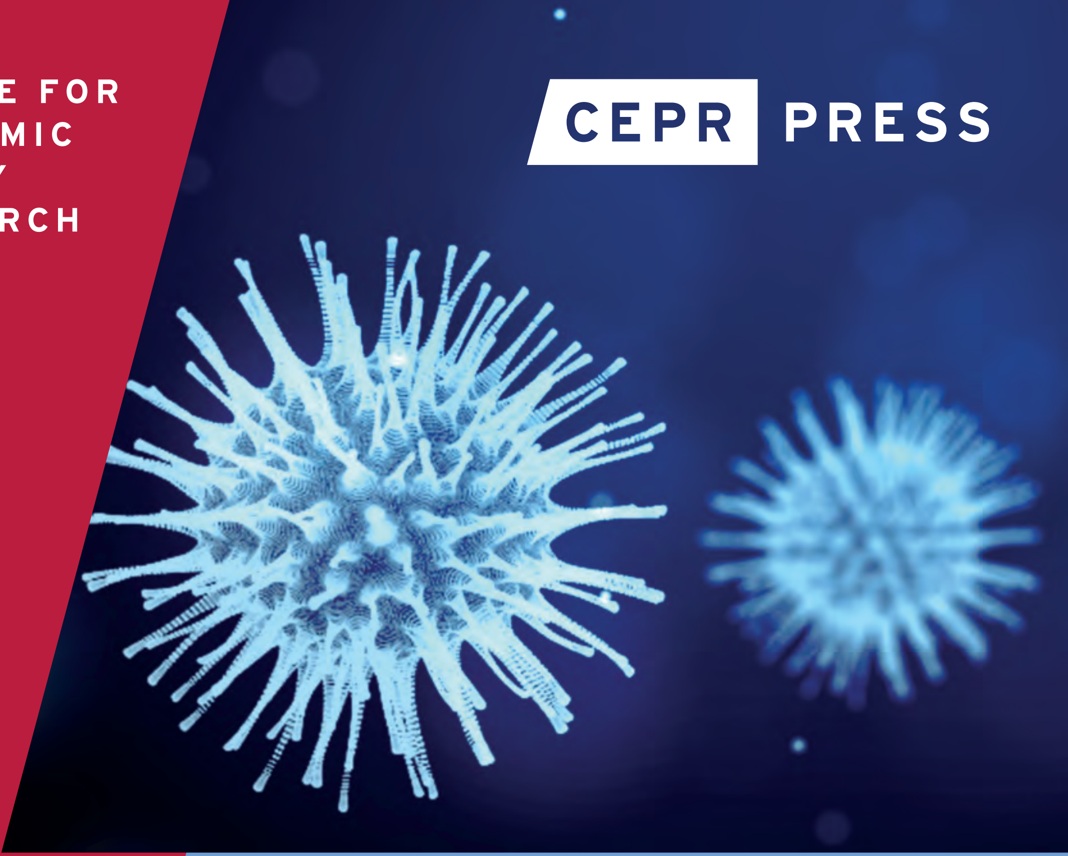
CENTRE FOR
ECONOMIC
POLICY
RESEARCH

CEPR PRESS



COVID ECONOMICS

VETTED AND REAL-TIME PAPERS

ISSUE 67
4 FEBRUARY 2021

Covid Economics
Vetted and Real-Time Papers

Covid Economics, Vetted and Real-Time Papers, from CEPR, brings together formal investigations on the economic issues emanating from the Covid outbreak, based on explicit theory and/or empirical evidence, to improve the knowledge base.

Founder: Beatrice Weder di Mauro, President of CEPR
Editor: Charles Wyplosz, Graduate Institute Geneva and CEPR

Contact: Submissions should be made at https://portal.cepr.org/call-papers-covid-economics. Other queries should be sent to covidecon@cepr.org.

The Centre for Economic Policy Research (CEPR)

The Centre for Economic Policy Research (CEPR) is a network of over 1,500 research economists based mostly in European universities. The Centre's goal is twofold: to promote world-class research, and to get the policy-relevant results into the hands of key decision-makers. CEPR's guiding principle is 'Research excellence with policy relevance'. A registered charity since it was founded in 1983, CEPR is independent of all public and private interest groups. It takes no institutional stand on economic policy matters and its core funding comes from its Institutional Members and sales of publications. Because it draws on such a large network of researchers, its output reflects a broad spectrum of individual viewpoints as well as perspectives drawn from civil society. CEPR research may include views on policy, but the Trustees of the Centre do not give prior review to its publications. The opinions expressed in this report are those of the authors and not those of CEPR.

Editorial Board

Ethics

Covid Economics will feature high quality analyses of economic aspects of the health crisis. However, the pandemic also raises a number of complex ethical issues. Economists tend to think about trade-offs, in this case lives vs. costs, patient selection at a time of scarcity, and more. In the spirit of academic freedom, neither the Editors of *Covid Economics* nor CEPR take a stand on these issues and therefore do not bear any responsibility for views expressed in the articles.

Submission to professional journals

The following journals have indicated that they will accept submissions of papers featured in *Covid Economics* because they are working papers. Most expect revised versions. This list will be updated regularly.

American Economic Journal, Applied Economics
American Economic Journal, Economic Policy
American Economic Journal, Macroeconomics
American Economic Journal, Microeconomics
American Economic Review
American Economic Review, Insights
American Journal of Health Economics
Canadian Journal of Economics
*Econometrica**
Economic Journal
Economics of Disasters and Climate Change
International Economic Review
Journal of Development Economics
*Journal of Econometrics**
Journal of Economic Growth
Journal of Economic Theory
*Journal of the European Economic Association**
Journal of Finance
Journal of Financial Economics
Journal of Health Economics
Journal of International Economics
*Journal of Labor Economics**
Journal of Monetary Economics
Journal of Public Economics
Journal of Public Finance and Public Choice
Journal of Political Economy
Journal of Population Economics
Quarterly Journal of Economics
*Review of Corporate Finance Studies**
Review of Economics and Statistics
*Review of Economic Studies**
Review of Financial Studies

(*) Must be a significantly revised and extended version of the paper featured in *Covid Economics*.

Covid Economics
Vetted and Real-Time Papers

Issue 67, 4 February 2021

Contents

Covid Economics **Issue 67, 4 February 2021**

Lockdown fatigue: The diminishing effects of quarantines on the spread of COVID-19

Patricio Goldstein,[1] Eduardo Levy Yeyati[2] and Luca Sartorio[3]

Date submitted: 1 February 2021; Date accepted: 2 February 2021

Non-Pharmaceutical Interventions (NPIs) have been for most countries the key policy instrument utilized to contain the impact of the COVID-19 pandemic. In this article, we conduct an empirical analysis of the impact of these policies on the virus' transmission and death toll, for a panel of 152 countries, from the start of the pandemic through December 31, 2020. We find that lockdowns tend to significantly reduce the spread of the virus and the number of related deaths. We also show that this benign impact declines over time: after four months of strict lockdown, NPIs have a significantly weaker contribution in terms of their effect in reducing COVID-19 related fatalities. Part of the fading effect of quarantines could be attributed to an increasing non-compliance with mobility restrictions, as reflected in our estimates of a declining effect of lockdowns on measures of actual mobility. However, we additionally find that a reduction in de facto mobility also exhibits a diminishing effect on health outcomes, which suggests that lockdown fatigues may have introduce broader hurdles to containment policies.

1 Research Fellow, Center for International Development, Harvard University.
2 Dean, School of Government, Universidad Torcuato Di Tella & The Brookings Institution.
3 Research Fellow, Center for Evidence-Based Policies, Universidad Torcuato Di Tella.

Covid Economics 67, 4 February 2021: 1-23

1. Introduction

Faced with the emergence and global spread of the COVID-19 virus pandemic, governments deployed restrictions on mobility and social life without precedents in peacetime. Lacking adequate vaccines or antiviral medications, non-pharmaceutical interventions (NPIs) to reduce SARS-CoV-2 transmission were implemented worldwide to constrain the spread of the virus. While these policies themselves (as well as voluntary reductions in social mobility) may have had a significantly detrimental effect on economic activity and individual livelihoods, there is a widespread belief that they were effective in containing the spread of the virus, avoiding congestion in the health system and ultimately reducing the toll of the pandemic. At the same time, there is an increasing sense that lockdown fatigue has placed limits on the efficacy of NPIs henceforth and on the ability to reintroduce them in the event of repeated peaks.

In this paper, we ask ourselves to what extent have NPIs and reductions in social mobility been effective in reducing the spread of COVID-19, and in improving the pandemic's epidemiological outcomes. We provide evidence that restrictions had a significant effect in the first weeks after their introduction. The effect of boosting NPIs on an estimate of the daily reproduction number R_t[1] peaks at about 10 days and disappears at about 20, consistent with a significant contribution to reducing the incidence of the pandemic. However, the initial effect cannot be replicated over time: after 120 (continuous or discontinuous) days or strict lockdown, the response flattens to a point that, even at its peak, it fails to reduce the spread significantly. A similar pattern is found when we measure impact in terms of cumulative or daily deaths per million. This suggests that restrictions applied for a long period or reintroduced late in the pandemic (for example, in the event of a resurgence of cases) would exert,

[1] The reproduction number R_t is an estimate of the rate of spread of COVID-19 and can be defined as the average number of secondary infections that is generated by a primary infection.

Covid Economics 67, 4 February 2021: 1-23

at best, a weaker, attenuated effect on the evolution of cases and casualties. We find a similar pattern when we use mobility as the proxy for the mobility-related NPIs instead of an index of containment measures. Overall, we conclude that restrictions played a role early on the pandemic but had a transient effect that will be hard to replicate going forward.

The paper is organized as follows. The second section provides a literature review of the recent empirical literature providing estimates of the effect of containment measures on health outcomes associated with the COVID-19 pandemic. The third section describes the data and the econometric methodology. The fourth section presents our main results both on the effect of containment measures and on the non-linearity of their effectiveness over time. The last section discusses the implications of our findings in the face of the next outbreaks of COVID-19 and concludes.

2. Literature Review

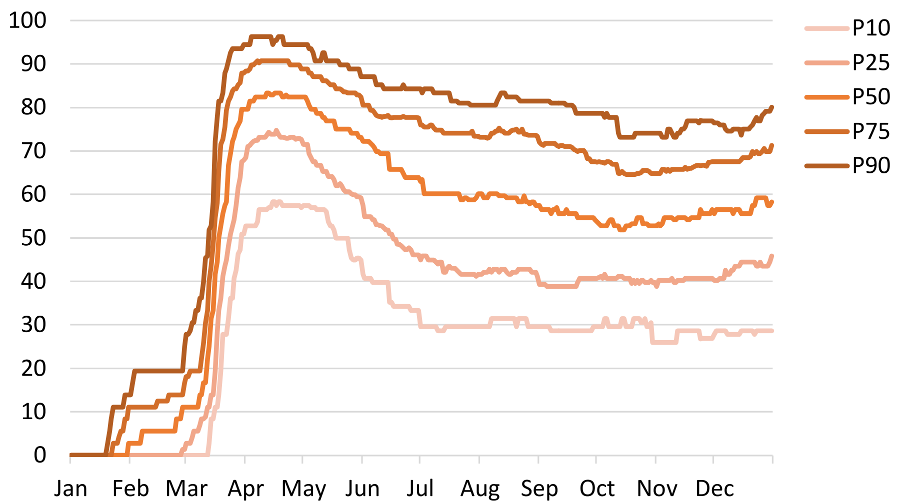
The start of the pandemic and the sudden advent of a global health, economic and social crisis has motivated the emergence of an increasingly sizeable and varied COVID-19 literature. Specifically, a strain of empirical studies has sought to improve our changing understanding of the causal impact of unprecedented non-pharmaceutical interventions on health outcomes, by providing statistical estimates of NPIs in key epidemiological variables. The majority of these studies have focused their analysis on the initial months of the pandemic and have for the most part documented significant effects of NPIs in reducing the spread of the virus. However, given their different time frames and econometric methods used, these studies have not arrived at uniform conclusions.

The analyses have benefitted from the publication of high-frequency cross-country metrics on *de jure* restrictions to social interactions and *de facto* compliance to these. The Oxford COVID-19 Government Response Tracker's (OxCGRT) "Stringency Index" has been amongst these the most

Covid Economics 67, 4 February 2021: 1-23

widely used (Hale et al. 2020). OxCGRT collects at a regular basis nineteen indicators of government responses to the virus (eight indicators on "containment and closure", four on economic policies and seven on health system policies). The "Stringency Index" is a composite indicator which combines information on the legal intensity of eight "containment and closure" policies: (i) school closures, (ii) workplace closures, (iii) public event bans, (iv) restrictions on private gatherings, (v) public transportation closures, (vi) "stay-at-home" requirements; (vii) restrictions on internal movement; and (viii) international travel controls. Analysis of the impact of *de jure* NPIs take advantage of the cross-country and time variation of the index and its components, as illustrated by *Figure 1*, which displays variations in the Stringency index for 160 countries up to January 15, 2021.

Figure 1. OxCGRT Stringency Index



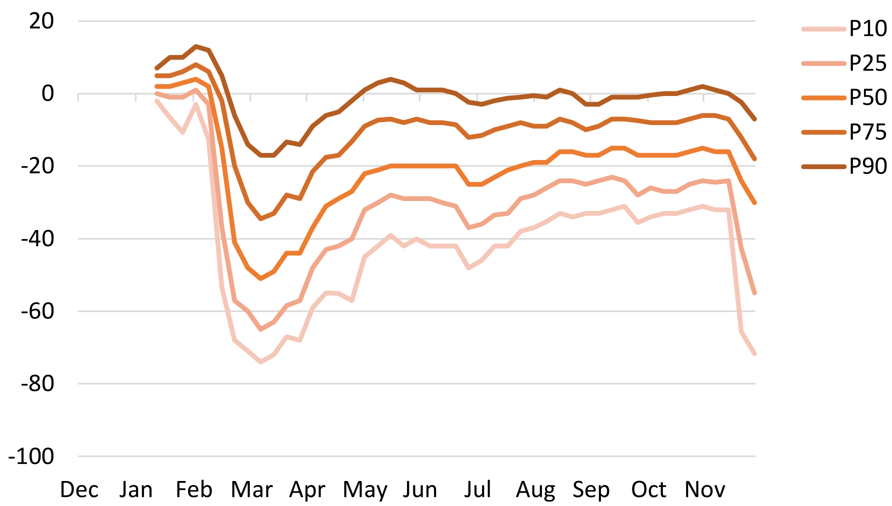
Source: Oxford's COVID-19 Government Response Tracker (OxCGRT)

Beyond policies implemented to contain social interactions, other studies have relied on measures of social mobility itself, as captured by anonymized location history data from Google Maps (or Apple Maps) users. Google Mobility Reports provide daily changes in mobility with respect to a January-

CEPR PRESS

February 2020 median baseline for each corresponding day of the week. The reports record changes in mobility for six different location categories: (i) workplaces, (ii) residential, (iii) transit stations, (iv) parks, (v) groceries and pharmacies, (vi) centers of retail and recreation. *Figure 2* illustrates the evolution of workplaces mobility for 120 countries up to January 15, 2021. The figure – and our corresponding analysis in the next section – averages out daily variations in the index though the week to reduce its strong seasonality.

Figure 2. Google Workplaces Mobility Index



Source: Google Mobility Reports

Leveraging within and between country variation in OxCGRT and Google mobility data, Askitas et al. (2020) presented in May a model to study the effects of NPIs both on epidemiological outcomes of COVID-19 and mobility. A multiple events model is developed by the authors in an effort to disentangle the distinct effect of concurrent interventions, using a panel data set of 135 countries. The authors conclude that the cancelation of public events and restrictions on private gatherings have the largest effects both on mobility and COVID-19 cases, followed by school and workplace closures. In

Covid Economics 67, 4 February 2021: 1-23

a similar fashion, Wong et al. (2020) analyzed the concurrent impact of NPIs as recorded by OxCGRT for 131 countries for the period between April 15 to April 30, including country-specific controls, and found more stringent containment associated with a better control of the pandemic.

In Deb et al. (2020), the dynamic cumulative effect of both NPIs and reduction in mobility is estimated for a panel of 129 countries until June 15 by adopting the methodology developed by Jordà (2005) to estimate impulse responses without specifications through local projections. In a second econometric specification, the authors allow for the effect of containment measures to vary according to country characteristics. A variety of controls such as temperature and humidity, testing and contact tracing policies are included, as well as country specific time trends and lags of the changes in the number of infected cases (this serving as a control for the reverse causality of infections on governments' response to the pandemic). The authors document a high effectiveness of measures implemented to containing the spread the pandemic, with high heterogeneity across countries depending on factors such as average daily temperature, countries' population density, the quality of their health system and their age structure. Authors also find that easing the stringency of NPIs has resulted in an increase in the number of cases and deaths lower than the reduction associated with tightening measures. Finally, Li et al. (2020) evaluates the effect of NPIs for 131 countries up to July 20 by observing their effect on an estimated country-specific and time-varying reproduction number. The authors find that the introduction of measures such as school closures, workplace closures, bans on public events, requirements to stay at home, and internal movement limits are associated with a decreasing trend over time in the reproduction number, although this association is only significant for the public events ban. The relaxation of these measures is conversely associated with an increase in the reproduction number, although only significant for the case of school reopening.

Covid Economics 67, 4 February 2021: 1-23

The nascent COVID-19 literature has for the most part agreed on the significance NPIs have had in reducing the spread and consequences of the pandemic, despite differences in both methodologies and econometric estimates (in particular, regarding the effect of specific NPIs). However, there are reasons to believe additional research is needed to characterize the pandemic's evolving impact. Published studies focused on the impact during the pandemic's "first wave", with data limited to the first semester of 2020, and as a result tested only partially for the presence of lockdown fatigue or, more generally, non-linear effects due to the cumulative economic and psycho-sociological burden of the restrictions and the diminishing degree of compliance.[2] Moreover, even when enforcement is high, improvements in protocols for economic, academic, and recreational activities, expansion of tracking and isolation capacities, and better treatments could render containment relatively less influential in improving epidemiological outcomes in the presence of new peaks.

3. Methodology and Data

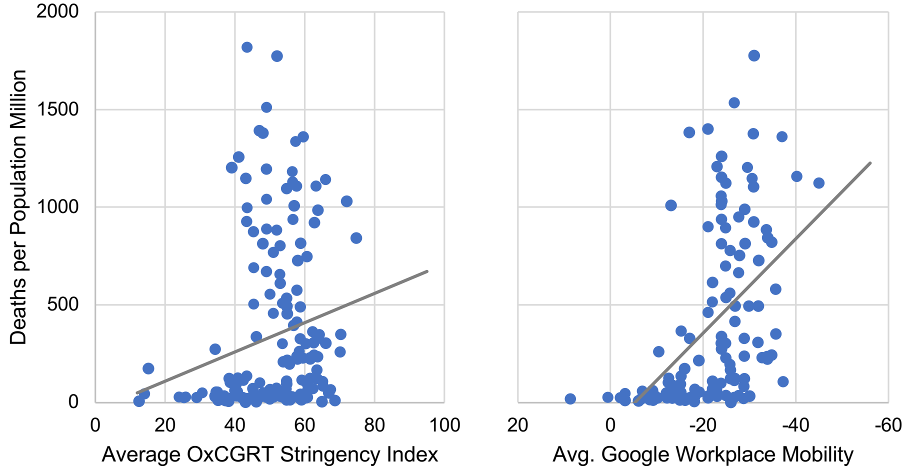
The key obstacles to isolate the effect of NPIs on the main epidemiological outcomes associated with COVID-19 are its time-varying nature and the associated non-linearity of the effect. As *Figure 3* shows, a simple comparison of the average intensity of *de jure* and *de facto* reductions in social mobility (from March through December 2020) with COVID 19-related deaths does not reveal a consistent and meaningful link. The presence of reverse causality (a higher death toll should elicit to more stringent containment measures) and country-specific factors (demographics, health system strength, urban density) that shape both the lethality of the virus and the willingness and ability to enforce NPIs make a basic two-way correlation uninformative. More to the focus of this paper, to the extent that the effectiveness of NPIs varies over time, an average over long periods is a poor proxy of

[2] As Levy Yeyati and Sartorio (2020) show for a broad set of developed, emerging and developing countries, the distance between the *de jure* severity of a lockdown and the *de facto* impact on mobility tends to grow steadily over time, the more so the lower the country´s per capita income and the degree of labor formality.

Covid Economics 67, 4 February 2021: 1-23

actual intensity, as the effectiveness of short periods of high intensity and long periods of moderate intensity may differ.

Figure 3. OxCGRT Stringency Index, Google Workplace Mobility and COVID-19 Deaths



Sources: Oxford's COVID-19 Government Response Tracker (OxCGRT), Google Mobility Reports

To estimate the effect of NPIs over time, we followed Deb et al. (2020) in their use of the local projections methodology first introduced in Jordà (2005). By estimating one-step-ahead ordinary regressions for each time period –instead of approximating the data globally through, for example, a vector autoregression– local projections provide impulse-response functions that are not only more suitable for non-linear and flexible relations but also less susceptible to misspecification and simpler for statistical inference.

To conduct our analysis, we use data on COVID-19 deaths provided by University of Oxford's Our World in Data COVID-19 tracker, and estimates of the effective reproduction number (R_t) from the Metrics COVID-19 Analysis website, published by epidemiologists from Harvard´s T.H. Chan School of Public Health (Adam 2020). These R_t estimates, based on the EpiEstim methodology, are calculated using the number of reported daily new cases. These could be lower than actual cases given under-reporting or insufficient testing capabilities, which could bias the estimates. In both cases, we have conducted our analysis with seven day averages of the COVID-19 outcome variables, to smooth out high frequency variations and short-lived reporting lags in the data. For robustness, we also estimated our main specifications using R_t estimates from Arroyo-Marioli et al. (2021), as well as data on COVID-19 cases. For the policy intervention variable, we use the OxCGRT Stringency Index (alternatively, we the workplace mobility estimate from Google Mobility Reports, re-indexed to account for seasonality). The panel dataset includes 152 countries with data from the onset of the pandemic until December 31, 2020. Only 146 countries have R_t estimates, and only 114 of these countries have Google mobility data.

We estimate the following two base specifications for both COVID-19 deaths and the disease's reproduction number R_t:

$$d_{i,t+z} - d_{i,t} = D_i + \mathrm{B}_{i,t} X_{i,t} + \beta_h S_{i,t} + \phi_{i,t}\left(d_{i,t} - d_{i,t-7}\right) + \gamma_t H_t + \varepsilon_{i,t+z} \tag{1}$$

$$d_{i,t+z} - d_{i,t+z-7} = D_i + +\mathrm{B}_{i,t} X_{i,t} + \beta_h S_{i,t} + \phi_{i,t}\left(d_{i,t} - d_{i,t-7}\right) + \gamma_t H_t + \varepsilon_{i,t+z} \tag{2}$$

where $d_{i,t+z} - d_{i,t}$ is the difference in logarithms of the variable of interest for country i between times t and $t + z$, and $d_{i,t+z} - d_{i,t+z-7}$ is the difference in logarithm at time $t + z$ and one week before that. The first regression measures the cumulative change in the dependent variable since the start of the intervention, while the second regression measures the intervention's impact in the weekly evolution of the variable. D_i are country fixed-effects and $S_{i,t}$ is our tested intervention (measures of intensity of *de jure* and *de facto* reduction in social interactions). We include as controls $X_{i,t}$ temperature and humidity, using daily data of the largest city of each country from the Air Quality Open Data Platform. We also estimate the effect of testing and contract tracing policies (using data from OxCGRT) as a

Covid Economics 67, 4 February 2021: 1-23

robustness check. Following Deb et al. (2020), we include a lag of the dependent variable as a control for the endogenous adoption of NPIs (as a response to an increase in the number of COVID-related deaths or in the reproduction number). Finally, when the dependent variable is based on COVID-19 deaths, we include the sample median of deaths per population at each point in time, as a proxy for the global evolution of the pandemic.

