons Attribution CC BY standard*. Available at: https://www.google.com/covid19/mobility/. Accessed: April 14, 2020.

Grossman, V., A. Mack, and E. Martínez-García (2014). A New Database of Global Economic Indicators. *The Journal of Economic and Social Measurement 39*(3), 163–197. https://www.doi.org/10.3233/JEM-140391. The database can be accessed at: https://www.dallasfed.org/institute/dgei.

Hadfield, J., C. Megill, S. M. Bell, J. Huddleston, B. Potter, C. Callender, P. Sagulenko, T. Bedford, and R. A. Neher (2018). Nextstrain: Real-Time Tracking of Pathogen Evolution. *Bioinformatics 34*(23), 4121Ű4123. https://doi.org/10.1093/bioinformatics/bty407. Genomic epidemiology of novel coronavirus - Global subsampling website: https://nextstrain.org/ncov/global.

Hale, T., S. Webster, A. Petherick, T. Phillips, and B. Beatriz Kira (2020). Oxford COVID-19 Government Response Tracker. *Blavatnik School of Government, Oxford University*. Creative Commons Attribution CC BY standard. Available at: https://www.bsg.ox.ac.uk/covidtracker. Accessed on: April 14, 2020.

Hammond, G. (2012). State of the Art of Inflation Targeting - 2012. *Centre for Central Banking Studies. Handbook - No. 29*. Bank of England. https://urlzs.com/xJvF.

Hauck, K. D. (2018). The Economics of Infectious Diseases. In A. Jones (Ed.), *Oxford Research Encyclopedia of Economics and Finance*. Oxford University Press. http://dx.doi.org/10.1093/acrefore/9780190625979.013.251.

Heisterkamp, S. H., E. van Willigen, P.-M. Diderichsen, and J. Maringwa (2017). Update of the nlme Package to Allow a Fixed Standard Deviation of the Residual Error. *The R Journal 9*(1), 239–251. https://doi.org/10.32614/rj-2017-010.

IHME (2020). Forecasting the Impact of the First Wave of the COVID-19 Pandemic on Hospital Demand and Deaths for the USA and European Economic Area Countries. *medRxiv/2020/074732*. IHME COVID-19 Health Service Utilization Forecasting Team, Institute for Health Metrics and Evaluation, University of Washington. https://bit.ly/3cNdcCf. Data accessible at: http://www.healthdata.org/covid.

IMF (2020). Policy Responses to COVID-19. *IMF On-Line Database*. https://www.imf.org/en/Topics/imf-and-covid19/Policy-Responses-to-COVID-19.

IMF WEO (2019). October 2019 World Economic Outlook Database. *World Economic and Financial Surveys, International Monetary Fund*. https://www.imf.org/external/pubs/ft/weo/2019/02/weodata/index.aspx.

Ingholt, M. M. (2020). Epidemics and the Economy: An Overview. *Bankplassen Blog*. Norges Bank. https://bit.ly/2A3Ujgh.

Kydland, F. E. and E. C. Prescott (1990). Business Cycles: Real Facts and a Monetary Myth. *Federal Reserve Bank of Minneapolis Quarterly Review 14*(2), 3–18. https://doi.org/10.21034/qr.1421.

Luo, J. (2020). Predictive Monitoring of COVID-19. *Working Draft, Singapore University of Technology and Design*. https://bit.ly/2WvYOb6. Related resources can be accessed at: https://ddi.sutd.edu.sg/.

Martínez-García, E. (2018). Modeling Time-Variation Over the Business Cycle (1960-2017): An International Perspective. *Studies in Nonlinear Dynamics and Econometrics 22*(5), 1–25. https://doi.org/10.1515/snde-2017-0101.

Martínez-García, E. (2020). Private Forecasters' COVID-19 Global Growth Outlook Takes Shape. *Dallas Fed Economics Blog*. May 5, 2020. https://www.dallasfed.org/research/economics/2020/0505.

Martínez-García, E., V. Grossman, and A. Mack (2015). A Contribution to the Chronology of Turning Points in Global Economic Activity (1980Ű2012). *Journal of Macroeconomics 46*, 170–185. https://doi.org/10.1016/j.jmacro.2015.09.003.

Roser, M., H. Ritchie, E. Ortiz-Ospina, and J. Hasell (2020). Coronavirus Disease (COVID-19). *OurWorldInData.org*. Creative Commons Attribution CC BY standard. Available at: https://ourworldindata.org/coronavirus. Accessed on: April 15, 2020.

Taubenberger, J. K. and D. M. Morens (2006). 1918 Influenza: The Mother of All Pandemics. *Emerging Infectious Diseases 12*(1), 15–22. https://doi.org/10.3201/eid1209.05-0979.

WHO (2020). International Health Regulations (2005) Monitoring Framework. *Global Health Observatory Data Repository*. World Health Organization (WHO). https://apps.who.int/gho/data/node.main.IHR?lang=en. Accessed: April 24, 2020. Note: The WHO excludes all data for Taiwan.

Worldometer (2020). COVID-19 Coronavirus Pandemic. *On-Line Resources by www.worldometers.info*. Available at: https://www.worldometers.info/. Accessed on: April 15, 2020.

Yilmazkuday, H. (2020, http://dx.doi.org/10.2139/ssrn.3571708). Stay-at-Home Works to Fight Against COVID-19: International Evidence from Google Mobility Data. *SSRN Working Paper No. 3571708*. http://dx.doi.org/10.2139/ssrn.3571708.