To account for the lockdown´s diminishing marginal effect, our second set of specifications includes a variable $T_{i,t}$ that estimates the cumulative past "intensity" of NPI measures as the number of days in the past for which the Stringency Index was at least 70, and an interaction between this variable and the intervention variable of interest:

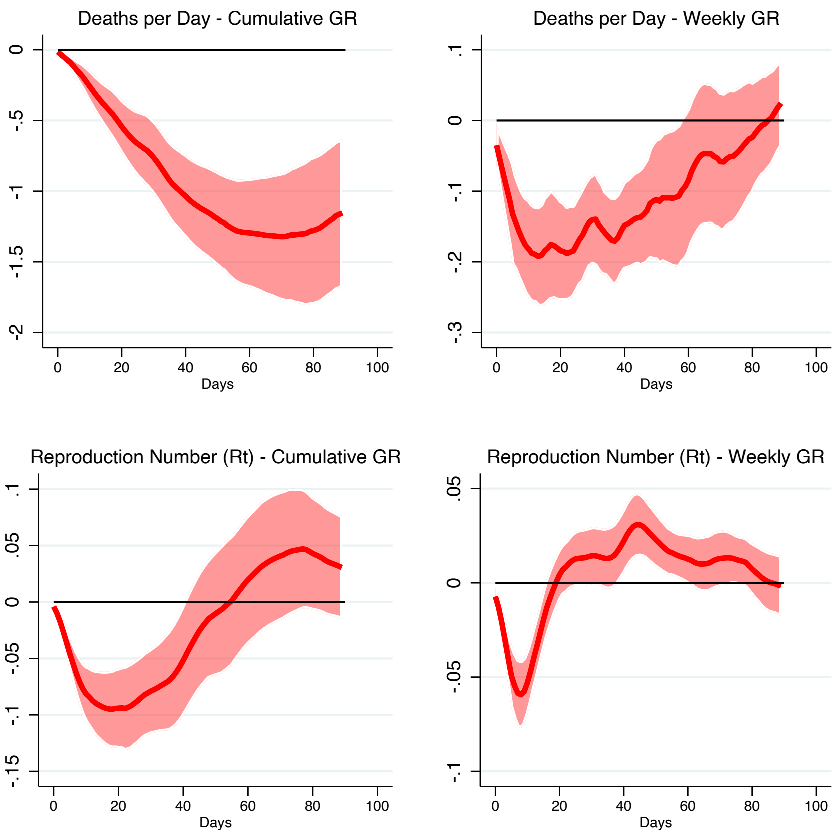
$$d_{i,t+z} - d_{i,t} = D_i + \mathrm{B}_{i,t}X_{i,t} + \beta_h S_{i,t} + \delta_h T_{i,t} + \gamma_{i,t}(S_{i,t} \times T_{i,t}) + \phi_{i,t}\left(d_{i,t} - d_{i,t-7}\right) + \gamma_t H_t + \varepsilon_{i,t+z} \quad (3)$$

$$d_{i,t+z} - d_{i,t+z-7} = D_i + \mathrm{B}_{i,t}X_{i,t} + \beta_h S_{i,t} + \delta_h T_{i,t} + \gamma_{i,t}(S_{i,t} \times T_{i,t}) + \phi_{i,t}\left(d_{i,t} - d_{i,t-7}\right) + \gamma_t H_t + \varepsilon_{i,t+z} \quad (4)$$

4. Results

Figure 4 shows the estimated dynamic cumulative response and corresponding daily growth rate of the two impact metrics – the reproduction number and the number of daily deaths – to a standard deviation change in the Stringency index over the 90-day period following the intensification of containment measures. The *de jure* rigidity of NPIs is associated with a gradual, significant and negative reduction of the spread of the virus and of COVID-related deaths. The effect in the evaluated time period is fairly persistent, as its cumulative effect on deaths peaks at about 60 days after the increase in NPI intensity; the effect on the reproduction rate peaks at 20 days. Specifically, a one standard deviation in the Stringency index yields a maximum cumulative 75% decline in deaths per million with respect to the 60-day evolution projected without intervention, and a maximum 10% decline in the reproduction number.[3]

Figure 4. Impact of OxCGRT Stringency Index on Effective Reproduction Rate and COVID-19 Related Deaths



[3] Since the results are presented in log differences, a one standard deviation increase in the index which yields a 1.37 log difference of the dependent variable is equivalent to a $e^{-1.37} - 1 = -0.75$ decline in weekly deaths per million.

Covid Economics 67, 4 February 2021: 1-23

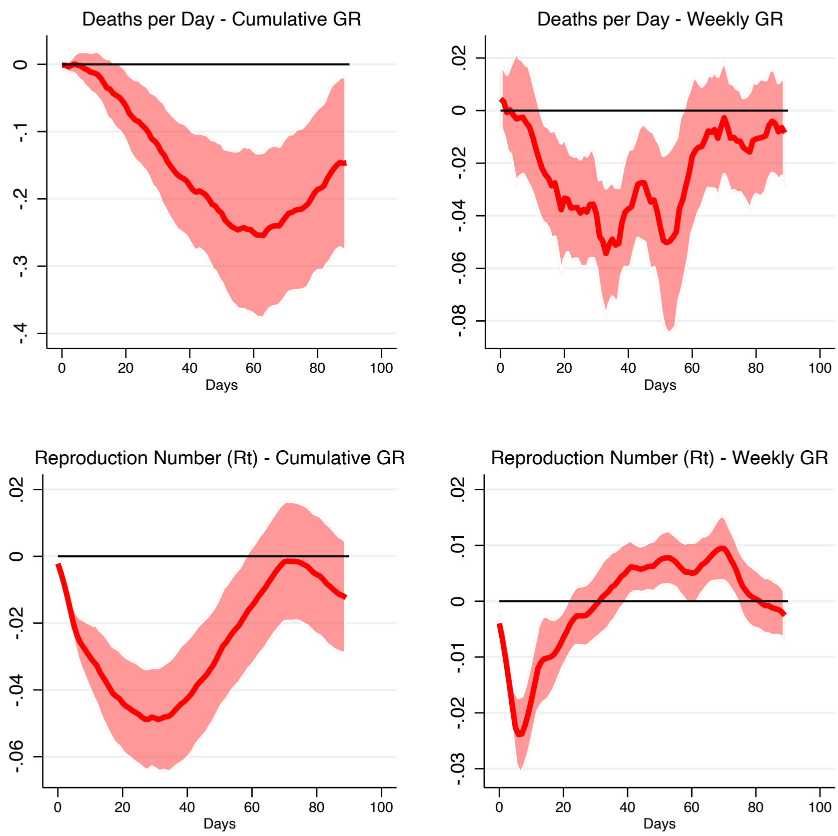
Note. The graph represents the estimated impulse response function for a one standard deviation change in the OxCGRT Stringency Index. The shaded area represents the 90% confidence interval for the coefficient.

These results are robust to a number of checks to the main econometric specification, which include: i) eliminating the climate control variables: temperature and humidity (*Figure A1*), ii) eliminating the time trend of the pandemic and the dependent variable lag (*Figure A2*) and iii) adding additional controls variables to identify the intensity of other relevant NPIs such as testing policies, contact tracing and public information campaigns (*Figure A3*). None of these changes to the baseline specification substantially altered the size of the impact, its statistical significance, and its fading time pattern.

As noted above, we replicate the previous estimations using Google Workplace Mobility index instead of the Stringency Index. This robustness check is of particular interest not only because mobility is not a policy variable but an outcome – and, as such, could be *a priori* less endogenous to COVID-related variables (although voluntary reductions in social mobility could also respond to the evolution of the pandemic)– but also because, as has been shown in the literature, lockdowns face diverse degrees of compliance, of which the evolution of the concomitant changes in workplace mobility are a good illustration. As can be seen in *Figure 5*, this proxy of the *de facto* consequences of a quarantine shows a similar to –albeit more muted pattern than–the Stringency Index: a one standard deviation reduction in mobility yields a maximum cumulative decline of near 22 pp in weekly deaths per million (with respect to baseline change expected in a 60-day period), and a nearly 5 pp cut in the reproduction coefficient (with respect to baseline change expected in a 30-day period). The more attenuated impact seems realistic: we conjecture that it possibly reflects a smoother variation of the intervention variable as well as the presence of channels other than mobility through which the lockdown influence health outcomes.

Covid Economics 67, 4 February 2021: 1-23

Figure 5. Impact of Google Workplace Mobility on Effective Reproduction Rate and COVID-19 Related Deaths



Note. The graph represents the estimated impulse response function for a one standard deviation change in the Google Workplace Mobility index. The shaded area represents the 90% confidence interval for the coefficient.

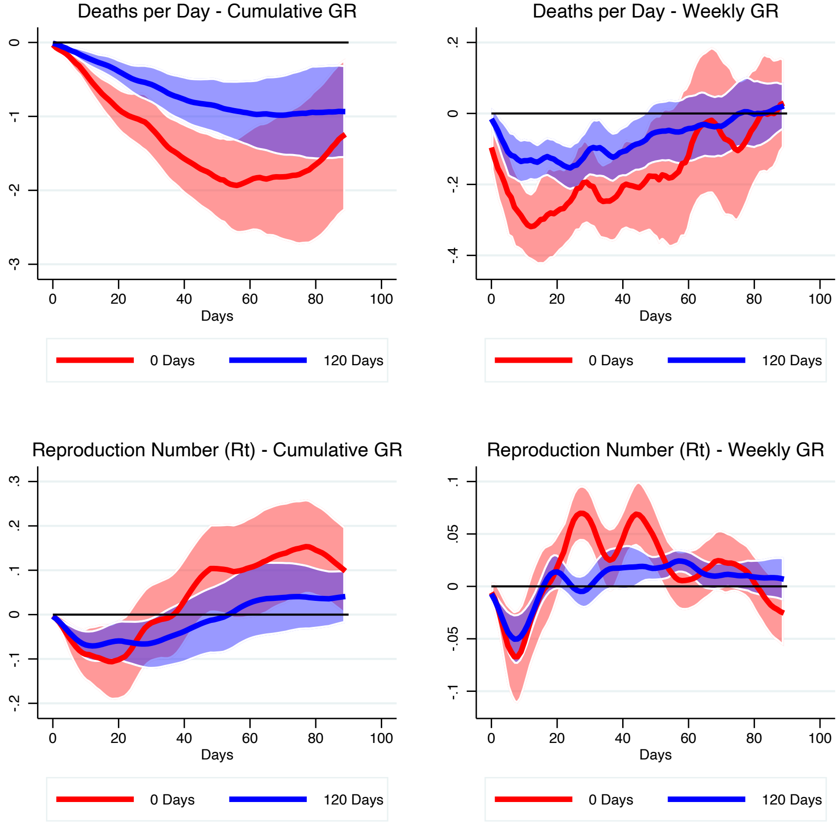
Having shown that, in general, NPIs do have a significant benign and persistent effect on the spread of the virus and its death toll, the natural follow-up question is: *for how long?* More precisely, how much is lost if we go from one-week to four-month lockdowns? The question is particularly relevant at a time when many countries facing a surprisingly strong second wave of infections are already re-imposing restrictions.

Taking advantage of an expanded year of COVID-19 data, we estimate a quantitative answer to this question by interacting restrictions with a proxy for "lockdown fatigue": the number of days (since the beginning of the pandemic) that the country had a strict lockdown (where a strict lockdown is defined as one with a Stringency Index at 70 or above) as in models (3) and (4) above.

Figure 6 shows the results of this exercise. As can be seen, there are significant differences in the effect of distancing measures in reducing deaths from COVID-19 when comparing the onset of the pandemic with the re-imposition after 120 days of strict (and possibly intermittent) lockdown, a scenario more similar to that faced by countries at the beginning of the second wave of contagions. Containment policies generate lower reductions in deaths from COVID-19 than in the first stage of the epidemic and the effect tends to lose its statistical significance faster. By contrast, no significant differences are observed between the two phases of the pandemic for impact on the reproduction rate.

Covid Economics 67, 4 February 2021: 1-23

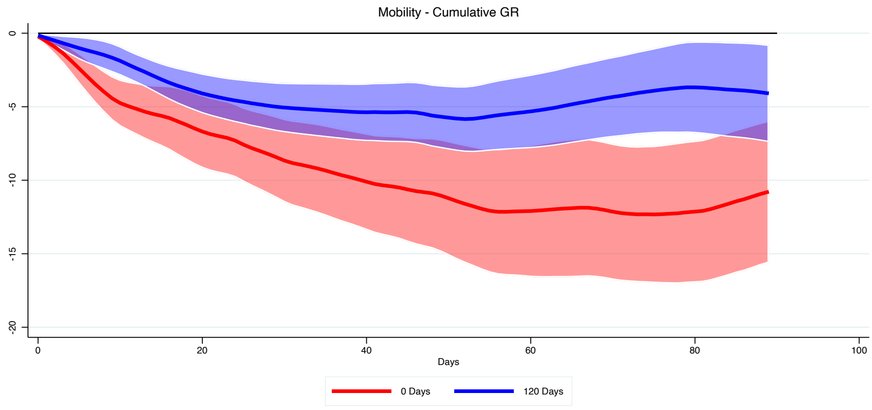
Figure 6. Impact of OxCGRT Stringency Index on Effective Reproduction Rate and COVID-19 Related Deaths (coefficient and interaction term at 120 days)



Note. The graph represents the estimated impulse response function for a one standard deviation change in the OxCGRT Stringency Index, including the effect of the duration-Stringency interaction valued at the specified period. The shaded area represents the 90% confidence interval for the linear combination.

A priori, it could be assumed that the fading impact of the lockdown may owe in part to the fact that compliance with mobility restrictions is hard to sustain economically and socially for long periods of time, as was highlighted by Levy Yeyati and Sartorio (2020). If that were the case, one would expect that the estimated effect of the *de jure* lockdown on COVID-related outcomes should decline by more than the effect the *de facto* mobility reductions, simply because de jure restrictions are increasingly ignored. Indeed, substituting workplace mobility for death per million in model (3) above, we can see both that a higher stringency index tends to generate a significant reduction in mobility, and that the impact looks more attenuated –albeit not significantly different– after 120 days of strict lockdown.

Figure 7. Impact of OxCGRT Stringency Index on Google Workplace Mobility (coefficient and interaction term at 120 days)

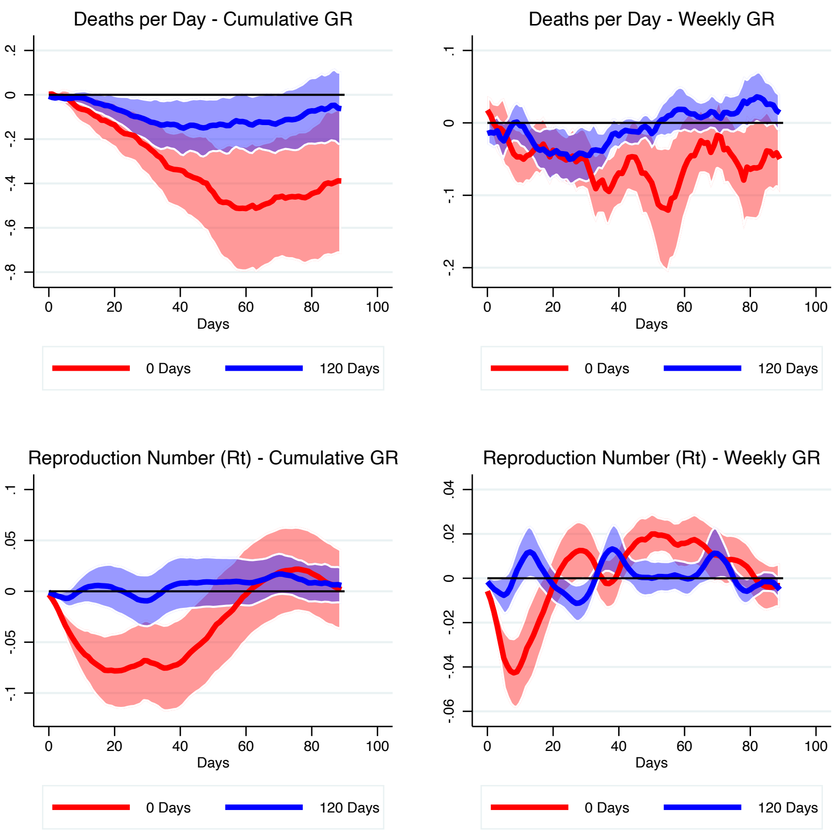


Note. The graph represents the estimated impulse response function for a one standard deviation change in the O xCGRT Stringency Index, including the effect of the duration-Stringency interaction valued at the specified period. The shaded area represents the 90% confidence interval for the linear combination.

However, even if we take as given an increase in *de facto* non-compliance, the fading effect of restrictions in reducing the impact of the pandemic is again significant when we estimate the differential (early vs. late) impact over time of a reduction in *mobility*: after 120 days of strict lockdown, a decrease in workplace mobility has a significantly more attenuated effect on the reduction of COVID deaths and does not have a significant impact on R_t (*Figure 8*).

CEPR PRESS

Figure 8. Impact of Google Workplace Mobility on Effective Reproduction Rate and COVID-19 Related Deaths (coefficient and interaction term at 120 days)



Note. The graph represents the estimated impulse response function for a one standard deviation change in the Google Workplace Mobility index, including the effect of the duration-Stringency interaction valued at the specified period. The shaded area represents the 90% confidence interval for the linear combination.

Covid Economics 67, 4 February 2021: 1-23

5. Final Remarks

Lockdowns, quarantines and curfews have been the most pivotal NPI used by governments worldwide in an effort to contain the spread of the COVID-19 pandemic. Their cost-effectiveness – balancing their ability to improve epidemiological outcomes and their social, economic and psychological costs – is still however at the center of an intense debate. In this paper, we contribute to this discussion by evaluating these interventions according to their ability to reduce the spread of the virus and its corresponding death toll, specifically addressing the question about whether and to what extent the development of lockdown fatigue in 2020 may have reduced their effectiveness as a resource to cope with new waves in 2021. In line with previous studies, we find that quarantines do have a significant and persistent effect on health outcomes. Additionally, we show that this effect weakens significantly after 120 days of strict lockdown.

We interpret the fact that *de facto* reductions in mobility also display a diminishing effect on epidemiological outcomes as an indication that lockdowns work through other channels *in addition* to mobility restrictions – such as, for example, social distancing behavior or the use of face masks – and that all of these channels are negatively affected by lockdown fatigue. Alternatively, it could be argued that over time, the development of better testing, tracking and isolating capabilities, as well as better treatment of cases may reduce the sensitivity of health outcomes to lockdowns and reductions in mobility, in the presence of nonlinearities not captured by our model. In any case, our results suggest that the heavy reliance on lockdowns that characterized the early stages of the pandemic should be qualified moving forward.

Covid Economics 67, 4 February 2021: 1-23

Bibliography

Adam, David. 2020. "A Guide to R — the Pandemic's Misunderstood Metric." *Nature* 583 (7816). https://www.nature.com/articles/d41586-020-02009-w.

Arroyo-Marioli, Francisco, Francisco Bullano, Simas Kucinskas, and Carlos Rondón-Moreno. 2021. "Tracking R of COVID-19: A New Real-Time Estimation Using the Kalman Filter." *PLoS One* 16 (1).

Askitas, Nikolaos, Konstantinos Tatsiramos, and Bertrand Verheyden. 2020. "Lockdown Strategies, Mobility Patterns and COVID-19." *Covid Economics* 23.

Deb, Pragyan, Davide Furceri, Jonathan D. Ostry, and Nour Tawk. 2020. "The Effect of Containment Measures on the Covid-19 Pandemic." *Covid Economics* 19.

Hale, Thomas, Anna Petherick, Toby Phillips, and Samuel Webster. 2020. "Variation in Government Responses to COVID-19." *Blavatnik School of Government Working Paper* 31.

Jordà, Òscar. 2005. "Estimation and Inference of Impulse Responses by Local Projections." *American Economic Review* 95 (1).

Levy Yeyati, Eduardo, and Luca Sartorio. 2020. "Take Me out: De Facto Limits on Strict Lockdowns in Developing Countries." *Covid Economics* 39.

Li, You, Harry Campbell, Durga Kulkarni, Alice Harpur, Madhurima Nundy, Xin Wang, and Harish Nair. 2020. "The Temporal Association of Introducing and Lifting Non-Pharmaceutical Interventions with the Time-Varying Reproduction Number (R) of SARS-CoV-2: A Modelling Study across 131 Countries." *The Lancet Infectious Diseases* 21 (2). http://www.sciencedirect.com/science/article/pii/S1473309920307854.

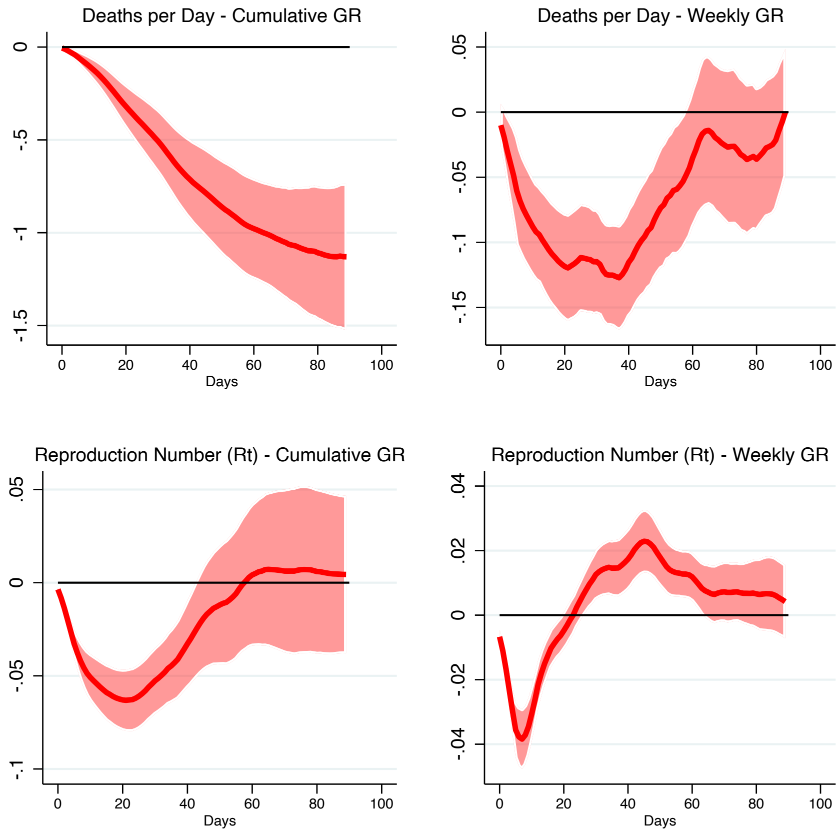
Wong, Martin CS, Junjie Huang, Jeremy Teoh, and Sunny H. Wong. 2020. "Evaluation on Different Non-Pharmaceutical Interventions during COVID-19 Pandemic: An Analysis of 139 Countries." *The Journal of Infection* 81 (3). https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7306102/.

Covid Economics 67, 4 February 2021: 1-23

Covid Economics 67, 4 February 2021: 1-23

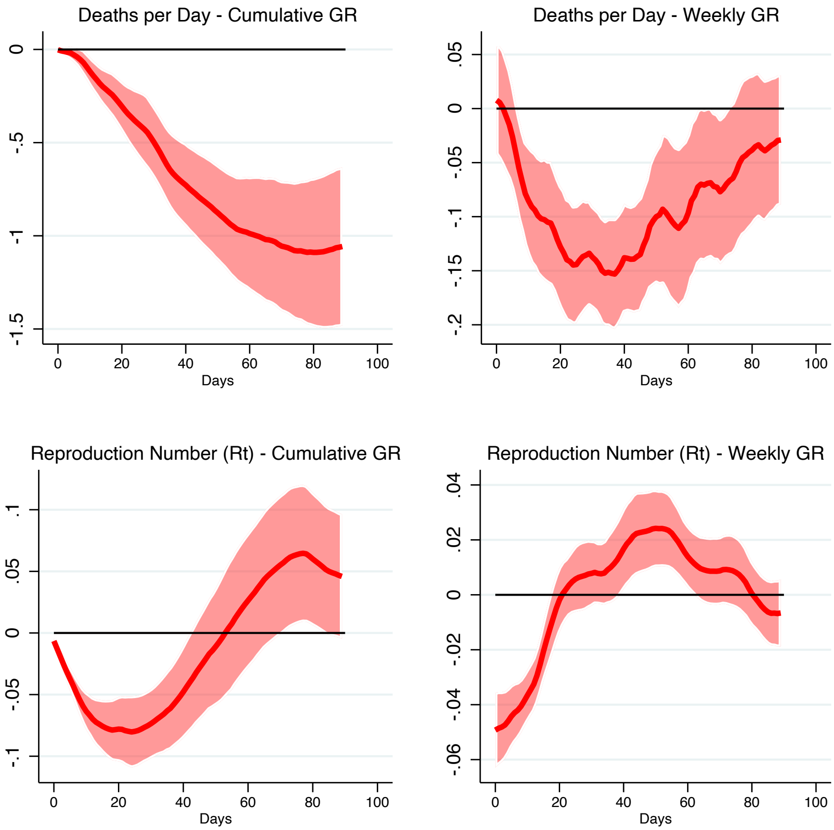
Appendix

Figure A1. Impact of OxCGRT Stringency Index on Effective Reproduction Rate and COVID-19 Related Deaths (No Temperature or Humidity covariates)



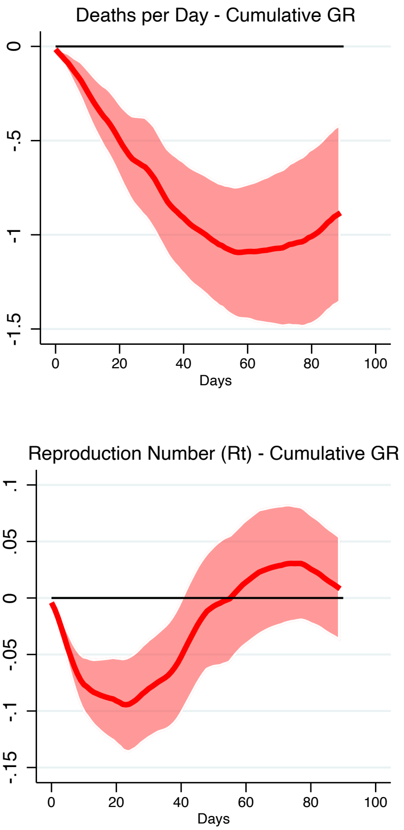
Note. The graph represents the estimated impulse response function for a one standard deviation change in the OxCGRT Stringency Index. The shaded area represents the 90% confidence interval for the coefficient.

Figure A2. Impact of OxCGRT Stringency Index on Effective Reproduction Rate and COVID-19 Related Deaths (No Trend or Lagged Dependent Variable)



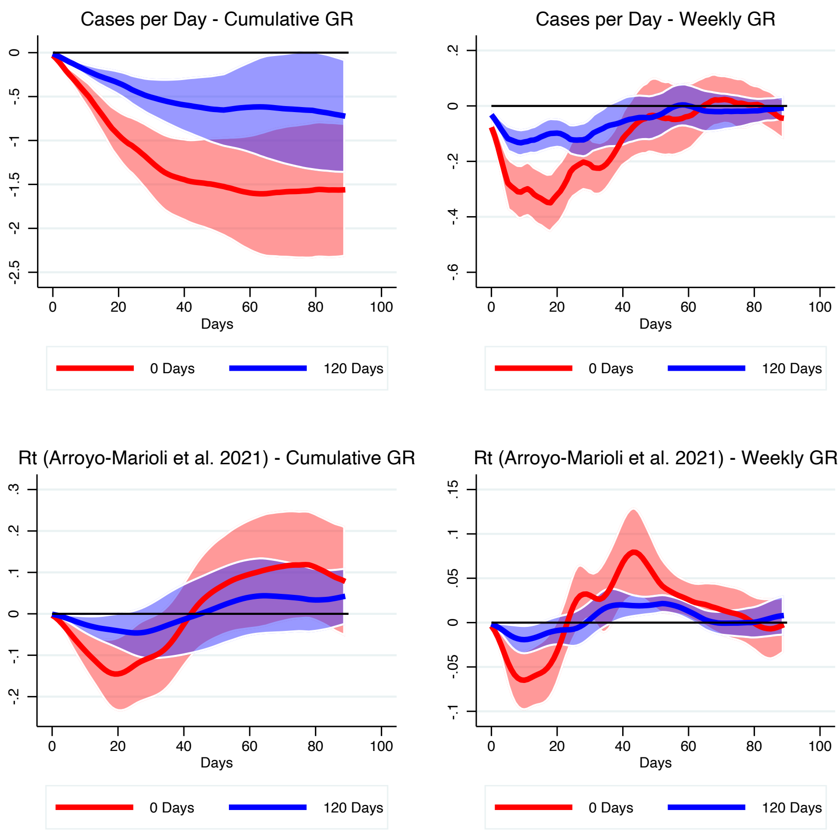
Note. The graph represents the estimated impulse response function for a one standard deviation change in the OxCGRT Stringency Index. The shaded area represents the 90% confidence interval for the coefficient.

Figure A3. Impact of OxCGRT Stringency Index on Effective Reproduction Rate and COVID-19 Related Deaths (including Testing, Contract Tracing and Information Campaigns)



Note. The graph represents the estimated impulse response function for a one standard deviation change in the OxCGRT Stringency Index. The shaded area represents the 90% confidence interval for the coefficient.

Figure A4. Impact of OxCGRT Stringency Index on Effective Reproduction Rate (Arroyo-Mario et al. 2021) and COVID-19 Related Cases (coefficient and interaction term at 120 days)



Levelling down and the COVID-19 lockdowns: Uneven regional recovery in UK consumer spending[1]

John Gathergood,[2] Fabian Gunzinger,[3]
Benedict Guttman-Kenney,[4] Edika Quispe-Torreblanca[5]
and Neil Stewart[6]

Date submitted: 26 January 2021; Date accepted: 2 February 2021

Covid Economics 67, 4 February 2021: 24-52

We show the recovery in consumer spending in the United Kingdom through the second half of 2020 is unevenly distributed across regions. We utilise Fable Data: a real-time source of consumption data that is a highly correlated, leading indicator of Bank of England and Office for National Statistics data. The UK's recovery is heavily weighted towards the "home counties" around outer London and the South. We observe a stark contrast between strong online spending growth while offline spending contracts. The strongest recovery in spending is seen in online spending in the "commuter belt" areas in outer London and the surrounding localities and also in areas of high second home ownership, where working from home (including working from second homes) has significantly displaced the location of spending. Year-on-year spending growth in November 2020 in localities facing the UK's new tighter "Tier 3" restrictions (mostly the midlands and northern areas) was 38.4% lower compared with areas facing the less restrictive "Tier 2" (mostly London and the South). These patterns had been further exacerbated during November 2020 when a second national lockdown was imposed.

1 The views expressed are the authors and do not necessarily reflect the views of Fable Data Limited. We are grateful to Suraj Gohil, Debbie Mulloy and Fiona Isaac at Fable Data Limited and Lindsey Melynk and Rich Cortez at Chicago Booth for their help facilitating this research. This work is supported by the UK Economic and Social Research Council (ESRC) under grant number ES/V004867/1 'Real-time evaluation of the effects of Covid-19 and policy responses on consumer and small business finances'.
2 Department of Economics, Nottingham University.
3 Warwick Business School, University of Warwick.
4 Chicago Booth School of Business, University of Chicago.
5 Saïd Business School, University of Oxford.
6 Warwick Business School, University of Warwick.

To prevent such COVID-19-driven regional inequalities from becoming persistent we propose governments introduce temporary, regionally-targeted interventions in 2021. The availability of real-time, regional data enables policymakers to efficiently decide when, where and how to implement such regional interventions and to be able to rapidly evaluate their effectiveness to consider whether to expand, modify or remove them.

Covid Economics 67, 4 February 2021: 24-52

CEPR PRESS

1 Introduction

Over the last few decades, developed countries have experienced inequality in economic growth at the regional level, with some regions not only experiencing less of the economic boom, but having longer-lasting pain from economic busts. The UK is one of, if not the most, geographically unequal developed countries.[1] A recent UK government aim is to address such disparities through policies to 'level-up' the regions that historically have experienced less benefits arising from globalization and national economic growth.

Yet COVID-19 creates a challenge to such an aim, as both the pandemic and policies undertaken by governments to slow the transmission of the virus can create uneven effects across many dimensions including financial and social capital, age, gender, industry, and locality given differing resilience of individuals and firms to the virus and restrictions. Understanding these uneven effects is of first order importance for policymakers seeking to address both the short-term economic and social effects of the pandemic and its longer-term implications for exacerbating pre-existing regional inequalities.

In this paper we use granular, real-time data on consumer spending to measure the uneven geography of recession and recovery across the United Kingdom. The granular data is provided by Fable Data, as previously used by Gathergood and Guttman-Kenney (2021) in analysis of the effects of localised lockdowns on local consumer spending.[2] Fable Data record hundreds of millions of transactions on consumer and SME spending across Europe from 2016 onwards and its real-time structure permits research to inform current policymaking. When aggregated, Fable's transaction data provides a highly correlated, leading indicator of official statistics - we find correlation coefficients with Bank of England and Office for National Statistics data of 0.91 and 0.87 respectively but, unlike official statistics, Fable Data is available in real-time: our research access to transactions data is with a one working day lag.

Using these data, we document the uneven geographic impact of COVID-19 on consumer spending in the UK during 2020, shown in total spending and in components of online

[1] https://www.ifs.org.uk/uploads/Green-Budget-2020-Levelling-up-where-and-how.pdf
[2] More information on Fable Data is available at www.fabledata.com.

Covid Economics 67, 4 February 2021: 24-52

and offline (i.e., in store) spending. Our headline results is that, while there has been an overall recovery in spending as "pent-up" demand has been realised, there is significant geographic variation in the recovery. Aggregate spending recovered from a low of a 29% year-on-year decline in April 2020 to a 12% year-on-year growth in October 2020. Such pent-up demand may be a combination of the lifting of restrictions, consumers becoming more confident to spend given less fear of the virus and improved economic prospects or increased fatigue reducing compliance with restrictions. We show three key results relating to the geographic variation in recovery.

First, the recovery in consumer spending has been faster in the South and "home counties" surrounding London. In contrast, the Midlands, Wales, the North-East and Scotland show the weakest year-on-year growth, or in the latter two cases close to no year-on-year growth at all. Moreover, the faster recovery in the South of England and the Eastern and Western regions is strongly driven by faster growth of online card spending. Notably, within England the fastest year-on-year growth is in the outer-West area of London, the South West and Eastern England – areas characterised by highly affluent communities and high level of second-home ownership. This suggests that, to a degree, spending growth is strongest in the work from home, or potentially work from second home, areas of the UK.

Second, the speed of recovery has been fastest outside large cities, in commuter-towns and affluent semi-countryside conurbations. We show that the variation in the speed of recovery can also be characterised as differing by types of urban settlements. In particular, the recovery has been fastest and strongest in 'business, education and heritage centres' – such areas are popular domestic tourist destinations and thus this is in line with consumers substituting foreign for domestic holidays. Recovery was less strong in 'countryside living' - predominately rural areas but still noticeably stronger than other, more urban, areas. For more urban areas, London has had a steady recovery whereas 'affluent England', 'services & industrial legacy', and 'urban settlements' are showing weaker recoveries.

Third, we show that as at the end of November 2020, the point when the second national lockdown was coming to an end to be replaced by the introduction of a revised

Covid Economics 67, 4 February 2021: 24-52

"Tier" system defining levels of restrictions across geographies, the highest Tier areas (known as "Tier 3") had experienced a much slower recovery in year-on-year spending, compared with the mid-Tier areas ("Tier 2").[3] Tier 2 and Tier 3 areas exhibit similar year-on-year growth rates in card spending in April and July 2020 (the period before this Tier system came into operation). However, by October this pattern diverges, with stronger recovering in overall spending in the Tier 2 areas compared with the Tier 3 areas. This divergence persists through November 2020, with localities facing the UK's new tighter "Tier 3" restrictions (mostly the midlands and northern areas) showing 38.4% lower year-on-year growth in overall spending compared with areas facing the less restrictive "Tier 2" (mostly London and the South). Our results corroborate recent evidence from labour market statistics that the pandemic is levelling down economic activity in the UK, thereby exacerbating regional inequality.

Our study further contributes to a burgeoning literature understanding the economic effects of COVID-19. A succession of studies demonstrate how consumer behaviour has been radically affected by COVID-19 and government policies to mitigate its effects. The first study to do so was Baker et al. (2020) using US fintech data. Following this, Opportunity Insights (Chetty et al., 2020a,b) produced a dashboard using multiple data sources to track regional US consumption behavior alongside other economic indicators.[4] Beyond the US similar exercises have been carried out to understand household consumption in the early stages of the pandemic – showing remarkably consistent results (Andersen et al., 2020; Bounie et al., 2020b,a; Bourquin et al., 2020; Campos-Vazquez and Esquivel, 2020; Carvalho et al., 2020; Chen et al., 2020; Chronopoulos et al., 2020; Davenport et al., 2020b; Hodbod et al., 2020; Horvath et al., 2020; Jaravel and O'Connell, 2020; O'Connell et al., 2020; Surico et al., 2020; Watanabe et al., 2020). Analysis of JP Morgan Chase data (Cox et al., 2020; Farrell et al., 2020) has described in detail how household balance sheets have changed as a result of the COVID-19 recession and how households have

[3]There are three Tiers of restrictions applied to geographies in England, Tiers 1-3. We exclude Tier 1 from the analysis as only very few, rural, localities are classed as Tier 1 as of December 2020 (accounting for only 1.3% of the UK adult population). Scotland is under a different but analogous regime while Wales and Northern Ireland operating under more different approaches.

[4]https://tracktherecovery.org

Covid Economics 67, 4 February 2021: 24-52

CEPR PRESS

responded to fiscal stimulus. A variety of studies have examined the effects of the first set of lockdowns on economic behavior and evaluated the degree to which there are trade-offs between policy interventions attempting to contain the virus and economic damage (Aum et al., 2020; Beach et al., 2020; Barro et al., 2020; Coibion et al., 2020; Correia et al., 2020; Cui et al., 2020; Dave et al., 2020; Friedson et al., 2020; Hacioglu et al., 2020; Glover et al., 2020; Goolsbee et al., 2020; Goolsbee and Syverson, 2020; Guerrieri et al., 2020; Hall et al., 2020; Lilley et al., 2020; Miles et al., 2020; O'Connell et al., 2020; Jones et al., 2020; Toxvaerd, 2020; Wang, 2020). A broader literature has sought to measure regional inequality and understand why it arises and its effects (e.g. Milanovic, 2005; Glaeser et al., 2008; Chetty and Hendren, 2018a,b; Iammarino et al., 2019; Carniero et al., 2020) with recent reports by UK think tanks evaluating the UK government's policy aim to 'level-up' regions.[5] New private sector data sources such as harnessed by Chetty et al. (2020a) in response to COVID-19 have been able to reveal in real-time how and why they are developing during this economic and health crisis.

Beyond the topicality and importance of the results, our paper serves to further demonstrate the value of granular, real-time account-level data for economic research. Fable Data contain transaction-by-transaction spending data, updated daily, for a large representative samples of European bank accounts and credit cards, with individual-level and geocode identifiers. As in our earlier paper, we show that these data remain a highly correlated, leading indicator of official statistics – data which are only available in aggregated form and with many months lag - in contrast to Fable Data which are available in real-time and disaggregated. Moreover, these data are applicable to a broad variety of questions in the analysis of individual consumption behavior. They further present a new opportunity for researchers to measure consumption in arguably more reliable ways

[5]Leunig and Overman (2008); Overman et al. (2009); Ludwig et al. (2013); Chetty et al. (2016); Geary and Stark (2016); Chetty et al. (2018); Gal and Egeland (2018); Manduca (2019); Agrawal and Phillips (2020); Bhattacharjee et al. (2020); Carrascal-Incera et al. (2020); Davenport et al. (2020a); Sensier and Devine (2020); Zymek and Jones (2020) https://www.ifs.org.uk/uploads/Green-Budget-2020-Levelling-up-where-and-how.pdf https://www.resolutionfoundation.org/app/uploads/2019/07/Mapping-Gaps.pdf urlhttps://www.smf.co.uk/wp-content/uploads/2020/01/Beyond-levelling-up.pdf https://www.centreforcities.org/wp-content/uploads/2020/02/Why-big-cities-are-crucial-to-levelling-up.pdf https://www.ippr.org/research/publications/state-of-the-north-2020-21

Covid Economics 67, 4 February 2021: 24-52

than using data from financial aggregators (a selected sample of consumers), scanner data (a selected subsample of expenditures) or consumption surveys, which has become less reliable in recent decades and has prompted a variety of initiatives aimed at improving the measurement of consumption (see Browning et al., 2014; Landais and Spinnewijn, 2020). In current research we are further exploring the potential of these data to analyze retail sectoral impacts.

The ability to measure regional, economic data in real-time using datasets such as Fable Data offers exciting potential to inform when, where and how to target regional policy interventions for evidence-based policymaking.[6] In particular, the ability to evaluate the causal effects of interventions across a breadth of economic outcomes in real-time provides a cost-effective way for governments to trial interventions in selected regions and quickly consider whether to expand, modify or remove such policies. This is a more nimble strategy than traditional government approaches of typically applying policies at a national level with limited abilities to assess their impacts.

In the context of this paper, the regional inequalities shown indicate that, in order to 'level-up' the historically less productive UK regions longer-term, there is a rationale for trialling short-term interventions to address the 'levelling-down' that has occurred in 2020 as a result of COVID-19. These could occur in 2021 once the virus outbreaks are under control and vaccinations have been more broadly rolled out. What could such measures look like? Encouraging spending in businesses located in harder hit areas could occur through business rate relief or VAT cuts. Other measures (e.g. travel vouchers) could try to encourage consumers to visit harder-hit parts of the UK. Or a less centralised approach would be for national governments to make temporary funding available to local governments in proportion to how adversely they have been impacted by the crisis for those local authorities to spend as they see fit (e.g. council tax reductions or rebates, funding local events or services). We hope our paper will prompt public discussion on other types of measures that could be feasibly implemented and evaluating their merits.

[6] To this end the authors have access to a variety of real-time, high-quality private-sector datasets for research to inform policymaking. If you are a data provider interested in joining this collaboration please contact the authors for further details on how to potentially partner in this initiative.

Covid Economics 67, 4 February 2021: 24-52

2 Data

2.1 Consumption Data

We use consumption data provided by Fable Data Limited as previously used in Gathergood and Guttman-Kenney (2021), and summarize again here the key features of the data.[7] Fable data record hundreds of millions of transactions on consumer and SME spending across European countries from 2016 onwards.[8] Fable's transaction data are anonymized and available in real-time: our research access is with a one working day lag. Fable sources data from a variety of banks and credit card companies: accounts cover both spending on credit cards and inflows and outflows on current (checking) accounts. Data is at the account-level and hence we can follow spending behavior on an individual account over time.[9] Fable data is similar to recently-available data sets from financial aggregators and service providers, but does not have some of the limitations of other datasets as Fable Data works solely with anonymised datasets, and has sourced data directly from banks and credit card issuers, rather than individual subscribers.[10]

For each spending transaction we observe a standard classification merchant category code for the spending type. Fable also produces its own categorizations of spending, utilizing the more granular information it has available from transaction strings. These data also differentiate between online and store-based transactions.

The data has an added feature of containing geo-tags for both the card holder's postcode sector and, where applicable, the address of the store or outlet in which a transaction is made. For each UK account we observe the postcode sector of the cardholder's address. In the UK, postcode sectors are very granular geographies: There are over 11,000 postcode sectors in the UK with each sector containing approximately 3,000 addresses.

[7] More information on Fable Data is available at www.fabledata.com.

[8] Commercial sensitivities mean we do not disclose the exact number of accounts and transactions available in the data.

[9] In cases where one individual has multiple accounts, we cannot link multiple accounts in the data to the individual but can aggregate to a geographic region.

[10] Baker (2018) provides validation and application of US financial aggregator data. Financial aggregator data for the UK is widely shared for research purposes by Money Dashboard, a UK-based fintech (Chronopoulos et al., 2020; Davenport et al., 2020b; Bourquin et al., 2020; Surico et al., 2020). Bourquin et al. (2020) analyse the characteristics of Money Dashboard users.

Covid Economics 67, 4 February 2021: 24-52

Where a transaction can be linked to a particular store, the full address of that store is available. Also, where a transaction is of a listed firm, Fable tags merchants to their parent groups and stock market tickers. For this study we focus on transactions denominated in British pounds sterling on UK-based credit card accounts held by consumers.

A feature of transaction-level spending data is that, even in data sets containing large volumes of transactions, the value and count of transactions tend to be highly volatile. Volatility arises across days of the week, weeks of the month, public holidays, and to some extent due to variations in the weather. Hence, to construct daily series for comparison with official statistics, we follow an approach to smooth the transaction volumes over time as used by Opportunity Insights on similar US data (Chetty et al., 2020b,a): aggregating spending by day at the level of geography of interest, taking a seven day moving average and dividing by the previous year's value.[11] We normalize these series setting an index to 1 using the mean value 8 - 28 January 2020. We also construct daily series using a 14 and 28 day moving average in an analogous fashion. Finally, for our geographic spending comparison, we calculate year-on-year monthly growth. We use both year-on-year and post-January 2020 calculations in our regional analysis.

2.2 Comparison with Official Statistics

One key advantage of Fable Data is the speed with which it can be made available to researchers and policymakers. This is among many features of the data which make it attractive for research – the timeliness (it is available the next working day, whereas official statistics are typically available only with a lag of several months), geographic granularity (being available at a lower level than official statistics) and, transaction-level (enabling a more flexible analysis than aggregated official statistics). These data can therefore potentially be used to construct leading indicators for policymakers and enable researchers to answer a broader set of research questions than was previously possible using more traditional data sources.

However, while these features are potentially valuable, their usefulness depends in part

[11] For 29 February 2020 we divide by an average of 28 February and 1 March 2019.

Covid Economics 67, 4 February 2021: 24-52

on how this data series relates to comprehensive, official data. To explore this, Figure 1 Panel A (which updates an earlier version of this figure as shown in Gathergood and Guttman-Kenney (2021)), compares the time series of Fable Data UK annual changes in monthly credit card spending to the Bank of England series and shows they are highly correlated: correlations 0.90 (January 2018 to September 2020), 0.87 (January 2019 to September 2020) and 0.90 (January 2020 to September 2020). Bank of England data is only published in aggregated form monthly and with a lag. This figure also compares to Office for National Statistics data on the value of retail sales (which is available at a slightly shorter time lag) and similarly shows Fable as a leading indicator of this with the two series to be highly correlated: correlations 0.87 (January 2018 to October 2020), 0.88 (January 2019 to October 2020) and 0.91 (January 2020 to October 2020).

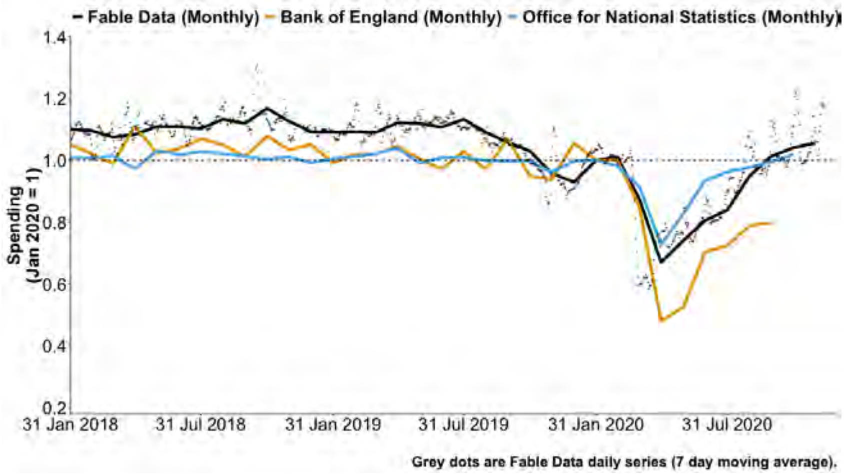
Figure 1, Panel B shows Fable data measures for 7, 14, 28 day moving averages – which can be calculated daily in real-time – compared to the monthly series (which requires waiting until the month end). These daily moving averages show the sharp drop in consumption in March 2020 far earlier than the monthly series. We thus conclude that we can use these data as a reliable real-time predictor of official data and as a reasonable proxy for measuring consumer spending.

On aggregate, we observe a sharp fall in UK credit card spending near the time of the spike in Covid-19 cases and the national lockdown announcement on 23 March 2020 and then a fairly steady recovery from May to August. Through to the first few weeks of December 2020, we observe that the recovery in credit card spending has continued, although not in a sharp "V-shape" but instead in a shape resembling a "tick-shape". This indicates that, in aggregate, there has been no evident bounce-back to account for lost spending through the second and third quarters of 2020. We also note that these patterns of spending are for UK residents who, without international travel, are spending more time (and therefore money) domestically but for considering the broader economy and particular sectors within it such growth in domestic spending is unlikely to be sufficient to compensate for the lack of spending by tourists to the UK.

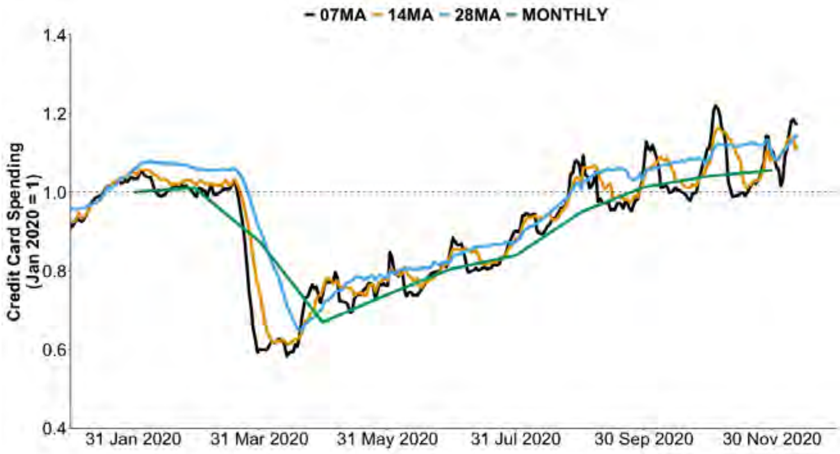
Covid Economics 67, 4 February 2021: 24-52

Figure 1: UK Credit Card Spending 2018 - 2020

A. Fable Monthly Data Compared to Bank of England & & Office for National Statistics Data, 2018 - 2020



B. Fable Daily Data, 2020 (7, 14, 28 day moving averages and monthly)



Notes: Bank of England monthly data is derived from LPMVZQH (monthly gross credit card lending to individuals). Office for National Statistics monthly data is derived from value of all retail sales (average weekly sales for all retailing including automative fuel). Fable Data monthly series is indexed to January 2020. Fable Data 7,14,28 day moving averages are the daily moving average de-seasoned by taking ratio of the moving average a year prior. Each daily series is then indexed to its moving average 8 - 28 January 2020. Fable Data to 12 December 2020.

CEPR PRESS

3 Results

3.1 Aggregate Card Spending

Table 1 summarises year-on-year changes in overall card spending and then disaggregate this into offline and online spending for April, July, October, and November 2020. In April the UK faced the first – and tightest – national lockdown including closure of all non-essential shops, a requirement or workers to work from home wherever possible, and limitations on exercise and leisure outside the home. Overall, card spending fell by more than one-quarter year-on-year, with a drop of over 40% in offline spending. While online spending increased, the increase year-on-year is a modest 2.4%, partly due to stock-piling prior to the onset of the first national lockdown and partly due to the limited capacity of retailers to increase the distribution of goods and services through online channels.

Through the two subsequent quarters of 2020, we see a recovery in card spending, notably dominated by large year-on-year increases in online spending. Through July, spending recovered to approximately 10% down year-on-year, but rebounded to approximately 10% up year-on-year as restrictions eased and some "pent-up" demand was realised. The modest recovery in offline spend, which was still 4% down in October, was greatly outstripped by a surge in online spend, which was 40% up in October, year-on-year. A series of local restrictions in the late summer and early autumn did not appear to result in large declines in spending (Gathergood and Guttman-Kenney, 2021). The second national lockdown in November (which saw some restrictions on non-essential shops, but not to the same extent as in April and May 2020) saw a further dip in offline spending, causing a fall of approximately 12% year-on-year, while online spending continued to grow, at at year-on-year rate of more than 50%. This contributed to a steady year-on-year increase in overall spending in November.

Covid Economics 67, 4 February 2021: 24-52

Table 1: UK Aggregate Card Spending (Year-on-Year % Changes)

	Month			
	April	July	October	November
Overall	-28.1%	-9.9%	+11.8%	+12.7%
Offline	-44.7%	-22.7%	-4.2%	-12.0%
Online	+2.4%	+12.7%	+ 39.7%	+ 53.1%

Notes: Year-on-year change in monthly credit card spending in the UK, including the estimated change in offline and online spending.

3.2 Regional Variation

Our focus in this paper is on the regional variation underlying the national trend. Table 2 repeats Table 1 showing year-on-year changes separately for Northern Ireland, Scotland, and Wales. This reveals how total and offline spending in Wales was noticeably lower in November 2020 than Scotland but both regions had similar online spending growth.

The flexibility of Fable's transaction-level data enables us to decide the most suitable level of geography to examine and measures to construct. To illustrate this, we calculate our two measures of consumer spending (year-on-year changes, and normalised to Jan 2020) at the mid-level geography of the UK, known as the Nomenclature of Territorial Units for Statistics Second Tier, or NUTS 2.

Figure 2 illustrates the year-on-year change in overall card spending (Panel A), offline spending (Panel B), and Online spending (Panel C). The colour shades have different scales on each panel but red indicates a decline in year-on-year spending, while the colour shades in blue indicate a growth in year-on-year spending and whiter shades indicate being closer to no year-on-year growth. The figures illustrate the aggregate trend in card spending, with a national decline in overall spending across the United Kingdom, driven by a particularly strong decline in offline spending and moderate growth in online spending.

Figure 3 reproduces the same illustrations for October 2020, a point at which the UK had emerged from the end of first national lockdown and instead briefly instigated three tiers of restrictions, applied at the local level. The figures show regional heterogeneity in the speed of recovery in spending. Overall, card spending shows the strongest year-on-year

Covid Economics 67, 4 February 2021: 24-52

CEPR PRESS

growth in the South of England and the Eastern and Western regions, while the Midlands, Wales, the North-East, and Scotland show weak year-on-year growth, or in the latter two cases close to no year-on-year growth.

Panels B and C demonstrate that the faster recovery in the south of England and the Eastern and Western regions is strongly driven by faster growth of online card spending. Notably, within England, the fastest year-on-year growth is in the outer-West area of London, the South West and Eastern England – areas characterised by highly affluent communities and high levels of second-home ownership. This suggests that, to a degree, spending growth is strongest in the work from home, or potentially work from second home areas of the UK - this is in line with US studies on the implications of COVID-19 for cities (e.g. Althoff et al., 2020; Bartik et al., 2020; Dingel and Neiman, 2020). In contrast, online spending shows a much slower recovery in the Midlands, North-East and Scotland.

A break-down of the fastest and slowest recovering areas is shown in Table 3. The strongest growth in overall spending year-on-year is seen in those regions of the South, East and to the West of London - in and around the "home counties" and the affluent second home ownership belt between London and Bristol. In contrast, the slowest growth is seen in Scotland, the North East (Cumbria and Lancashire), the East Midlands (Derbyshire and Nottinghamshire) and West Wales.

Covid Economics 67, 4 February 2021: 24-52

Table 2: Aggregate Card Spending Across Regions (Year-on-Year % Changes)

(a) Northern Ireland

	Month			
	April	July	October	November
Overall	-30.6%	-13.6%	1.6%	10.9%
Offline	-41.0%	-18.2%	-6.0%	-1.1%
Online	-11.6%	-5.4%	14.8%	30.3%

(b) Scotland

	Month			
	April	July	October	November
Overall	-29.0%	-15.3%	5.0%	9.3%
Offline	-44.3%	-26.6%	-8.9%	-6.2%
Online	-3.1%	3.4%	28.0%	33.0%

(c) Wales

	Month			
	April	July	October	November
Overall	-27.2%	-16.0%	2.9%	6.0%
Offline	-43.6%	-26.6%	-13.4%	-9.1%
Online	2.9%	3.1%	31.0%	30.4%

Notes: Year-on-year change in monthly credit card spending across regions, including the estimated change in offline and online spending.

Table 3: Top & Bottom 5 UK Geographies by Growth in Overall Card Spending (November 2020, Year-on-Year % Changes)

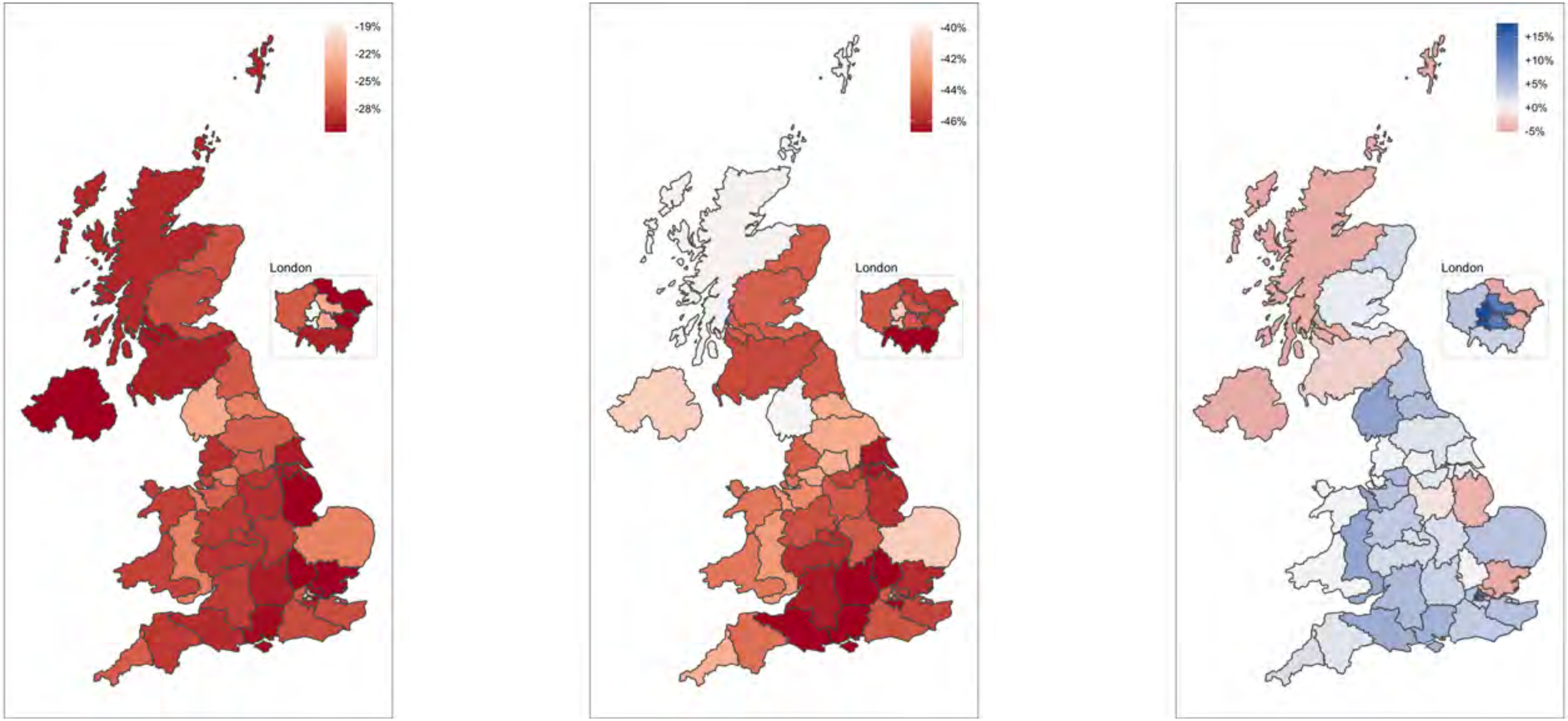
Top 5	% Change	Bottom 5	% Change
Outer London - South	16.8%	Southern Scotland	3.9%
Outer London - East	15.8%	Cumbria	3.9%
Gloucestershire, Wiltshire	14.6%	Derbyshire & Nottinghamshire	4.3%
Berkshire, Bucks & Oxfordshire	13.5%	West Wales	5.2%
Hampshire & Isle of Wight	12.1%	Lancashire	5.3%

Notes: Top and bottom five NUTS 2 areas with the largest annual change in credit card spending during November.

Covid Economics 67, 4 February 2021: 24-52

Covid Economics 67, 4 February 2021: 24-52

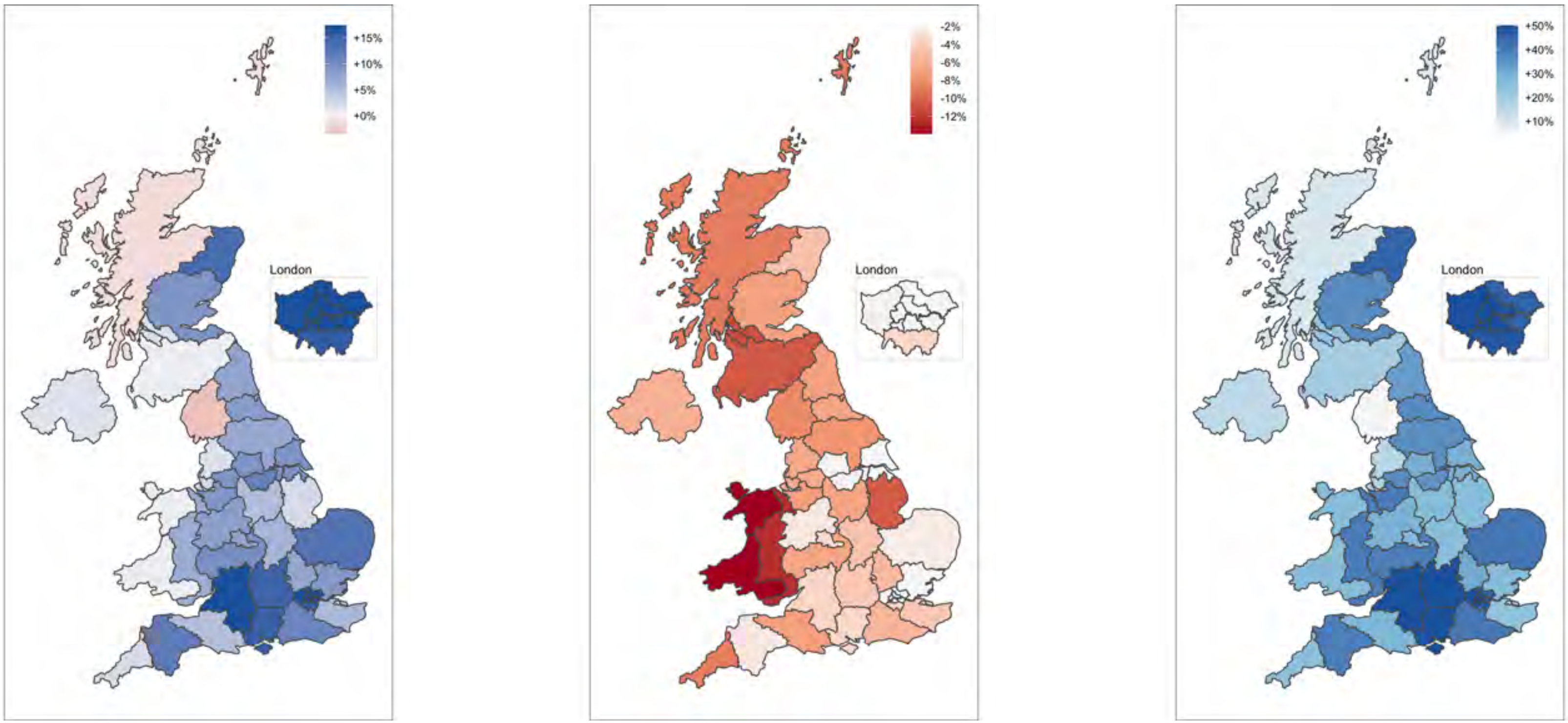
Figure 2: April 2020 Card Spend by Geographic Area (Year-on-Year % Change)



(a) Overall (b) Offline (c) Online

Notes: Geographic regions are NUTS 2 (Nomenclature of Territorial Units for Statistics) of the United Kingdom.

Figure 3: October 2020 Card Spend by Geographic Area (Year-on-Year % Change)



(a) Overall (b) Offline (c) Online

Notes: Geographic regions are NUTS 2 (Nomenclature of Territorial Units for Statistics) of the United Kingdom.

Covid Economics 67, 4 February 2021: 24-52

Covid Economics 67, 4 February 2021: 24-52

3.3 Variation Across Urban Geographies

To understand the potential of these data further, and the heterogeneous impacts of the COVID-19 crisis, we disaggregate the national series by urban geographies. This updates earlier analyses presented in Gathergood and Guttman-Kenney (2021). Figure 4 disaggregating by eight urban-rural categories created by the UK national statistics agency – the Office for National Statistics (ONS).[12] The figures illustrate that recovery has been fastest and strongest in 'business, education and heritage centres' – such areas are popular domestic tourist destinations and thus this is in line with consumers substituting foreign for domestic holidays. Recovery was less strong in 'countryside living' – predominately rural areas – but still noticeably stronger than other, more rural areas. In more urban areas, 'London cosmopolitan' followed by 'ethnically diverse metropolitan living' have had a steady recovery, whereas 'affluent England', 'services & industrial legacy', and 'urban settlements' are showing weaker recoveries.

3.4 Variation Across Lockdown "Tiers"

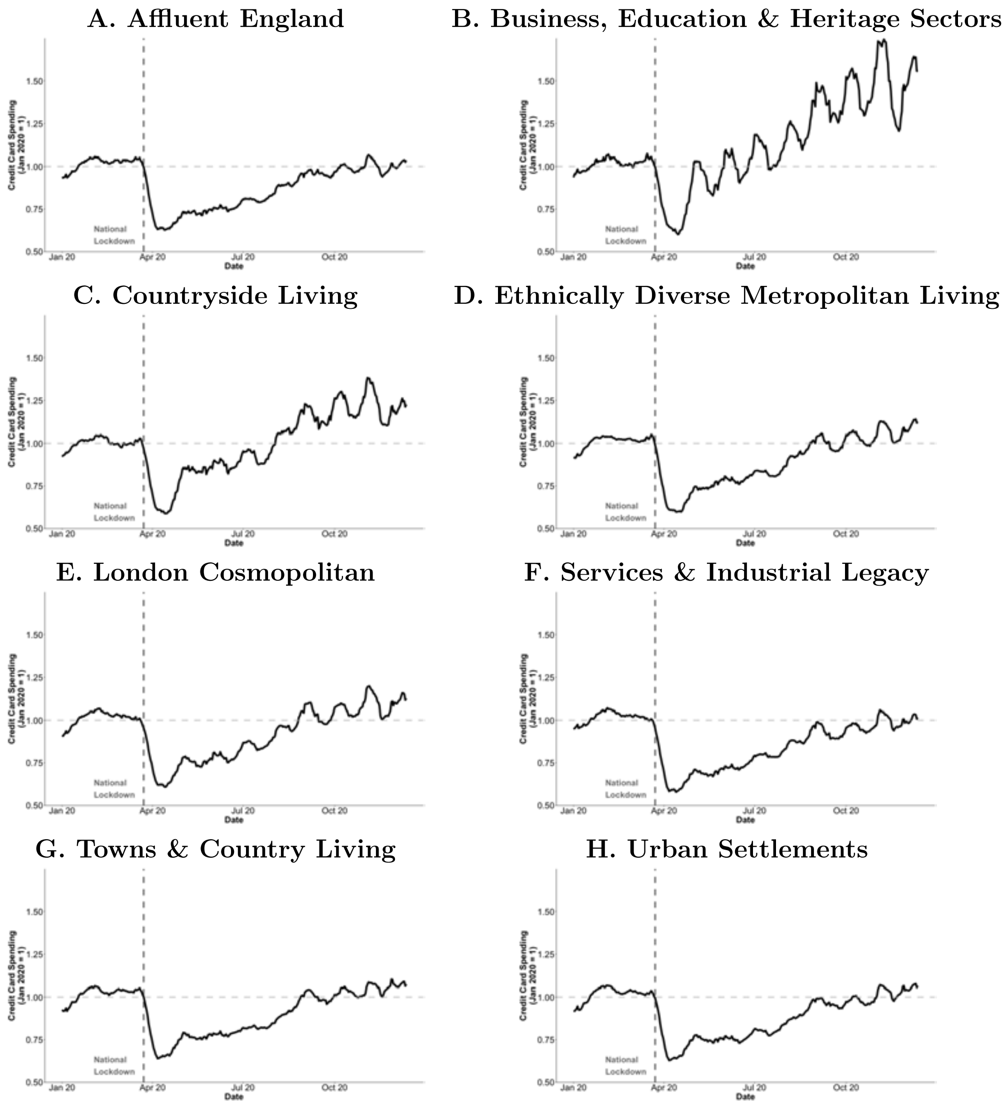
Over 2020, the UK has adopted a variety of "Tier" systems to impose more or less encroaching limitations on individual movement and social interaction. Following the re-opening after the first national lockdown, a process that began in early May and ended in mid-July, the UK government adopted a policy of "local lockdowns", initially on an ad-hoc basis. Particular cities or areas with spikes in positive COVID-19 test rates were subject to these ad hoc restrictions, such as Leicester in the Midlands and Aberdeen in North-East Scotland. The effects of this local lockdown strategy on COVID-19 positive case rates and on card spending are evaluated in Gathergood and Guttman-Kenney (2021).

In October 2020, the England adopted a formal Tier system, defining three Tiers of restrictions (a similar system was also introduced in Scotland).[13] These tiers were

[12]For maps, methodologies and a detailed description of each category see: `https://www.ons.gov.uk/methodology/geography/geographicalproducts/areaclassifications/2011areaclassifications`.

[13]For details, see `https://en.wikipedia.org/wiki/First_COVID-19_tier_regulations_in_England`.

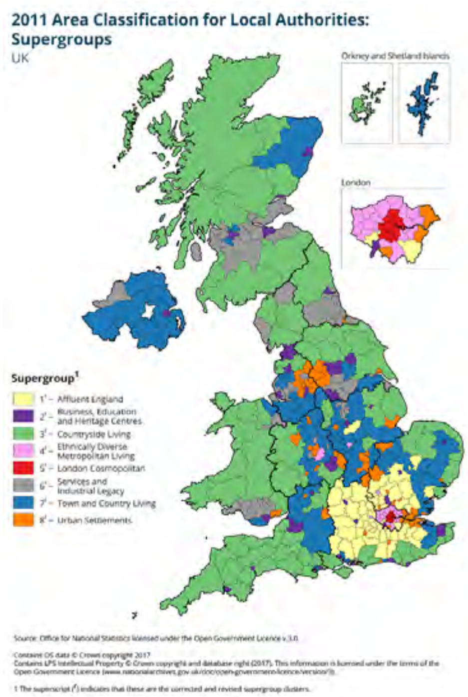
Figure 4: Credit Card Spending by Urban-rural Classifications (1 January - 12 December 2020)



Notes: Credit card spending is 14 day moving average de-seasoned by taking ratio of the 14 day moving average a year prior. The series is then indexed to its moving average 8 - 28 January 2020. Urban areas presented are the UK official statistics agency the Office for National Statistics (ONS) Super Groups where areas are classified based on the 2011 census. A UK map of these areas can be found in Figure 5 and further details can be found at: `https://www.ons.gov.uk/methodology/geography/geographicalproducts/areaclassifications/2011areaclassifications`

Covid Economics 67, 4 February 2021: 24-52

Figure 5: UK Urban-rural areas (Super Groups)



Source: Office for National Statistics (ONS)

labelled as "Medium", "High" and "Very High". While most of England was placed in the Tier 1 category, areas around East of London, the Midlands, and areas of the North were categorised into Tiers 2 or 3. Under the rules, in Tier 3 areas certain types of business premises were required to close, while nightclubs and hospitality venues saw their opening hours restricted and their services limited to sit-down meals. Moreover, no mixing between households was permitted indoors or in outdoor private spaces (e.g. gardens), with household mixing allowed only in groups of up to 6 in public outdoor spaces.

By November 2020, the UK government enforced a second national lockdown in England in the form of a four-week period during which pubs, restaurants, leisure centres and non-essential shops would close (in addition to the restrictions in place under Tier 3, as described above).[14] The UK government re-introduced the job furlough scheme in a

[14]Northern Ireland, Scotland and Wales also introduced further restrictions with Table 2 showing results

Covid Economics 67, 4 February 2021: 24-52

form closely resembling that offered in the first national lockdown. This second lockdown ended in early December 2020, with localities being again placed into one of the three Tiers. The allocation of localities to Tiers through 2020 is highly persistent. Localities which have been allocated to Tiers 2 or 3 in October 2020 were all placed in Tier 3 in December 2020. However, a notable difference in the December 2020 classification of areas to Tiers is that very few areas are classified as Tier 1 (these areas together host less than 1.5% of the UK population).

To provide an indication of the effects of the distribution of the cumulative effects of national and local lockdowns across England, in Table 4 we classify NUTS 2 regions by their Tier status as of the start of December 2020 (London, parts of Essex and Hertfordshire was later reclassified into Tier 3 in mid-December and then into a new Tier 4 category on 20 December following an outbreak of a more contagious new, mutant strain of the virus). The tables provide a breakdown of year-on-year growth in overall, offline and online spending for April, July, October, and November.

Table 4 shows two main patterns. First, Tier 2 and Tier 3 areas exhibit similar year-on-year growth rates in card spending in April and July 2020 (the period before the Tier system came into operation). However, by October this pattern diverges, with stronger recoveries in overall spending in the Tier 2 areas compared with the Tier 3 areas. This divergence persists through November 2020, with localities facing the new tighter "Tier 3" restrictions (mostly the Midlands and Northern Areas) showing 38.4% lower year-on-year growth in overall spending compared with areas facing the less restrictive "Tier 2" (mostly London and the South). These findings corroborate recent evidence from labour market statistics that the pandemic is levelling down economic activity in the UK, thereby exacerbating regional inequality. Thus far there is little evidence such lost output of the Tier 3 areas most affected by COVID-19 would naturally recover and so these areas may fall even further behind regions that entered the pandemic with stronger regional economies.

for these areas.

Covid Economics 67, 4 February 2021: 24-52

Table 4: Aggregate Card Spending in England by Dec 2020 Tiers (Year-on-Year % Changes)

Tier 2	Month			
	April	July	October	November
Overall	-28.1%	-9.1%	+15.6%	+15.1%
Offline	-45.3%	-22.6%	-3.2%	-12.4%
Online	+3.6%	+17.2%	+ 47.9%	+ 60.3%

Tier 3	Month			
	April	July	October	November
Overall	-27.9%	-10.1%	+8.5%	+9.3%
Offline	-44.5%	-22.4%	-4.8%	-14.9%
Online	+2.3%	+9.8%	+ 31.9%	+ 49.4%

Notes: Year-on-year change in monthly credit card spending by Tier group.

4 Real-Time Rebalancing Policies

Addressing regional inequalities that have persisted in the UK and other countries for decades is a hard problem with no quick fixes. However, the inequalities we document here are more short-term - having developed in 2020. This offers a potential opportunity for temporary policy interventions targeted at 'levelling-up' the regions worst affected by the COVID-19 pandemic to prevent such inequalities becoming persistent. Such measures could be safely introduced in 2021 once virus outbreaks are deemed to be under control and vaccinations have been more broadly rolled out.

The ability to measure regional economic data in real-time using datasets such as Fable Data offers a groundbreaking potential to inform when, where, and how to target such regional policy interventions.[15] Previously, governments would lack sufficiently real-time data to be able to effectively target interventions in such a rapidly moving crisis. Even in 'normal' times it is extremely difficult to predict the effectiveness of policies but in volatile economic conditions can become even more so. The ability to evaluate the causal effects of interventions across a breadth of economic outcomes in real-time provides a

[15] To this end, the authors have access to a variety of real-time, high-quality private-sector datasets for research to inform policymaking. If you are a data provider interested in joining this collaboration, please contact the authors for further details on how to potentially partner in this initiative.

Covid Economics 67, 4 February 2021: 24-52

cost-effective way for governments to trial interventions in selected regions at small scale and quickly consider whether to expand, modify or remove such policies. This is a more nimble strategy than traditional government approaches of typically applying policies at a national level with limited (if any) ability to assess their impact until it is too late to scale up or down such measures to address the original policy aims.

What could such targeted, regional measures look like? We provide a few examples to stimulate public discussions evaluating their relative merits and feasibility of these and other proposals. Given the clear impacts of offline retailers in particular locations, providing relief to such businesses can help to sustain them and enable them to pass through savings to increase demand for their business. This could take the form of business rate relief or VAT cuts based on the location of stores.

Given some regions have recovered rather well, providing incentives to encourage residents in those locations to visit harder-hit parts of the UK could be an effective way to generate spending in depressed areas. One method for doing so would be providing vouchers for discounted travel to and spend in particular destinations —potentially through a lottery system to enable some individuals to have large incentives to do so. Such initiatives may also yield broader, longer-term benefits for consumers living in different regions. It may make the labor market more geographically mobile and repair cultural divides. A less centralised approach would be for national governments to make temporary funding available to local governments. This could be done in proportion to how adversely such regions have been impacted by the crisis and adjust the duration and amount of funding to local authorities in response to real-time indicators. Such funding could be allocated to particular uses, however, it may be more efficient to provide flexibility to enable local authorities to use their local knowledge and engage with local residents to use as they consider would be its most productive use. For example, some areas may decide to use this to provide council tax reductions or rebates to act as a direct form of redistribution. Other areas may consider forms of spending to be more efficient, such as funding local events or services or initiatives targeted at providing relief to socio-economic groups of people most adversely affected by the pandemic.

Covid Economics 67, 4 February 2021: 24-52

5 Conclusion

The impact of the COVID-19 pandemic, and the restrictions imposed by the government to limit infections, is geographically uneven. We use newly-available transaction-level credit card data provided by Fable Data to examine geographic variation in the recovery in card spending across the UK. Our analysis shows that the recovery in aggregate spending in the UK masks significant heterogeneity across regions. The recovery is heavily weighted towards the "home counties" around outer London and the South, which have shown strong growth in online spending in particular. The strongest recovery in spending is seen in online spending in the "commuter belt" areas in outer London and the surrounding localities, and also in areas of high second home ownership, where working from home (including working from second homes) has significantly displaced the location of spending.

We hope by documenting such regional inequalities, our paper helps to provoke informed discussion on this topic and what policy tools could be harnessed to rebalance them in 2021. The availability of real-time data offers the potential for governments to trial a variety of regionally-targeted policies and get real-time feedback on their effectiveness in order to nimbly, expand, modify or remove such measures. While this paper has focused on the regional impacts of COVID-19, a broad range of other unequal impacts have also developed (e.g. financial and social capital, age, gender, and industry) where partnerships between governments, private sector data providers and academics can help to better measure, understand these impacts and develop well-targeted interventions to attempt to recover lost potential output and rebalance inequalities.

Covid Economics 67, 4 February 2021: 24-52

References

Agrawal, S. and Phillips, D. (2020). Catching up or falling behind? geographical inequalities in the uk and how they have changed in recent years. *IFS Briefing Note*.

Althoff, L., Eckert, F., Ganapati, S., and Walsh, C. (2020). The city paradox: Skilled services and remote work. *CESIfo Working Paper*.

Andersen, A. L., Hansen, E. T., Johannesen, N., and Sheridan, A. (2020). Consumer responses to the covid-19 crisis: Evidence from bank account transaction data. *Covid Economics*.

Aum, S., Lee, S. Y. T., and Shin, Y. (2020). Covid-19 doesn't need lockdowns to destroy jobs: The effect of local outbreaks in korea. *NBER Working Paper*.

Baker, S. R. (2018). Debt and the response to household income shocks: Validation and application of linked financial account data. *Journal of Political Economy*, 126(4):1504–1557.

Baker, S. R., Farrokhnia, R. A., Meyer, S., Pagel, M., and Yannelis, C. (2020). How does household spending respond to an epidemic? consumption during the 2020 covid-19 pandemic. *Review of Asset Pricing Studies*.

Barro, R. J., Ursúa, J. F., and Weng, J. (2020). The coronavirus and the great influenza pandemic: Lessons from the "spanish flu" for the coronavirus's potential effects on mortality and economic activity. *NBER Working Paper*.

Bartik, A. W., Cullen, Z. B., Glaeser, E. L., Luca, M., and Stanton, C. T. (2020). What jobs are being done at home during the covid-19 crisis? evidence from firm-level surveys. *NBER Working Paper*.

Beach, B., Clay, K., and Saavedra, M. H. (2020). The 1918 influenza pandemic and its lessons for covid-19. *NBER Working Paper*.

Bhattacharjee, A., Nguyen, D., and Venables, T. (2020). The prospects for regional disparities in the uk in times of brexit and covid-19. *National Institute Economic Review*, 253:R1–R3.

Bounie, D., Camara, Y., Fize, E., Galbraith, J. W., Landais, C., Lavest, C., Pazem, T., and Savatier, B. (2020a). Consumers' mobility, expenditure and online-offline substitution response to covid-19: Evidence from french transaction data. *Covid Economics*.

Bounie, D., Camara, Y., and Galbraith, J. W. (2020b). Consumers' mobility, expenditure and online-offline substitution response to covid-19: Evidence from french transaction data. *Working Paper*.

Bourquin, P., Delestre, I., Joyce, R., Rasul, I., and Waters, T. (2020). The effects of coronavirus on household finances and financial distress. *IFS Briefing Note*.

Browning, M., Crossley, T. F., and Winter, J. (2014). The measurement of household consumption expenditures. *Annu. Rev. Econ.*, 6(1):475–501.

Covid Economics 67, 4 February 2021: 24-52

Campos-Vazquez, R. and Esquivel, G. (2020). Consumption and geographic mobility in pandemic times: Evidence from mexico. *Covid Economics*.

Carniero, P., Cattan, S., Dearden, L., van der Erve, L., Krutikova, S., and Macmillan, L. (2020). The long shadow of deprivation: Differences in opportunities across england. Technical report, Technical report.

Carrascal-Incera, A., McCann, P., Ortega-Argilés, R., and Rodríguez-Pose, A. (2020). Uk interregional inequality in a historical and international comparative context. *National Institute Economic Review*, 253:R4–R17.

Carvalho, V. M., Hansen, S., Ortiz, A., Garcia, J. R., Rodrigo, T., Rodriguez Mora, S., and Ruiz de Aguirre, P. (2020). Tracking the covid-19 crisis with high-resolution transaction data. *CEPR Discussion Paper*.

Chen, H., Qian, W., and Wen, Q. (2020). The impact of the covid-19 pandemic on consumption: Learning from high frequency transaction data. *Working Paper*.

Chetty, R., Friedman, J. N., Hendren, N., Jones, M. R., and Porter, S. R. (2018). The opportunity atlas: Mapping the childhood roots of social mobility. *NBER Working Paper*.

Chetty, R., Friedman, J. N., Hendren, N., Stepner, M., and "the Opportunity Insights Team" (2020a). The economic impacts of covid-19: Evidence from a new public database built from private sector data. *NBER Working Paper*.

Chetty, R., Friedman, J. N., Hendren, N., Stepner, M., and "the Opportunity Insights Team" (2020b). Real-time economics: A new platform to track the impacts of covid-19 on people, businesses, and communities using private sector data. *NBER Working Paper*.

Chetty, R. and Hendren, N. (2018a). The impacts of neighborhoods on intergenerational mobility i: Childhood exposure effects. *The Quarterly Journal of Economics*, 133(3):1107–1162.

Chetty, R. and Hendren, N. (2018b). The impacts of neighborhoods on intergenerational mobility ii: County-level estimates. *The Quarterly Journal of Economics*, 133(3):1163–1228.

Chetty, R., Hendren, N., and Katz, L. F. (2016). The effects of exposure to better neighborhoods on children: New evidence from the moving to opportunity experiment. *American Economic Review*, 106(4):855–902.

Chronopoulos, D., Lukas, M., and Wilson, J. (2020). Consumer spending responses to the covid-19 pandemic: An assessment of Great Britain. *Covid Economics*.

Coibion, O., Gorodnichenko, Y., and Weber, M. (2020). The cost of the covid-19 crisis: Lockdowns, macroeconomic expectations, and consumer spending. *Covid Economics*.

Correia, S., Luck, S., and Verner, E. (2020). Pandemics depress the economy, public health interventions do not: Evidence from the 1918 flu. *Working Paper*.

Covid Economics 67, 4 February 2021: 24-52

Cox, N., Ganong, P., Noel, P., Vavra, J., Wong, A., Farrell, D., and Greig, F. (2020). Initial impacts of the pandemic on consumer behavior: Evidence from linked income, spending, and savings data. *Brookings Papers on Economic Activity*.

Cui, Z., Heal, G., and Kunreuther, H. (2020). Covid-19, shelter-in place strategies and tipping. *NBER Working Paper*.

Dave, D. M., Friedson, A. I., Matsuzawa, K., Sabia, J. J., and Safford, S. (2020). Were urban cowboys enough to control covid-19? local shelter-in-place orders and coronavirus case growth. *NBER Working Paper*.

Davenport, A., Farquharson, C., Rasul, I., Sibieta, L., and Stoye, G. (2020a). The geography of the covid-19 crisis in england. *Institute for Fiscal Studies*.

Davenport, A., Joyce, R., Rasul, I., and Waters, T. (2020b). Spending and saving during the covid-19 crisis: evidence from bank account data. *IFS Briefing Note*.

Dingel, J. I. and Neiman, B. (2020). How many jobs can be done at home? *Journal of Public Economics*, 189.

Farrell, D., Ganong, P., Greig, F., Liebeskind, M., Noel, P., and Vavra, J. (2020). Consumption effects of unemployment insurance during the covid-19 pandemic. *JP Morgan Chase Institute*.

Friedson, A. I., McNichols, D., Sabia, J. J., and Dave, D. (2020). Did california's shelter-in-place order work? early coronavirus-related public health effects. *NBER Working Paper*.

Gal, P. and Egeland, J. (2018). Reducing regional disparities in productivity in the united kingdom. Technical report, OECD.

Gathergood, J. and Guttman-Kenney, B. (2021). The english patient: Evaluating local lockdowns using real-time covid-19 & consumption data. *Covid Economics*, 64:73–100.

Geary, F. and Stark, T. (2016). What happened to regional inequality in b ritain in the twentieth century? *The Economic History Review*, 69(1):215–228.

Glaeser, E. L. et al. (2008). *Cities, agglomeration, and spatial equilibrium*. Oxford University Press.

Glover, A., Heathcote, J., Krueger, D., and Ríos-Rull, J.-V. (2020). Health versus wealth: On the distributional effects of controlling a pandemic. *Covid Economics*.

Goolsbee, A., Luo, N. B., Nesbitt, R., and Syverson, C. (2020). Covid-19 lockdown policies at the state and local level. *Working Paper*.

Goolsbee, A. and Syverson, C. (2020). Fear, lockdown, and diversion: Comparing drivers of pandemic economic decline 2020. *NBER Working Paper*.

Guerrieri, V., Lorenzoni, G., Straub, L., and Werning, I. (2020). Macroeconomic implications of covid-19: Can negative supply shocks cause demand shortages? *NBER Working Paper*.

Covid Economics 67, 4 February 2021: 24-52

Hacioglu, S., Känzig, D., and Surico, P. (2020). The distributional impact of the pandemic. *CEPR Discussion Paper*.

Hall, R. E., Jones, C. I., and Klenow, P. J. (2020). Trading off consumption and covid-19 deaths. *NBER Working Paper*.

Hodbod, A., Hommes, C., Huber, S. J., and Salle, I. (2020). Is covid-19 a consumption game changer? evidence from a large-scale multi-country survey. *Covid Economics*.

Horvath, A., Kay, B., and Wix, C. (2020). The covid-19 shock and consumer credit: Evidence from credit card data. *Covid Economics*.

Iammarino, S., Rodríguez-Pose, A., and Storper, M. (2019). Regional inequality in europe: evidence, theory and policy implications. *Journal of economic geography*, 19(2):273–298.

Jaravel, X. and O'Connell, M. (2020). High-frequency changes in shopping behaviours, promotions, and the measurement of inflation: evidence from the great lockdown. *IFS Briefing Note*.

Jones, C. J., Philippon, T., and Venkateswaran, V. (2020). Optimal mitigation policies in a pandemic: Social distancing and working from home. *NBER Working Paper*.

Landais, C. and Spinnewijn, J. (2020). Introduction to the special issue:"new perspectives on consumption measures".

Leunig, T. and Overman, H. (2008). Spatial patterns of development and the british housing market. *Oxford Review of Economic Policy*, 24(1):59–78.

Lilley, A., Lilley, M., and Rinaldi, G. (2020). Public health interventions and economic growth: Revisiting the spanish flu evidence. *Working Paper*.

Ludwig, J., Duncan, G. J., Gennetian, L. A., Katz, L. F., Kessler, R. C., Kling, J. R., and Sanbonmatsu, L. (2013). Long-term neighborhood effects on low-income families: Evidence from moving to opportunity. *American economic review*, 103(3):226–31.

Manduca, R. A. (2019). The contribution of national income inequality to regional economic divergence. *Social Forces*, 98(2):622–648.

Milanovic, B. (2005). *Half a World: Regional inequality in five great federations*. The World Bank.

Miles, D., Stedman, M., and Heald, A. (2020). Living with covid-19: balancing costs against benefits in the face of the virus. *National Institute Economic Review*, 253:R60–R76.

O'Connell, M., de Paula, A., and Smith, K. (2020). Preparing for a pandemic: spending dynamics and panic buying during the covid-19 first wave. *IFS Briefing Note*.

Overman, H. G., Gibbons, S., and Tucci, A. (2009). The case for agglomeration economies. Technical report, Manchester Independent Economic Review.

Covid Economics 67, 4 February 2021: 24-52

Sensier, M. and Devine, F. (2020). Understanding regional economic performance and resilience in the uk: trends since the global financial crisis. *National Institute Economic Review*, 253:R18–R28.

Surico, P., Känzig, D., and Hacioglu, S. (2020). Consumption in the time of covid-19: Evidence from uk transaction data. *CEPR Discussion Paper*.

Toxvaerd, F. (2020). Equilibrium social distancing. *Covid Economics*.

Wang, J. (2020). The financial impact of covid-19 in the united states. *Slidepack*.

Watanabe, T., Omori, Y., et al. (2020). Online consumption during the covid-19 crisis: Evidence from japan. *Covid Economics*.

Zymek, R. and Jones, B. (2020). Uk regional productivity differences: an evidence review. *Report for the Industrial Strategy Council*.

Covid Economics 67, 4 February 2021: 24-52

A model of crisis management[1]

Fei Li[2] and Jidong Zhou[3]

Date submitted: 22 January 2021; Date accepted: 27 January 2021

We propose a model of how multiple societies respond to a common crisis. A government faces a "damned-either-way" policy-making dilemma: aggressive intervention contains the crisis, but the resulting good outcome makes people skeptical of the costly response; light intervention worsens the crisis and causes the government to be faulted for not doing enough. This dilemma can be mitigated for the society that encounters the crisis first if another society faces it afterward. Our model predicts that the later society does not necessarily perform better despite having more information, while the earlier society might benefit from a dynamic counterfactual effect.

Covid Economics 67, 4 February 2021: 53-93

1 We are grateful to Attila Ambrus, Mark Armstrong, Heski Bar-Isaac, Gary Biglaiser, Florian Ederer, Jonathan Feinstein, Yunzhi Hu, Ilwoo Hwang, Jin Li, Navin Kartik, Leslie Marx, Peter Norman, Benjamin Polak, Larry Samuelson, Yangbo Song, various seminar audiences, and especially Barry Nalebuff for helpful comments.
2 Associate Professor of Economics, Department of Economics, University of North Carolina at Chapel Hill.
3 Associate Professor of Economics, School of Management, Yale University.

Covid Economics 67, 4 February 2021: 53-93

1 Introduction

Many crises can be contained or even prevented if proper measures are taken in a timely manner. However, people are often uncertain about the severity of the threat, and they assess a policymaker's response only after seeing the consequences and updating their opinion accordingly. This can pose a challenge to the policymaker: if an aggressive action is taken and the crisis is prevented, people may then underestimate the severity of the problem and view the costly aggressive action as unnecessary; if a less aggressive action is taken and the crisis gets out of control, people may then blame the policymaker for not having taken the necessary precautions. This leads to a "damned if you do, damned if you don't" *policy-making dilemma*. Such a dilemma is relevant in a wide range of circumstances such as how to respond to infectious diseases or terrorism threats, whether to take precautionary economic measures to prevent a potential economic recession or financial crisis, or how to regulate manufacturing or cyber-security.[1] If policymakers are more concerned about being accused of overreacting, they may then choose a light intervention even if they know the threat is severe, resulting in an inefficient response.[2]

The dilemma would be resolved if the public could observe the counterfactual outcome under alternative policies. This is possible if other jurisdictions or societies face a similar threat but somehow respond differently. For instance, if one society acts aggressively but the other does not, then if the crisis gets out of control in the latter society, the policymaker in the former society can point to the bad outcome in the latter as justification for having taken the aggressive policy.

In this paper, we argue that when multiple societies face a common crisis, they may endogenously adopt distinct policies (even if they are otherwise identical), so that some societies can escape from the policy-making dilemma. To illustrate the idea, we consider the case when societies handle a crisis sequentially, though, as we point out later, a similar idea

[1]In his State of the Union Address in 1962, President John F. Kennedy said, "The time to repair the roof is when the sun is shining" to advocate his economic policy for preventing another recession. This was widely supported as the country had just experienced the 1960 recession. Such preventive economic policies, however, are often less popular when the economy is in a good state, as Christine Lagarde commented in her speech "A Time to Repair the Roof" at Harvard University in October 2017.

[2]There is anecdotal evidence that the concern of being blamed for overreacting is well justified. For example, in U.S. history of epidemics, neither Woodrow Wilson's 1918 influenza pandemic failure nor Dwight Eisenhower's misguided response to the 1957 influenza pandemic was faulted. However, in 1976 Gerald Ford was widely criticized and ridiculed thanks to his heavily publicized effort to prevent a new variant of influenza which turned out to be less deadly than expected. See Skidmore (2016) and Stasavage (2020). Also see Healy and Malhotra (2009) for evidence that voters do not reward the incumbent presidential party for disaster preparedness spending.

applies to the simultaneous-move case as well. When a society that encounters the crisis first takes the precaution and the crisis is contained, the public in the subsequent society, after seeing the outcome in the first society, may then become more optimistic. This boosted optimism makes it harder for the policymaker in the second society to follow suit. Thus the aggressive action in the first society can mislead the public in the second society and prevent its policymaker from adopting the right policy. The resulting adverse outcome, however, can then be used to justify the first policymaker's initially unpopular policy choice. We refer to this as a *dynamic counterfactual effect*.

A consequence of this counterfactual effect is that, all else equal, societies that encounter the crisis later may handle it worse than early-hit societies. Later movers can learn from earlier movers' experiences, but having more information is not necessary a blessing: people may become too optimistic after seeing good outcomes in early-hit societies. Conversely, the early-hit societies, foreseeing the possible counterfactual from subsequent countries, are more willing to adopt costly but more effective policies.

We develop a model of sequential crisis management to capture both the "damned-either-way" policy-making dilemma and the dynamic counterfactual effect. The policy-making dilemma relies on two modeling ingredients: each policy option is more likely to yield an outcome that induces people to believe some alternative option would have worked better;[3] and the policymaker is held accountable for their policy after its consequence is observed. Both are natural in the context of crisis control and prevention. Due to the policy-making dilemma, it is possible that the policymaker panders to public opinion on the severity of the crisis, causing a suboptimal policy choice. The dynamic counterfactual effect further relies on the assumption that people in each society evaluate their policymaker after observing policy consequences in all societies. This is plausible when the policy consequence in each society is realized relatively quickly and is publicly observable.

An obvious application of our model is the ongoing COVID-19 pandemic. Every country's government faces the policy-making dilemma due to the public's initial uncertainty about the severity of the virus. Since some countries were hit earlier than others, it makes the dynamics across countries important. Our model provides a new angle to understand the response disparity among societies, complementing a spectrum of possible explanations from cultural differences to institutional heterogeneity. In particular, our model predicts: (i)

[3]This paper focuses on policies which can influence people's judgment of the severity of the crisis. See Section 4 for a discussion of another type of policies which aim to reduce the damage of a crisis after its severity is already known.

Covid Economics 67, 4 February 2021: 53-93

CEPR PRESS

early-hit countries are less hesitant to adopt aggressive and precautionary measures such as massive testing and tracking, mandatory quarantine and even lock-downs from the early stage; (ii) subsequent countries face a stronger political hurdle to take strict measures; (iii) the strict measures adopted by early-hit countries may be initially criticized, but later lauded after the adverse consequences under alternative responses are observed.

There are other relevant examples. For instance, when a terrorism threat spreads internationally, governments need to decide, often in a sequential manner depending on where the threat first emerges, how aggressively to tackle it when the public is initially uncertain about its severity; trading off between free expression and public safety, a social media platform or regulator often falls into a damned-either-way trap, but its hands can be untied by the possible loose regulation and adverse consequence from other platforms or societies.[4]

To deliver the main idea transparently, we adopt two perhaps unconventional assumptions. First, we assume that the public does not believe that the policymaker possesses any superior information on the true state (e.g., due to a mistrust) and so does not attempt to infer information on the state merely from their chosen policy. In other words, the public learns the state only from the policy outcome. This shuts down a potential signaling channel. However, we show in an extension in Appendix B that apart from an extreme case, adding the signaling channel does not affect our main insight. Second, we assume that the public evaluates the policy using their updated belief of the state after seeing the policy outcome. This is different from the usual approach where the public evaluates the policymaker based on some underlying characteristics such as their competence or preferences which can be learned from policy choices. We report such a "reputation" modelling approach in Appendix B and show that it delivers similar results but with somewhat different underlying economics.

Finally, notice that although we choose the sequential-move model to deliver our main message, the counterfactual effect is also present when societies make decisions simultaneously. In that case, asymmetric equilibria with different responses across societies or even mixed-strategy equilibria can arise. For instance, if the policymaker in one society expects the other to take an aggressive action, they then anticipate a more severe domestic policymaking dilemma and so will be more hesitant to adopt the same policy. The policymaker in the other society, anticipating a light action and so a counterfactual from this society, will

[4]Despite being criticized for "an act of modern totalitarianism," many tech giants are waging wars to counter the spread of disinformation, hate speech and extremism on social media. See, e.g., https://econ.st/3e2FgmL.

Covid Economics 67, 4 February 2021: 53-93

indeed take the aggressive action.

Related literature. With a single society, our model predicts that due to the policy-making dilemma, the policymaker, in spite of knowing that the state is severe, may choose a light intervention, appearing to pander to public opinion when people are initially optimistic. This pander-to-the-prior effect is not new in the literature and can arise in various contexts. For example, in the political economy literature, this can occur when an incumbent politician tries to signal their competency (e.g., Harrington (1993), Canes-Wrone, Herron, and Shotts (2001), and Prat (2005)) or preferences (e.g., Maskin and Tirole (2004)) by choosing a policy which panders to public opinion. This also happens when a firm manager who has a share price concern makes decisions the market wants to see (e.g., Brandenburger and Polak (1996)), or when a media slants its report toward its readers' prior to build a reputation for quality (e.g., Gentzkow and Shapiro (2006)). Also related is the literature on the adverse effect of reputation concern. In particular, Morris (2001) and Ely and Välimäki (2003) show that an agent chooses Pareto-dominated information revelation or action to avoid damaging their reputation.

The policy-making dilemma highlighted in our paper differs from the trade-offs in the aforementioned papers. In those works, either the outcome of an action is unobservable, or when an action matches the state, it is more likely to generate an observable outcome which induces the agent to approve the chosen action. This is opposite to the "damned-either-way" feature of our model: when a strict policy is adopted, a good outcome is realized more likely regardless of the state, which makes people more optimistic about the underlying state and so induces them to disapprove the chosen policy. Moreover, most of these works do not consider a meaningful interaction among multiple decision makers. An exception is Brandenburger and Polak (1996), which we will discuss in more detail in Appendix B.3. But an important difference is that in their model, having multiple sequential decision makers does not restore the earlier movers' incentives to take the efficient action.

The mechanism in our model with multiple societies is the resolution of the belief conflict between the policymaker and the public in a dynamic environment. Hirsch (2016) is a related work in this respect. He studies a two-period model where a principal and an agent initially disagree on the optimal policy to achieve their shared objective. If the principal compromises in the first period and implements the "wrong" policy the agent favors, the agent will then make more effort and eventually learns a more informative signal of the true state. This helps them reach consensus and implement the optimal policy more efficiently

Covid Economics 67, 4 February 2021: 53-93

Covid Economics 67, 4 February 2021: 53-93

in the second period.[5] This idea could also be relevant in our crisis management context: the policymaker can take a light action first and let people learn the true severe state, and then switch to an aggressive action. Such a trial-and-error way to resolve the belief conflict can be rather costly, especially when policy experimentation is time-consuming or an initial incorrect action could have a severe lasting adverse impact. Our model highlights a novel channel to resolve the belief conflict, which is to let the agent learn from the failure of late movers' alternative policy choices.

In our model with multiple societies, strategic players may take some action which appears against their current interest but benefits them in the long run by generating information that influences followers' decisions.[6] Broadly speaking, this insight is related to the strategic experimentation literature. For example, Bolton and Harris (1999) study a strategic bandit problem among multiple long-lived agents. Besides the standard free-rider effect, they also discover an encouragement effect by which each agent has an incentive to experiment more than in the single-agent case, in the hope of generating positive information to incentivize other agents to experiment further in the future. Callander and Hummel (2014) demonstrate that a politician holding on to power temporarily will use preemptive policy experimentation to set the path of their successor's experimentation in their favor.

The rest of the paper is organized as follows: Section 2 introduces the benchmark case with a single society and shows the policy-making dilemma. Section 3 studies the case of multiple societies where the dynamic counterfactual effect arises. Section 4 concludes. The omitted proofs are relegated to Appendix A. Appendix B contains some extensions and alternative models.

2 Single Society

Suppose that a society faces a potential crisis, and the crisis can be *severe* or *mild*. There are two players: a policy-maker or government and a representative citizen. We assume that the government has learned the true state, which is severe. The citizen, however, is uncertain

[5] There are other works which study the interaction between learning and prior disagreement. For instance, Che and Kartik (2009) argue that with conflicting beliefs, individuals will have more incentives to acquire information to persuade each other. This can, for example, render hiring people with different opinions optimal in organization design.

[6] In terms of dynamic information spillover across players, our paper is also related to the literature on social learning. In the standard models in that literature (e.g., Banerjee (1992) and Bikhchandani, Hirshleifer, and Welch (1992)), however, early players have no strategic incentives to influence later players' choices.

about the state, and believes that the crisis is severe with probability $\mu_0 \in (0,1)$ and is mild with probability $1-\mu_0$. We assume that the government cannot convince the citizen of the true severity of the crisis and fully resolve their opinion difference, and they agree to disagree. This assumption implies that the citizen does not believe that the government has superior information on the state. Then the prior difference $1-\mu_0$ can be regarded as the citizen's mistrust of the government.

The government has two possible options to handle the crisis: $a \in \{l,h\}$, where l stands for a "low" action or light intervention, and h stands for a "high" action or heavy intervention.[7] An outcome, which can be *good* (denoted by $x=0$) or *bad* (denoted by $x=1$), will be realized after the government takes its action. When the state is mild, we assume that the outcome will be good regardless of the government's action. When the state is severe, however, the outcome will depend on the government's action: $x=0$ with probability q_a for $a \in \{l,h\}$ where

$$0 \leq q_l < q_h \leq 1 \,,$$

i.e., a high action generates a good outcome more likely.[8]

The citizen observes the government action and the outcome, and updates her belief about the state by Bayes' rule. Once a bad outcome occurs, the citizen will be convinced that the state is indeed severe since a mild state always yields a good outcome.[9] A good outcome, however, will make the citizen more optimistic about the state. More precisely, after seeing $a=h$ and $x=0$, the citizen's posterior belief about the state is

$$T_h(\mu_0) = \frac{\mu_0 q_h}{\mu_0 q_h + 1 - \mu_0} \,,$$

where T_h is a Bayesian updating operator. Similarly, after seeing $a=l$ and $x=0$, the

[7]For simplicity we assume here that the government takes action only once. In a more realistic setting, the government is perhaps able to make decisions dynamically and the citizen then learns information on the state over time. The high action here is a reduced-form way to capture an in-time response, while the low action corresponds to a sluggish response which squanders the opportunity to keep the crisis under control while allowing the citizen to learn more about the true state.

[8]In some examples (e.g., a pandemic), the citizen's effort also matters for containing the crisis. A more optimistic citizen may make less effort, making the government's action less effective in controlling the crisis. This can strengthen our main point in the two-society model later: making people in the second society more optimistic will not only induce the government there to take the low action but also reduce people's effort there. This will increase the chance of a bad outcome in the second society and so more likely help justify the first government's choice of high action.

[9]As we will discuss in Appendix B, this assumption of bad-news information structure is not crucial for the main sights of this paper.

Covid Economics 67, 4 February 2021: 53-93

citizen's belief is updated to

$$T_l(\mu_0) = \frac{\mu_0 q_l}{\mu_0 q_l + 1 - \mu_0} .$$

It is clear that

$$T_l(\mu_0) < T_h(\mu_0) \leq \mu_0 . \tag{1}$$

That is, seeing a good outcome realized when the action is low makes the citizen more optimistic than when the action is high. Also, T_a, $a = h, l$, increases in q_a and approaches the prior μ_0 as q_a goes to 1. That is, a good outcome becomes less informative when an action becomes more effective in containing the crisis. The exact form of belief updating is not important, and what matters for our subsequent analysis is property (1). Note that under our agree-to-disagree assumption, there is no interim Bayesian updating after seeing the government action but before seeing the outcome.

The citizen's utility depends on the government's action a and the outcome x:

$$u(a, x) = -c \times \mathbb{I}_{a=h} - x, \tag{2}$$

where $\mathbb{I}_{a=h}$ is an indicator function and $c > 0$. A heavy intervention imposes a cost c on the citizen, while a light intervention involves a lower cost, which is normalized to 0. When the outcome turns out to be bad, the citizen further suffers a loss, which is normalized to 1. This double normalization makes c the cost difference between two actions relative to the citizen's disutility from the bad outcome. Relative to action l, action h imposes a cost c regardless of the true state but generates a benefit $q_h - q_l$ only when the state is severe. Therefore, the citizen finds action h to be optimal if and only if she is convinced that the state is severe with a sufficiently high probability, i.e., her belief is no less than

$$\hat{\mu} \equiv \frac{c}{q_h - q_l} .$$

To make our problem interesting, we assume henceforth $c < q_h - q_l$ so that $\hat{\mu} \in (0, 1)$. Under this condition, the first-best policy, given the true state is severe, should be heavy intervention. It is easy to see that $\hat{\mu}$ increases in c and q_l, but decreases in q_h. Intuitively, action h will be less favored by the citizen if it is more costly to enforce (higher c) or less effective in containing the crisis (smaller $q_h - q_l$).

The government will be held accountable for its action *after* its consequence is observed. The citizen will evaluate the government's action according to her *posterior* belief, i.e., she

Covid Economics 67, 4 February 2021: 53-93

Covid Economics 67, 4 February 2021: 53-93

prefers to approve the government's action if and only if it maximizes her expected utility based on her updated belief μ. As a consequence, action h will be approved if $\mu \geq \hat{\mu}$, and otherwise action l will be approved. We will discuss more about the citizen's evaluation rule later. The government cares only about the citizen's evaluation (say, for the policy maker's political career such as reelection or personal legacy purpose),[10] and its payoff is 1 if its action is approved by the citizen and is 0 otherwise. The government's objective is therefore to maximize the probability that its action gets approved.[11]

Discussion. Before proceeding, we discuss two main modelling assumptions that enable us to deliver the main insights in a parsimonious way.

(i) Non-common prior and agree-to-disagree. We assume that the government and the citizen hold different priors of the state and agree to disagree.[12] We interpret it as a consequence of the citizen's mistrust of the government. This mistrust prevents the government from convincing the citizen of the true state. With this agree-to-disagree assumption, the citizen does not infer any information on the state directly from the government's action, and so there is no signaling issue in our model. This simplifies the analysis, especially in the dynamic case with multiple societies. For simplicity, we have also assumed that the government holds a degenerated prior belief and know the true state for sure. In Appendix B.3 we will discuss an extension with the signaling channel and a more general prior and show that it delivers similar insights though in a less concise way. We choose to use the model without signaling also because we are inclined to believe that in many cases the public may not be sophisticated enough to make inferences based on their conjectured government policy strategy.

(ii) Policy evaluation and political accountability. The more important assumption is that the citizen uses her posterior of the state (after seeing the policy outcome) to evaluate the government policy. This is the source of the agency problem in our model (i.e., the government may pander to public opinion and choose the inefficient policy).

One interpretation is that the citizen is purely an assessor of the government policy, and she enjoys supporting the policy if it is optimal according to her posterior belief and de-

[10]This government preference specification applies not only in democracies but also in autocracies where winning public support is critical for the government to legitimate and stabilize its governance.

[11]We will discuss a more general government payoff specification in Appendix B. For example, when the government takes action h but a bad outcome is realized, it may suffer from being regarded as having a poor enforcement ability. It is also possible that conditional on being disapproved, the government may have different payoffs, depending on whether it is criticized for overreacting or underreacting. We will show that our main insights are robust to these possible generalizations.

[12]See, for example, Morris (1995) for a comprehensive discussion on the heterogeneous-prior assumption.

nouncing it otherwise. That the citizen uses her posterior, instead of her prior, to evaluate the policy is related to the well-known *hindsight bias*: people tend to incorporate the newly available information into their evaluation of a decision, even if they know that the information was not available when the decision was made. This bias is widely documented in the psychology and behavioral economics literature (see, e.g., Fischhoff (1975), and Camerer, Loewenstein, and Weber (1989)), and is plausible in our context when people mistrust the government.

Another interpretation is that the policy outcome in our model is just an informative signal of the policy effectiveness realized in the beginning phase of the crisis. If the citizen believes that her opinion of the policy will determine the government's decision of whether to continue the same policy or adopt a new one, it is then rational for her to evaluate the current policy based on her posterior after seeing the signal.

As we will see more clearly later, what really matters for the main results of this paper is that the government's payoff, when it chooses action h (l), is higher if the citizen *ex post* believes the state is more likely severe (mild). We believe this is a sensible feature of the government payoff structure in the context of crisis management.

Notice also that the way we model political accountability differs from the conventional approach. The standard approach assumes the government or policy-maker has some private characteristics such as her preferences or competence. The citizen learns information on her characteristics from her policy choice and if possible also from the consequence, and then decides whether or not to reelect her.[13] On the contrary, our model assumes that the citizen assesses the policy *per se*. Certainly in many circumstances the citizen may care more about some basic characteristics of the policy-maker such as her empathy for the public, and her ability to gather relevant information and to implement policies, etc. In Appendix B.4, we will report an alternative reputation model in this vein, and show that it delivers similar results but somewhat different underlying economics.

[13]This is the so-called forward-looking voting in the retrospective voting literature since the voter uses the information learned from past behavior to select between the incumbent politician and future challengers. See, e.g., the survey by Healy and Malhotra (2013). The other well-known strand in that literature, initiated by Key (1966) and Barro (1973), is about backward-looking voting where the voter sanctions or rewards politicians based on the outcome of their past behavior. Our modelling approach is closer to the latter in spirit.

Covid Economics 67, 4 February 2021: 53-93

2.1 Analysis

Given the citizen's evaluation rule, the government trades off being blamed for underreacting against for overreacting. Heavy intervention is more able to generate a good outcome, but this also means that it will more likely convince the citizen that the state is mild and the adoption of costly heavy intervention is unnecessary. On the contrary, light intervention will relieve the government from a criticism of overreaction, but it will more likely result in a bad outcome and therefore cause an accusation of underreaction. The more optimistic the citizen is initially, the more optimistic she will be after seeing a good outcome and so the more likely she will favor light intervention. Therefore, intuitively the government has a higher incentive to take the low action when the citizen's prior μ_0 is lower.

If the government takes action h, its expected payoff, given the true state is severe, is

$$q_h \mathbb{I}_{T_h(\mu_0) \geq \hat{\mu}} + 1 - q_h \ . \tag{3}$$

When the good outcome is realized, the high action is approved if and only if $T_h(\mu_0) \geq \hat{\mu}$; when the bad outcome is realized, the high action is approved for sure since the true severe state is perfectly revealed. If the government takes action l, its expected payoff is

$$q_l \mathbb{I}_{T_l(\mu_0) < \hat{\mu}} \ . \tag{4}$$

When the good outcome is realized, the low action is approved if and only if $T_l(\mu_0) < \hat{\mu}$; when the bad outcome is realized, the low action is disapproved for sure.

Let $\hat{\mu}_1$ solve

$$T_h(\hat{\mu}_1) = \hat{\mu} \ . \tag{5}$$

It is the prior level from which the citizen's belief will be updated downward to the cut-off level $\hat{\mu}$ after seeing a high action and a good outcome. Similarly, let $\tilde{\mu}_1$ solve $T_l(\tilde{\mu}_1) = \hat{\mu}$. Note that property (1) implies $\hat{\mu} \leq \hat{\mu}_1 < \tilde{\mu}_1$.

Figure 1 plots expressions (3) and (4) and clearly shows the government's trade-off. When the high action is taken and a good outcome is realized (which occurs with probability q_h), the action will be disapproved if $T_h(\mu_0) < \hat{\mu}$, or equivalently if $\mu_0 < \hat{\mu}_1$. In this case, the government will be criticized for overreacting. In contrast, when the low action is taken and a bad outcome is realized (which occurs with probability $1 - q_l$), the government

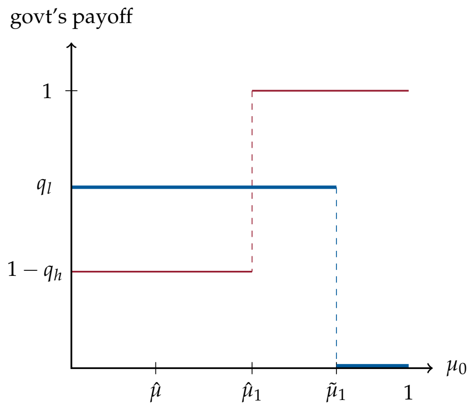


Figure 1: The red thin line corresponds to the government's payoff under action h (expression in (3)); while the blue thick line corresponds to the payoff under action l (expression in (4)), where condition (6) holds and $T_l(\tilde{\mu}_1) = \hat{\mu}$ and $T_h(\hat{\mu}_1) = \hat{\mu}$.

will be faulted for underreacting. Therefore, when

$$q_h > 1 - q_l \, , \tag{6}$$

the risk of being accused of overreacting dominates, and so the government will take action l if $\mu_0 < \hat{\mu}_1$. If $\mu_0 \geq \hat{\mu}_1$, the government will take the first-best action h since the citizen is too pessimistic about the state to disapprove the action even after seeing a good outcome. Figure 1 describes this case under condition (6).[14]

It is also clear from Figure 1 that when the citizen has a sufficiently optimistic prior ($\mu_0 < \hat{\mu}_1$), either action will be disapproved with some probability. This formally captures the aforementioned "damned-either-way" policy-making dilemma. This dilemma arises in our model because each action is more likely to generate an outcome which induces the citizen to believe the alternative action would be better. It does not rely on the randomness of the policy outcome. In fact the dilemma is the most prominent when the randomness vanishes, i.e., when both $q_h = 1$ and $q_l = 0$.

When condition (6) fails, the government's concern of being accused of underreacting dominates, and so it will always take the high action which achieves the first-best outcome.

[14]In the edge case with $q_h = 1$ and $q_l = 0$, the equality of (6) holds. There are many possible ways to break the tie. For example, we can assume that action h is more costly to enforce for the government than action l.

Covid Economics 67, 4 February 2021: 53-93

In the rest of the paper, we assume (6) and focus on the more interesting case depicted in Figure 1 unless otherwise stated. Then we have the following result:

Proposition 1. *The government takes action h if and only if* $\mu_0 \geq \hat{\mu}_1$.

Therefore, in the single-society case the first-best outcome is achieved if and only if the citizen is initially sufficiently pessimistic; otherwise, the government will pander to public opinion and make a sub-optimal decision.[15] Given $T_h(\cdot)$ increases in q_h and the definition of $\hat{\mu}$ in expression (2), it is easy to see that $\hat{\mu}_1$ decreases in q_h and increases in q_l and c. That is, as expected a higher q_h or a lower q_l or c widens the range of μ_0 in which the government takes the first-best action.

Implication for pandemics. We apply the single-society model to the government's optimal policy in a pandemic crisis. It helps to understand the source of political hurdles of choosing strict measures.

Public mistrust. There has been a great consensus that the public's trust in technocratic expertise and professional elites is crucial in shaping a society's response to a pandemic crisis.[16] A low public trust prevents the government from convincing people of the severity of the crisis, resulting in a large divergence between the government's and people's belief (as captured by $1-\mu_0$ in our model) and so a suboptimal policy choice. Low public trust may be caused by dysfunctional states and poor leadership, or it is simply a reflection of the polarization of a society.

Cost of strict measures. The government's hesitation to take an aggressive policy also grows as its cost on the public increases. Recall that parameter c corresponds to the cost difference between strict measures and light intervention relative to the citizen's loss from the bad crisis outcome. This relative cost is influenced by many economic and non-economic factors. First, strict measures inevitably cause significant economic damages, threatening the survival of a vast majority of people living paycheck to paycheck in societies with a low saving rate. In such a case the corresponding c should be large. By the same logic, a stimulus payment or tax relief to the public helps to lower the cost of strict measures. Second, in a society with a younger population or with more advanced critical care infrastructure, the

[15] A similar result holds when the government knows the state is mild. The government will then find it optimal to take the unnecessary high action to comfort the citizen if and only if she is sufficiently paranoid about the threat (i.e., if μ_0 is sufficiently large).

[16] See, for example, Francis Fukuyama, "The thing that determines a country's resistance to the Coronavirus," *The Atlantic*, March 2020.

Covid Economics 67, 4 February 2021: 53-93

damage caused by a pandemic is smaller, making c larger. Third, if a society has a lower tolerance of temporarily restricted civil liberties, it tends to have a larger c.

Doubts about strict measures. The government's political cost of choosing strict measures also depends on people's perceived benefit of doing so $(q_h - q_l)$. Characteristics such as geographic isolation and low population density contribute to a large q_l, while controversial views on the effectiveness of strict measures (e.g. wearing face masks) may lead to a small q_h.[17] These will increase the government's incentive to take a light approach.

3 Multiple Societies

Now suppose that two *identical* societies $i = 1, 2$ face the threat of a *common* crisis sequentially. (We will consider the case with more than two societies later.) As in the single-society case, there are two players in each society: a government and a representative citizen. Each government knows the crisis is severe, while the citizen in each society initially believes that the crisis is severe with probability $\mu_0 \in (0, 1)$. They agree to disagree as in the single-society case. As before, each government has two possible actions $a_i \in \{l, h\}$ to choose from. The outcome in each society, which is publicly observable, depends only on the state and the government's action in that society.

The timing is as follows: Government 1 moves first and chooses its action a_1. The outcome x_1 in society 1 is then realized. After seeing a_1 and x_1, citizen 2 updates her belief of the state and government 2 chooses its action a_2. Then the outcome x_2 in society 2 is realized. Finally, citizens 1 and 2 evaluate their own government based on the information from *both* societies.

Since a bad outcome in any society perfectly reveals the true state, we need only to specify the updated belief when the outcome is good in both societies. When a citizen sees a high action and a good outcome in both societies, her posterior belief will be $T_h^{[2]}(\mu_0)$, where $T_h^{[2]}$ denotes applying the operator T_h twice. Similarly, her posterior will be $T_l^{[2]}(\mu_0)$ after seeing a low action and a good outcome in both societies, and $T_h \circ T_l(\mu_0)$ after seeing a high action, a low action and two good outcomes. Similar to (1), we have

$$T_l^{[2]} < T_h \circ T_l = T_l \circ T_h < T_h^{[2]}, \tag{7}$$

[17] See, e.g., https://nyti.ms/2YOMNiS on "More Americans should probably wear masks for protection" in *The New York Times*.

Covid Economics 67, 4 February 2021: 53-93

and $T_a^{[2]} \leq T_a$. As in the single-society model, government i's action will be evaluated according to citizen i's posterior μ. Action h will be approved if $\mu \geq \hat{\mu}$, and otherwise action l will be approved.

It is worth pointing out two implicit assumptions in this two-society model: First, we assume a common prior for the public across the two societies.[18] The case with heterogeneous priors can be analyzed similarly, but does not add particularly new insights. Second, we also assume that the crisis will arise in the second society regardless of the action and the outcome in the first society. This is not crucial as long as a high action or a good outcome in the first society does not completely halt the spread of the crisis.

3.1 Analysis

Let $\hat{\mu}_2$ solve $T_h(\hat{\mu}_2) = \hat{\mu}_1$, or equivalently

$$T_h^{[2]}(\hat{\mu}_2) = \hat{\mu} \, .$$

This is the prior level from which the citizen's belief will be updated downward to the cut-off level $\hat{\mu}$ after seeing a high action and a good outcome in both societies. Clearly we have that $\hat{\mu} \leq \hat{\mu}_1 \leq \hat{\mu}_2$. A condition we will often refer to in the subsequent analysis is

$$q_l(q_h + q_l) \leq 1 \, . \tag{8}$$

For any given q_h, this condition holds if q_l is sufficiently small.

The following result reports the equilibrium outcome of the two-society game:

Proposition 2. *When there are two societies,*

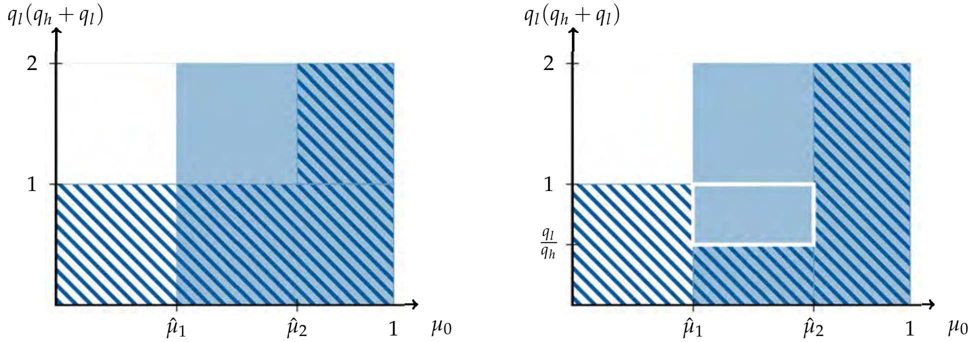
(i) if $\mu_0 \geq \hat{\mu}_2$, both governments take action h;

(ii) if $\mu_0 < \hat{\mu}_2$, government 1 takes action h if and only if condition (8) holds, and government 2 takes action h if and only if a bad outcome is realized in the first society.

Proposition 2 identifies the condition under which government 1 is relieved from the policy-making dilemma. When $\mu_0 \geq \hat{\mu}_2$ (which implies $T_h^{[2]}(\mu_0) \geq \hat{\mu}$), citizens are sufficiently pessimistic, and governments can safely choose the first-best action without being blamed for overreacting.

[18] With a common prior, our subsequent analysis remains unchanged if there is only a "common" citizen in both societies, or a common principal facing two agents.

Covid Economics 67, 4 February 2021: 53-93



(a) Government 1's choice: equilibrium model.

(b) Government 1's choice: hypothetical situation.

Figure 2: The solid rectangle area describes the set of parameters where government 1 chooses action h in the single-society model. The hatched area in (a) describes the set of parameters where government 1 chooses action h in the two-society model. The region $(0, \hat{\mu}_1) \times [0, 1]$ corresponds to the positive sampling effect, while the region $[\hat{\mu}_1, \hat{\mu}_2) \times [q_l/q_h, 2]$ corresponds to the negative sampling effect. The white-framed region $[\hat{\mu}_1, \hat{\mu}_2) \times [q_l/q_h, 1]$ in (b) corresponds to the strategic effect.

The more interesting case is when $\mu_0 < \hat{\mu}_2$. In this case, the presence of society 2 may help government 1 by providing a counterfactual for citizen 1 to better see the consequence of different policy options. More precisely, let us analyze the problem backward. First, notice that a successful crisis management by government 1 always makes citizen 2 more optimistic. With $\mu_0 < \hat{\mu}_2$, we have $T_{a_1}(\mu_0) < \hat{\mu}_1$ for any action $a_1 \in \{h, l\}$. From the analysis in the single-society case, it is then immediate that government 2 will take action l if $x_1 = 0$ and action h if $x_1 = 1$, regardless of government 1's action. Next, we consider government 1's incentive. If government 1 takes action h, it will be approved if and only if the crisis is out of control in at least one society, which happens with probability $1 - q_h q_l$. Instead, if government 1 takes action l, it will be approved if and only if both societies succeed in containing the crisis, which occurs with probability q_l^2. Therefore, government 1 prefers action h if and only if $1 - q_h q_l \geq q_l^2$, i.e., if condition (8) holds.

By comparing Propositions 1 and 2, it is easy to see that society 1 can either benefit or suffer from the presence of the second society.

Corollary 1. *Having the second society induces government 1 to switch from taking action l to taking action h if $\mu_0 < \hat{\mu}_1$ and (8) holds, and the reverse is true if $\hat{\mu}_1 \leq \mu_0 < \hat{\mu}_2$ and (8) does not hold. In the remaining cases, having the second society has no impact on government 1's policy choice.*

Covid Economics 67, 4 February 2021: 53-93

This result is illustrated in Figure 2a. Three forces influence government 1's decision: First, independent of government 1's action, the presence of society 2 increases the chance that the true severe state is revealed. This encourages government 1 to take action h. We call this a *positive sampling effect*. Second, independent of government 1's action, the presence of society 2 also generates the possibility that the good outcome is realized in both societies, in which case citizens will become rather optimistic. This is called a *negative sampling effect*, and it encourages government 1 to take action l instead. Finally, government 1's action can influence citizen 2's interim belief and so government 2's policy. In particular, when it takes action h, it makes it more likely that citizen 2 becomes optimistic so that government 2 takes action l, which increases the chance that the true state is revealed and government 1's policy is justified. We call this third effect a *strategic effect*.

To disentangle the strategic effect from the two sampling effects, we consider the following hypothetical situation: suppose that citizen 2 *cannot* observe what has happened in society 1, but citizen 1 can observe how the crisis unfolds in society 2. In this case, government 1's policy choice is only affected by the sampling effects. Following a similar argument as in the proof of Proposition 2, one can readily show that government 1's action can be different when $\hat{\mu}_1 \leq \mu_0 < \hat{\mu}_2$, in which case it will take action h if and only if

$$q_h(q_h + q_l) \leq 1 \,, \tag{9}$$

which is equivalent to $q_l(q_h + q_l) \leq q_l/q_h$. This is a more stringent condition than (8). The gap between these two conditions, as illustrated as the white-framed region in Figure 2b, captures the strategic effect. Intuitively, when $\hat{\mu}_1 \leq \mu_0 < \hat{\mu}_2$, if citizen 2 does not observe what has happened in society 1, her pessimistic prior induces government 2 to take action h. While in our model, after seeing $x_1 = 0$ citizen 2 will become sufficiently optimistic ($T_h(\mu_0) < \hat{\mu}_1$) so that government 2 will take action l instead, which increases the chance that the true state is revealed.

Next, we compare all parties' (ex ante) welfare between the two societies to see whether there is a first-mover advantage in our model. The citizen's welfare is measured according to the true state.

Corollary 2. *If $\mu_0 \geq \hat{\mu}_2$, both the citizen and the government are equally well across societies. If $\mu_0 < \hat{\mu}_2$ and (8) holds, citizen 1 does better than citizen 2, and government 1 does better than government 2 if and only if $2q_l \leq 1$. If $\mu_0 < \hat{\mu}_2$ and (8) does not hold, both the citizen and the government in society 2 do better than in society 1.*

Covid Economics 67, 4 February 2021: 53-93

The first society can influence the second society's belief and action in favor of its own welfare. But the second society has more information when it is its turn to make the decision. This, however, is not always a blessing, given the citizen's welfare is measured according to the true state instead of her own belief. When a good outcome is realized in the first society, it will mislead citizen 2 to be over-optimistic. Of course, when a bad outcome is realized in the first society, it helps the second society. The above result suggests that if the citizen is initially sufficient optimistic ($\mu_0 < \hat{\mu}_2$) and the low action has a sufficiently small chance in containing the crisis (q_l sufficiently small), the first society has the first-mover advantage. (Recall that a smaller q_l amplifies the strategic effect as action l by government 2 will reveal the true state more likely.)

Implication for pandemics. The two-society model also has some useful implications for the pandemic crisis.

Misleading success. A key force in our model is that a successful crisis control in the first society will give people in the second society a false sense of safety. This confidence inflation is greater if, all else equal, the first society is perceived as less developed in health infrastructure (corresponding to smaller q_{a_1}). In this case the political hurdle to strict measures in the second society will be larger.

Information manipulation. We assume free information flow across countries, but it is straightforward to see that governments have incentives to influence the information flow. Government 1, if it has succeeded in containing the crisis, can benefit from downplaying the threat by broadcasting its success to inflate people's doubts in society 2 about the severity of the crisis. Meanwhile, it also has an incentive to broadcast the failure of society 2's light intervention to its own people to justify its strict policy. Government 2, on the other hand, has an incentive to downplay or sow doubt about society 1's success to minimize the confidence inflation among its own people and therefore the political hurdle to strict measures.

Commitment to strict measures. The first mover takes advantage from the aforementioned strategic effect by pushing up the political hurdle faced by government 2. To counter this force, government 2 could make a preemptive commitment to strict measures. As shown in Figure 2b, such a commitment will turn the tables in some circumstances: it can induce government 1 to take the low action and so help justify government 2's aggressive policy.

Covid Economics 67, 4 February 2021: 53-93

3.2 More societies

It is not difficult to extend our analysis to the case with n societies. The main insights remain, but the general case also yields some new insights such as the societies in the middle of the sequence may perform the worst. We first report the equilibrium in this general case.

Proposition 3. *Let $\hat{\mu}_n$ solve $T_h^{[n]}(\hat{\mu}_n) = \hat{\mu}$. When there are n societies,*

(i) if $\mu_0 \geq \hat{\mu}_n$, all the governments take action h;

(ii) if $\mu_0 < \hat{\mu}_n$, for any $i = 1, 2, ..., n$, (a) if $x_j = 1$ in at least one predecessor society $j < i$, government i takes action h; (b) if $x_j = 0$ for all $j < i$ or if $i = 1$, government i takes action h if and only if $q_l^{n-i}(q_h + q_l) \leq 1$.

A few simple observations follow. First, since $\hat{\mu}_n$ increases in n, result (i) implies that it becomes harder for all the governments to take action h when there are more societies. Second, when $\mu_0 < \hat{\mu}_n$, having more societies increases the i_{th} government's incentive to take action h more likely if the true state has not been revealed. This is because, when there are more societies, both the positive sampling effect (i.e., the true state is revealed in some subsequent society) and the strategic effect become stronger, while the negative sampling effect (i.e., the good outcome is realized in all the subsequent societies) becomes weaker. Similarly, when $\mu_0 < \hat{\mu}_n$ and the history is good so far, earlier governments are more likely to take action h.

To illustrate the point that the society in the middle of the sequence may perform the worst, consider an example with three societies and suppose $\mu_0 < \hat{\mu}_3$ and $q_l^2(q_h + q_l) \leq 1 < q_l(q_h + q_l)$. From the proposition above, it is easy to see that government 1 will take action h, which is the best for its citizen. If $x_1 = 1$, then the true state is revealed and so the other two governments will take action h as well, in which case the three societies are equally well. If $x_1 = 0$, government 2 will take action l for sure, which is the worst for its citizen, while government 3 will take action h with some chance (i.e., when $x_2 = 1$), which puts its citizen in the middle of the ranking. Intuitively, the first society enjoys the greatest positive sampling effect and the strategic effect, while the third society has the most information and its government will take the first-best policy if the true state has been revealed.

Covid Economics 67, 4 February 2021: 53-93

Covid Economics 67, 4 February 2021: 53-93

4 Conclusion

This paper provides a framework for studying crisis management with multiple jurisdictions or societies. We first highlight a "damned-either-way" policy-making dilemma: sufficient precautions can contain a crisis, but people may then become skeptical of the severity of the problem and question the costly response; light intervention is less costly but often fails to control the crisis, and people will then accuse the policymaker of underreacting. Such a dilemma can raise the political cost for the government to take an efficient policy. We then argue that the dilemma will be mitigated if people can see the counterfactual policy outcome. One possibility is when another society faces the same crisis afterward. The success under an aggressive policy in the first society boosts the optimism of people in the second society, increasing the chance for the second society to adopt a light approach and experience an outbreak, which in turn justifies the first society's policy choice. This helps explain, for example, why similar societies might respond to a common crisis differently, and why societies that handle the crisis later may perform worse despite having more information.

This paper has focused on "preventive" policies that if succeed cause the public to question the severity of a potential crisis. In the pandemic example, they are policies such as wide testing and tracking, mandatory quarantine, travel bans and even strict lock-downs from the early stage. Another type of policies which we do not study in this paper are "mitigating" policies that aim to reduce the damage of a crisis when it already outbreaks and its severity is already known. In the pandemic example, they are policies such as stockpiling ventilators, subsidizing medicine and vaccine research, and stimulus payment. When the government is constrained by the policy-making dilemma from implementing preventive policies, it may then reply more on mitigating measures.[19] The counterfactual effect predicts that early-hit countries tend to focus more on preventive measures while later countries on mitigating measures.

Another interesting perspective is to consider countries with different cultures, institutions, or public infrastructures, etc. Depending on which countries are hit first by a crisis, the dynamics of crisis management may vary significantly, resulting in rather different welfare outcomes.

[19] Fox and Van Weelden (2015) study a model of crisis prevention when a policy maker can allocate effort across multiple tasks, but the essential economic force there is different from ours.

References

BANERJEE, A. V. (1992): "A Simple Model of Herd Behavior," *Quarterly Journal of Economics*, 107(3), 797–817.

BARRO, R. (1973): "The Control of Politicians: An Economic Model," *Public Choice*, 14(1), 19–42.

BIKHCHANDANI, S., D. HIRSHLEIFER, AND I. WELCH (1992): "A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades," *Journal of Political Economy*, 100(5), 992–1026.

BOLTON, P., AND C. HARRIS (1999): "Strategic Experimentation," *Econometrica*, 67(2), 349–374.

BRANDENBURGER, A., AND B. POLAK (1996): "When Managers Cover Their Posteriors: Making the Decisions the Market Wants to See," *RAND Journal of Economics*, 27(3), 523–541.

CALLANDER, S., AND P. HUMMEL (2014): "Preemptive Policy Experimentation," *Econometrica*, 82(4), 1509–1528.

CAMERER, C., G. LOEWENSTEIN, AND M. WEBER (1989): "The Curse of Knowledge in Economic Settings: An Experimental Analysis," *Journal of Political Economy*, 97(5), 1232–1254.

CANES-WRONE, B., M. C. HERRON, AND K. W. SHOTTS (2001): "Leadership and Pandering: A Theory of Executive Policymaking," *American Journal of Political Science*, 45(3), 532–550.

CHE, Y.-K., AND N. KARTIK (2009): "Opinions as Incentives," *Journal of Political Economy*, 117(5), 815–860.

COATE, S., AND S. MORRIS (1995): "On the Form of Transfers to Special Interests," *Journal of Political Economy*, 103(6), 1210–1235.

ELY, J. C., AND J. VÄLIMÄKI (2003): "Bad Reputation," *Quarterly Journal of Economics*, 118(3), 785–814.

FISCHHOFF, B. (1975): "Hindsight Is Not Equal to Foresight: The Effect of Outcome Knowledge on Judgment under Uncertainty," *Journal of Experimental Psychology: Human Perception and Performance*, 1(3), 288–299.

FOX, J., AND R. VAN WEELDEN (2015): "Hoping for the Best, Unprepared for the Worst," *Journal of Public Economics*, 130, 59–65.

GENTZKOW, M., AND J. M. SHAPIRO (2006): "Media Bias and Reputation," *Journal of Political Economy*, 114(2), 280–316.

HARRINGTON, J. E. (1993): "Economic Policy, Economic Performance, and Elections," *American Economic Review*, 83(1), 27–42.

HEALY, A., AND N. MALHOTRA (2009): "Myopic Voters and Natural Disaster Policy," *American Political Science Review*, pp. 387–406.

——— (2013): "Retrospective Voting Reconsidered," *Annual Review of Political Science*, 16, 285–306.

HIRSCH, A. V. (2016): "Experimentation and Persuasion in Political Organizations," *American Political Science Review*, 110(01), 68–84.

KEY, V. (1966): *The Responsible Electorate: Rationality in Presidential Voting, 1936-1960*. Harvard University Press.

KREPS, D. M., AND R. WILSON (1982): "Reputation and Imperfect Information," *Journal of Economic Theory*, 27(2), 253–279.

MAILATH, G. J., AND L. SAMUELSON (2015): "Reputations in Repeated Games," in *Handbook of Game Theory with Economic Applications*, vol. 4, pp. 165–238. Elsevier.

MASKIN, E., AND J. TIROLE (2004): "The Politician and the Judge: Accountability in Government," *American Economic Review*, 94(4), 1034–1054.

MORRIS, S. (1995): "The Common Prior Assumption in Economic Theory," *Economics and philosophy*, 11, 227–253.

——— (2001): "Political Correctness," *Journal of Political Economy*, 109(2), 231–265.

PRAT, A. (2005): "The Wrong Kind of Transparency," *American economic review*, 95(3), 862–877.

Covid Economics 67, 4 February 2021: 53-93

SKIDMORE, M. J. (2016): *Presidents, Pandemics, and Politics*. Springer.

STASAVAGE, D. (2020): "Democracy, Autocracy, and Emergency Threats: Lessons for COVID-19 From the Last Thousand Years," *International Organization*, pp. 1–17.

A Appendix: omitted proofs

Proof of Proposition 2. (i) Suppose $\mu_0 \geq \hat{\mu}_2$. If government 1 takes action h and the outcome is $x_1 = 1$, both citizens learn the true state, in which case government 1's action will be approved and government 2 will take action h as well. If government 1 takes action h and the outcome is $x_1 = 0$, then citizen 2's interim belief will be $T_h(\mu_0) \geq \hat{\mu}_1$, in which case government 2 will take action h as well. The two citizens' posterior will then be at least $T_h^{[2]}(\mu_0) \geq \hat{\mu}$, and so both governments' actions will be approved. Therefore, if government 1 takes action h, it will always get approved and have an expected payoff 1.

Conversely, if government 1 takes action l, with probability $1 - q_l$ the true severe state will be revealed, in which case its action will be disapproved, and so its payoff is at most $q_l < 1$. Therefore, government 1's optimal choice is action h. The above argument then implies that government 2 will take action h as well.

(ii) Suppose now $\mu_0 < \hat{\mu}_2$. If government 1 takes action l, it will be approved if and only if $x_1 = x_2 = 0$. When $x_1 = 0$, citizen 2's interim belief will be updated to $T_l(\mu_0) < \hat{\mu}_1$, and so government 2 will take action l. Therefore, $x_1 = x_2 = 0$ occurs with probability q_l^2, and this is government 1's expected payoff.

If government 1 takes action h, with probability $1 - q_h$, $x_1 = 1$, in which case government 1's payoff is 1. With probability q_h, $x_1 = 0$, in which case citizen 2's interim belief will be $T_h(\mu_0) < \hat{\mu}_1$, and so government 2 will take action l. For government 1' action h to be approved, we need $x_2 = 1$, which happens with probability $1 - q_l$. (Otherwise, the citizen's posterior would be $T_h \circ T_l(\mu_0) < \hat{\mu}$ and she would not approve action h.) Hence, government 1's expected payoff is $(1 - q_h) + q_h(1 - q_l) = 1 - q_h q_l$.

Therefore, government 1's optimal choice is action h if and only if $q_l^2 \leq 1 - q_h q_l$, which is equivalent to (8). □

Proof of Corollary 2. When $\mu_0 \geq \hat{\mu}_2$, both governments take the same action h, and so all parties' expected payoff must be the same across societies.

Covid Economics 67, 4 February 2021: 53-93

When $\mu_0 < \hat{\mu}_2$ and (8) holds, government 1 takes action h while government 2 takes action h if and only if $x_1 = 1$. So citizen 1 must do better given the high action is the first-best action. As we have shown in the proof of Proposition 2, in this case government 1's payoff is $1 - q_h q_l$. Government 2's payoff is $1 - q_h + q_h q_l$. (When $x_1 = 1$, government 2 will take action h, in which its payoff is 1. When $x_1 = 0$, government 2 will take action l, in which case its action will be approved if and only if $x_2 = 0$.) Comparing these two payoffs yields the condition stated in the result.

When $\mu_0 < \hat{\mu}_2$ and (8) does not hold, government 1 takes action l while government 2 takes h if $x_1 = 1$. So the citizen in society 2 must do better. As we have shown in the proof of Proposition 2, in this case government 1's payoff is q_l^2. Government 2's payoff is at least q_l^2 because when $x_1 = 0$ government 2 will take action l, and this will be approved by the citizen if $x_2 = 0$. □

Proof of Proposition 3. (i) Let us use induction and suppose the claim is true when there are $n-1$ societies. If $a_1 = h$, then all the citizens in the subsequent societies will update their interim beliefs to $\mu = 1$ (if $x_1 = 1$) or $\mu = T_h^{[1]}(\mu_0) \geq \hat{\mu}_{n-1}$ (if $x_1 = 0$). In either case, according to the induction assumption, all the subsequent governments will take action h. When $x_1 = 1$, government 1 gets 1; when $x_1 = 0$, it gets 1 as well because even if $x_j = 0$ for all $j > 1$ the posterior will be $T_h^{[n]}(\mu_0) \geq \hat{\mu}$. Hence, government 1's expected payoff, when it takes the high action, is 1. If $a_1 = l$, government 1 gets zero if $x_1 = 1$, and so its payoff is at most q_l. Therefore, government 1 should take action h.

(ii) Part (a) is obvious given a bad outcome in any society reveals the true severe state. Again we use induction and suppose (b) is true when there are $n-1$ societies. Consider government 1's decision when there are n societies. There are $n-1$ cases. We call the case of $q_l(q_h + q_l) \leq 1$ "case 1," the case of $q_l^k(q_h + q_l) \leq 1 < q_l^{k-1}(q_h + q_l)$ "case k" if $2 \leq k \leq n-2$, and the case of $q_l^{n-2}(q_h + q_l) > 1$ "case $n-1$."

If government 1 takes action h, it will be approved if and only if the true severe state is revealed at some point. With probability $1 - q_h$, $x_1 = 1$, in which case government 1 gets 1. With probability q_h, $x_1 = 0$, in which case the citizens in the subsequent societies have an interim belief $T_h^{[1]}(\mu_0) < \hat{\mu}_{n-1}$ and so the induction assumption can be applied. Then government 1's payoff depends on how many subsequent governments will take action h and how many will take action l. In case 1, all the subsequent governments but the last one will take action h if the history is good so far. So among them the chance that the true state is revealed is $1 - q_h^{n-2} q_l$. Then government 1's payoff is $1 - q_h + q_h(1 - q_h^{n-2} q_l) = 1 - q_h^{n-1} q_l$. In case k, all the subsequent governments but the last k will take action h if the history is

CEPR PRESS

good so far. Then government 1's payoff is $1 - q_h^{n-k} q_l^k$. In case $n-1$, all the subsequent government will take action l if the history is good so far. Then government 1's payoff is $1 - q_h q_l^{n-1}$.

If government 1 takes action l instead, it will be approved if and only if the true state is never revealed. With probability $1 - q_l$, $x_1 = 1$, in which case its payoff is zero. With probability q_l, $x_1 = 0$, in which case the citizens in the subsequent societies have an interim belief $T_l^{[1]}(\mu_0) < \hat{\mu}_{n-1}$ and so the induction assumption can be applied. The analysis is then similar as above. In case 1, all the subsequent governments but the last one will take action h if the history is good so far, and so the chance that $x_i = 0$ among all the subsequent societies is $q_h^{n-2} q_l$. Thus, government 1's payoff is $q_h^{n-2} q_l^2$. In case k, all the subsequent governments but the last k will take action h if the history is good so far, and so government 1's payoff is $q_h^{n-k-1} q_l^{k+1}$. In case $n-1$, all the subsequent government will take action l if the history is good so far, and so government 1's payoff is q_l^n.

It is then straightforward to verify: in case 1, government 1 prefers action h if and only if $q_h^{n-2} q_l (q_h + q_l) \leq 1$, which is implied by the condition of case 1; in case k, government 1 prefers action h if and only if $q_h^{n-k-1} q_l^k (q_h + q_l) \leq \tau$, which is also implied by the condition of case k; in case $n-1$, government 1 prefers action h if and only if $q_l^{n-1}(q_h + q_l) \leq 1$, which implies the condition of case $n-1$. Therefore, we can conclude that government 1 will take action h if and only if $q_l^{n-1}(q_h + q_l) \leq 1$. This completes the proof. □

Covid Economics 67, 4 February 2021: 53-93

Covid Economics 67, 4 February 2021: 53-93

B Appendix: extensions and alternative models

In this appendix, we report three extensions: one with a more general government payoff structure, another with a more general information structure, and the third with a signaling channel; and we also explore an alternative "reputation" model.

B.1 More general government payoff

In the baseline model, we assume a simple payoff structure for the government: it gets 1 if its action is approved and 0 otherwise. We now consider a more general payoff structure as in the table below:

	$x = 0$	$x = 1$
a approved	1	$\beta \in [0, 1]$
a disapproved	α_o if $a = h$ and $T_h(\mu_0) < \hat{\mu}$ α_u^+ if $a = l$ and $T_l(\mu_0) \geq \hat{\mu}$	$\alpha_u^- \equiv 0$

In the first cell, the action is approved and the outcome is good, in which case the government gets the highest possible payoff 1. In the second cell, the action is approved but the outcome is bad, which can happen only if $a = h$. In this case the citizen may doubt the government's enforcement ability, and we assume the government's payoff is $\beta \in [0, 1]$. In the third cell, the action leads to a good outcome but it is disapproved. If the action is h, the government must be criticized for overreacting, in which case its payoff is $\alpha_o < 1$; if the action is l, the government must be criticized (perhaps mildly) for underreacting, in which case its payoff is $\alpha_u^+ < 1$. In the last cell, the action is disapproved and the outcome is bad, which can happen only if $a = l$. In this case the government should suffer from a more severe criticism for underreacting, and let its payoff be $\alpha_u^- \leq \alpha_u^+$ and we normalize it to 0. In sum, we assume the parameters satisfy $0 = \alpha_u^- \leq \alpha_u^+, \beta \leq 1$ and $\alpha_o < 1$. In particular, $\alpha_o < 0$ is allowed to reflect the possibility that the citizen strongly dislikes overreaction. Note that our baseline model corresponds to the case with $\beta = 1$ and the three α parameters being 0.

The single-society case can be analyzed similarly as before. The government's expected payoff, if it takes action h, is $q_h(\mathbb{I}_{T_h(\mu_0)\geq\hat{\mu}} + \alpha_o \mathbb{I}_{T_h(\mu_0)<\hat{\mu}}) + (1 - q_h)\beta$, and otherwise it is $q_l(\mathbb{I}_{T_l(\mu_0)<\hat{\mu}} + \alpha_u^+ \mathbb{I}_{T_h(\mu_0)\geq\hat{\mu}})$. By a similar argument as in the baseline case, one can check that Proposition 1 (i.e., the government takes action h if and only if $\mu_0 \geq \hat{\mu}_1$) still holds if we replace condition (6) by

$$q_l > q_h \alpha_o + (1 - q_h)\beta \, .$$

This is easier to be satisfied when α_o, the payoff associated with overreaction, is smaller. (If $\alpha_o < 0$, this condition is even satisfied in the polar case with $q_l = 0$ and $q_h = 1$.) Given the cut-off rule in the single-society case, the main economic force in the two-society model remains unchanged as well. For example, when the three α parameters are zero, Proposition 2 still holds if we replace condition (8) by $q_l(q_h + q_l) \leq \beta + (1-\beta)q_h$.

The government's payoff can be generalized in other aspects as well. For instance, the citizen's prior may also directly affect her evaluation of the government's policy, and the so-called "outcome bias" (i.e., a good outcome will be praised while a bad outcome will be criticized regardless of the action) may also play some role. Also, the government may directly care about the citizen's welfare to some extent. However, provided that the evaluation component based on the citizen's posterior is sufficiently important, our main insights should carry over.[20]

B.2 Beyond bad-news information structure

In the baseline model we assume that when the state is mild, the outcome is always good regardless of the government action. Now we relax this assumption and let the outcome under the mild state be stochastic as well. More specifically, suppose $x = 0$ with probability q'_a for $a \in \{l, h\}$ under the mild state. It is natural to assume $q'_a > q_a$ and

$$q_h - q_l > q'_h - q'_l \,. \tag{10}$$

The latter implies the "marginal" effect of taking the high action in containing the crisis is higher when the state is severe.

As in the baseline model, let $\hat{\mu}$ be the threshold in the citizen's evaluation rule. It now solves

$$c = \mu(q_h - q_l) + (1-\mu)(q'_h - q'_l) \tag{11}$$

since the high action can also lower the chance of a bad outcome under the mild state. Under condition (10) the citizen will approve action h if and only if her posterior is greater than $\hat{\mu}$.

[20]Generally, we can define $\tilde{v}_a(x, \mu, \mu_0)$ as the government's payoff when it takes action a, the realized outcome is x, the citizen's posterior is μ, and the citizen's prior is μ_0. Since μ is function of (a, x, μ_0), we can rewrite the payoff function as $v_a(x, \mu_0)$. Let $\bar{v}_a(\mu_0) \equiv q_h v_a(0, \mu_0) + (1-q_h)v_a(1, \mu_0)$ be the expected payoff function associated with action a. Then we have the cut-off result if $\bar{v}_h(\mu_0)$ increases in μ_0, $\bar{v}_l(\mu_0)$ decreases in μ_0, $\bar{v}_h(0) < \bar{v}_l(0)$, and $\bar{v}_h(1) > \bar{v}_l(1)$. At this level of generality, of course it can be complex to specify the primitive conditions for all these conditions to be satisfied.

Covid Economics 67, 4 February 2021: 53-93

Covid Economics 67, 4 February 2021: 53-93

Let $T_{a,x}(\mu_0)$ be the citizen's posterior of the state after seeing action a and outcome x. When a good outcome is realized, we have

$$T_{h,0}(\mu_0) = \frac{\mu_0 q_h}{\mu_0 q_h + (1-\mu_0)q'_h};\ T_{l,0}(\mu_0) = \frac{\mu_0 q_l}{\mu_0 q_l + (1-\mu_0)q'_l}\ .$$

Both are less than μ_0 since observing a good outcome makes the citizen more optimistic. The opposite is true when a bad outcome is realized, in which case we have

$$T_{h,1}(\mu_0) = \frac{\mu_0(1-q_h)}{\mu_0(1-q_h)+(1-\mu_0)(1-q'_h)};\ T_{l,1}(\mu_0) = \frac{\mu_0(1-q_l)}{\mu_0(1-q_l)+(1-\mu_0)(1-q'_l)}\ .$$

Notice that condition (10) implies $q'_h/q'_l < q_h/q_l$ and so $T_{l,0}(\mu_0) < T_{h,0}(\mu_0)$.[21] Let $\hat{\mu}_{a,x}$ solve $T_{a,x}(\hat{\mu}_{a,x}) = \hat{\mu}$. Then we have

$$\hat{\mu}_{h,1}, \hat{\mu}_{l,1} < \hat{\mu} < \hat{\mu}_{h,0} < \hat{\mu}_{l,0}\ .$$

Notice that $\hat{\mu}_{h,0}$ and $\hat{\mu}_{l,0}$ are the counterparts of $\hat{\mu}_1$ and $\tilde{\mu}_1$ in the baseline model.

Given the government knows the true state is severe, its expected payoff if it takes action h is

$$q_h \mathbb{I}_{T_{h,0}(\mu_0)\geq\hat{\mu}} + (1-q_h)\mathbb{I}_{T_{h,1}(\mu_0)\geq\hat{\mu}}\ ,$$

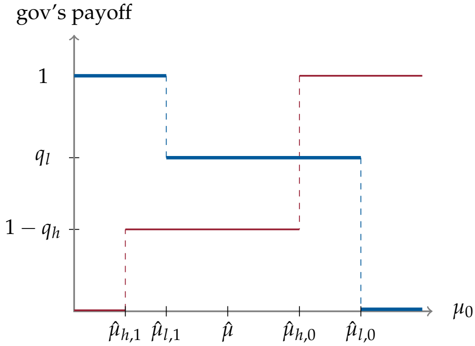
and its expected payoff if it takes action l is

$$q_l \mathbb{I}_{T_{l,0}(\mu_0)<\hat{\mu}} + (1-q_l)\mathbb{I}_{T_{l,1}(\mu_0)<\hat{\mu}}\ .$$

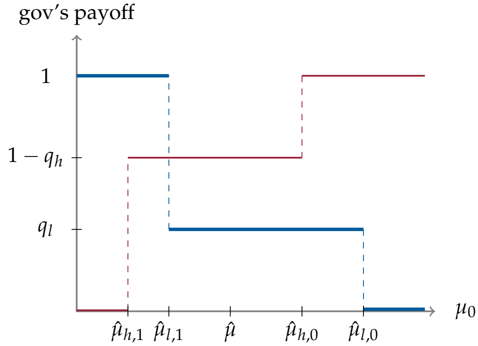
The main difference, compared to the baseline case, is that now action l can also be approved when the outcome is bad, which occurs when the citizen was initially very optimistic. As a result, no action will dominate the other over all possible priors μ_0 as illustrated in Figure 3. (In the baseline model with $q'_h = q'_l = 1$, both $\hat{\mu}_{h,1}$ and $\hat{\mu}_{l,1}$ degenerate at 0. In that case action h dominates in Figure 3b.)

If $q_l > 1-q_h$ as in the baseline case, the government takes action h if and only if $\mu_0 \geq \hat{\mu}_{h,0}$ as illustrated in Figure 3a; in contrast, if $q_l < 1-q_h$, the government takes action h if and only if $\mu_0 \geq \max\{\hat{\mu}_{h,1}, \hat{\mu}_{l,1}\}$ as illustrated on Figure 3b. In the former case, overreaction arises under action h more likely than underreaction under action l, so the government takes h less

[21] But condition (10) does not necessarily imply $(1-q'_h)/(1-q'_l) < (1-q_h)/(1-q_l)$, and so the ranking between $T_{h,1}(\mu_0)$ and $T_{l,1}(\mu_0)$ is unclear.



(a) $1 - q_h < q_l$



(b) $1 - q_h > q_l$

Figure 3: Government's payoff under general information structure: the red thin line corresponds to the government's payoff under action h, while the blue thick line corresponds to the payoff under action l.

likely than the citizen herself would do according to her prior; in the latter case, however, the opposite is true, so that the government takes h more likely than the citizen herself would do. It is also clear that when the citizen's prior is rather extreme, the government will take the action consistent with her prior, in which case it always gets approved. The policy-making dilemma now arises when μ_0 is in the middle range.

Since the single-society case still features a cut-off rule as in the baseline model, the main economic force in the two-society case remains unchanged as well. However, with more societies it is possible for a belief-and-action cycle to arise, which differs from the baseline case. For example, consider the case when a low action in an early society leads to a bad outcome. Since the bad outcome is no longer conclusive about the state, if it leads to a high action and a good outcome in the next society, societies afterward can become optimistic enough to adopt a low action again.

B.3 Asymmetric state information and signaling

This section discusses an extension where the citizen believes that the government possesses superior information concerning the state. As a result, the citizen will attempt to infer the state from the government action as well, based on her rational expectation of the government's policy strategy. This signaling channel was intentionally shut down in our main model. Here we demonstrate that having this signaling channel does not change the main

Covid Economics 67, 4 February 2021: 53-93

insights except in the polar case when the government perfectly knows the true state.

Let us first consider the single-society case. Let ω denote the state, and it can be bad/severe (B) or good/mild (G). The citizen's prior is $\Pr(\omega = B) = \mu_0$, and the government's prior is $\Pr(\omega = B) = \nu_0$. When $\mu_0 = \nu_0$, we have the common-prior case, but as we will see these two priors play completely separate roles, and so here we present the more general case. Before choosing its policy the government observes a private signal $s \in \{b, g\}$ of the state, and it is commonly known that the signal structure is $\Pr(b|B) = \Pr(g|G) = \delta \in [\frac{1}{2}, 1]$. It is assumed that the government is unable to convey its private information directly to the citizen (e.g., because the state information is too complex to communicate). The other aspects of the model remain unchanged, and we focus on the interior case with $0 < q_l < q_h < 1$. The major difference now is that the citizen can also infer some information on the state from the government's action alone based on her equilibrium belief of the government's strategy. The government strategy is denoted by $\sigma \equiv (\sigma_b, \sigma_g)$, where σ_s is the probability the government takes action h after receiving signal s.

Let

$$\nu_s = \frac{\nu_0 \Pr(s|B)}{\nu_0 \Pr(s|B) + (1 - \nu_0) \Pr(s|G)}$$

be the government's updated belief that the state is bad after receiving signal s. This is what matters for its policy decision. The interesting case is when $\nu_g < \hat{\mu} < \nu_b$, i.e., when the efficient policy, from the government's point of view, is h (l) after seeing a bad (good) signal. This requires δ to be sufficiently high.

For the citizen, what matters for her evaluation of the government policy is her posterior after seeing both the action and the outcome. If the outcome is bad ($x = 1$), it perfectly reveals state B. If the outcome is good ($x = 0$), let $T_a^\sigma(\mu_0)$ denote the citizen's posterior when the government takes action a and it is believed to be using strategy σ. Specifically,

$$T_h^\sigma(\mu_0) = \frac{\mu_0 \sigma_B q_h}{\mu_0 \sigma_B q_h + (1 - \mu_0) \sigma_G} = \frac{1}{1 + \frac{1-\mu_0}{\mu_0} \frac{\sigma_G}{\sigma_B} \frac{1}{q_h}},$$

and

$$T_l^\sigma(\mu_0) = \frac{\mu_0 (1 - \sigma_B) q_l}{\mu_0 (1 - \sigma_B) q_l + (1 - \mu_0)(1 - \sigma_G)} = \frac{1}{1 + \frac{1-\mu_0}{\mu_0} \frac{1-\sigma_G}{1-\sigma_B} \frac{1}{q_l}},$$

where $\sigma_B \equiv \delta \sigma_b + (1 - \delta) \sigma_g$ and $\sigma_G \equiv (1 - \delta) \sigma_b + \delta \sigma_g$ are respectively the expected probability that the government takes action h under strategy (σ_b, σ_g) when the true state is B or G. (We stipulate $1/0 = \infty$.) Both posteriors are increasing in μ_0 as in the baseline model, but now they also depend on the government's policy strategy σ. Let $\hat{\mu}_a^\sigma$ solve $T_a^\sigma(\mu) = \hat{\mu}$ whenever this is well defined, i.e., it is the prior from which the citizen's belief will be updated to the threshold level $\hat{\mu}$ after seeing action a and a good outcome. (Note that $\hat{\mu}_1$ and $\tilde{\mu}_1$ in the baseline model are respectively equal to $\hat{\mu}_h^{1,1}$ and $\hat{\mu}_l^{0,0}$.)

Let

$$p_{s,a} \equiv \nu_s q_a + 1 - \nu_s$$

denote the government's expected probability, after receiving signal s, that a good outcome will be realized if it takes action a. For a given signal s, the government's expected payoff is

$$\pi_{s,h} \equiv p_{s,h} \mathbb{I}_{T_h^\sigma(\mu_0) \geq \hat{\mu}} + 1 - p_{s,h}$$

if it takes action h, and is

$$\pi_{s,l} \equiv p_{s,l} \mathbb{I}_{T_l^\sigma(\mu_0) < \hat{\mu}}$$

if it takes action l. Similar to the baseline model, the government's optimal strategy is then determined by comparing $\pi_{s,h}$ and $\pi_{s,l}$, and in equilibrium it should be consistent with σ.

We maintain the assumption $q_h + q_l > 1$ as in the baseline model. Then it is ready to check that we must have $p_{s,h} + p_{s,l} > 1$, and so the payoffs $\pi_{s,a}$ defined above, as functions of μ_0, are similar to those in Figure 1 (with q_l replaced by $p_{s,l}$ and $1 - q_h$ replaced by $1 - p_{s,h}$). In particular, for any μ_0 it is impossible that $\pi_{s,h} = \pi_{s,l}$ given our payoff specification. This implies that in our model the government will never play a mixed strategy.

In the polar case with $\delta = 1$ (i.e., when the government's signal perfectly reveals the true state), if the citizen ignores the outcome information once she can perfectly infer the state from the government's policy choice, then there is a separating equilibrium with $\sigma_b = 1$ and $\sigma_g = 0$ (i.e., the government takes action h (l) for sure upon seeing a bad (good) signal). In this equilibrium, since the citizen perfectly infers the state from the government's action, the government action is always proved and so it has no incentive to deviate. Notice, however, this equilibrium is not "strict" in the sense that given the citizen's belief the government is actually indifferent between the two actions. In the following, we ignore this knife-edge case and focus on the more realistic case of $\delta < 1$.

Once we go beyond the polar case, as shown in Proposition 4 below, the separating equilibrium with $\sigma_b = 1$ and $\sigma_g = 0$ can no longer be sustained and the equilibrium must be pooling. (The intuition is discussed below after Proposition 4.) Therefore, the government's policy choice alone does not convey any information on the state, and so the outcome is the

Covid Economics 67, 4 February 2021: 53-93

same as in our baseline model and features a similar policy-making dilemma.

Now consider the two-society case where the state is common but each government receives an independent signal of the state with precision $\delta < 1$. In this case, we show in Proposition 4 below that having the second society can restore the first government's incentive to take the efficient separating strategy, which is again similar to the result in the baseline model.

Proposition 4. *Suppose the government's signal is not perfect (i.e., $\delta < 1$).*

(i) In the single-society case, there are no separating equilibria with $\sigma_s = 1$ and $\sigma_{s'} = 0$; any equilibrium must be a pure-strategy pooling equilibrium. In particular, there is a pooling equilibrium with proper off-equilibrium beliefs in which regardless of its private signal, the government takes action h (i.e., $\sigma_b = \sigma_g = 1$) if $\mu_0 \geq \hat{\mu}_1$ and action l (i.e., $\sigma_b = \sigma_g = 0$) if $\mu_0 < \hat{\mu}_1$, where $\hat{\mu}_1$ takes the same value as (5) in the baseline model.

(ii) Suppose the pooling equilibrium in the single-society case takes the form in (i). Then in the two-society case, there is an equilibrium in which the first government takes the separating strategy $\sigma_b = 1$ and $\sigma_g = 0$ if $T_h^{1,1} \circ T_h^{1,0}(\mu_0) < \hat{\mu}$ and $p_{b,l}(p_{b,h} + p_{b,l}) < 1 < p_{g,l}(p_{g,h} + p_{g,l})$.

Proof. (i) In the single-society case, we prove that if $\delta < 1$ there is no equilibrium with $\sigma_b = 1$ and $\sigma_g = 0$. (The proof for the other case of $\sigma_b = 0$ and $\sigma_g = 1$ is similar and so omitted.)

For the sake of contradiction, suppose that such an equilibrium exists. The citizen believes that the government is playing the above separating strategy, her posterior after seeing a good outcome will be

$$T_h^{1,0}(\mu_0) = \frac{1}{1 + \frac{1-\mu_0}{\mu_0}\frac{1-\delta}{\delta}\frac{1}{q_h}}; \quad T_l^{1,0}(\mu_0) = \frac{1}{1 + \frac{1-\mu_0}{\mu_0}\frac{\delta}{1-\delta}\frac{1}{q_l}}.$$

When $\delta < 1$, both are well-behaved strictly increasing functions. It is also clear that given $\delta \geq \frac{1}{2}$ and $q_h > q_l$, we must have $\frac{1-\delta}{\delta}\frac{1}{q_h} < \frac{\delta}{1-\delta}\frac{1}{q_l}$ and so $T_h^{1,0}(\mu_0) > T_l^{1,0}(\mu_0)$. This implies $\hat{\mu}_h^{1,0} < \hat{\mu}_l^{1,0}$. From a graph similar to Figure 1, it is ready to see that regardless of signal s, we have $\pi_{s,h} > \pi_{s,l}$ if $\mu_0 \geq \hat{\mu}_h^{1,0}$ and $\pi_{s,h} < \pi_{s,l}$ otherwise. Therefore, for a given μ_0, the separating strategy cannot be sustained in equilibrium. Essentially, this is because given $p_{s,h} + p_{s,l} > 1$, the ranking of $\pi_{s,h}$ and $\pi_{s,l}$ is independent of the signal s.

We have explained in the main text that there is no mixed-strategy equilibrium. Hence, only pure-strategy pooling equilibria remain possible. Suppose first the citizen believes that

Covid Economics 67, 4 February 2021: 53-93

the government's policy strategy is $\sigma_b = \sigma_g = 1$ (i.e., it always takes action h regardless of its signal). Then

$$T_h^{1,1}(\mu_0) = \frac{1}{1 + \frac{1-\mu_0}{\mu_0}\frac{1}{q_h}} . \tag{12}$$

Let us specify the off-equilibrium belief so that $T_l^{1,1}(\mu_0) < T_h^{1,1}(\mu_0)$. (This is reasonable since without the signaling channel a low action with a good outcome is more convincing evidence that the state is good.) Then we have $\hat{\mu}_h^{1,1} < \hat{\mu}_l^{1,1}$, and so the government will indeed always take action h if $\mu_0 \geq \hat{\mu}_h^{1,1}$. Now consider the case when the citizen believes that the government's policy strategy is $\sigma_b = \sigma_g = 0$ (i.e., it always takes action l regardless of its signal). Then

$$T_l^{0,0}(\mu_0) = \frac{1}{1 + \frac{1-\mu_0}{\mu_0}\frac{1}{q_l}} . \tag{13}$$

A reasonable off-equilibrium belief is $T_h^{0,0}(\mu_0) > T_l^{0,0}(\mu_0)$, in which case we have $\hat{\mu}_h^{0,0} < \hat{\mu}_l^{0,0}$ and so the government will indeed always take action l if $\mu_0 < \hat{\mu}_h^{0,0}$. If we assume $T_h^{0,0}(\mu_0)$ takes the same form as (12) (which can be justified if both σ_b and σ_g converge to 0 at the same speed), then $\hat{\mu}_h^{0,0} = \hat{\mu}_h^{1,1}$. This is the pooling equilibrium described in the proposition.

(ii) In the two-society case, let us consider the possibility of the equilibrium where government 1 adopts the efficient separating strategy $\sigma_b = 1$ and $\sigma_g = 0$. When the citizen in either society believes that government 1 is taking this strategy, her belief of the state, after seeing action a and a good outcome, is updated to $T_a^{1,0}(\mu_0)$. From the definition of $\hat{\mu}_h^{1,1}$, we can see that $T_a^{1,0}(\mu_0) < \hat{\mu}_h^{1,1}$ if and only if $T_h^{1,1} \circ T_a^{1,0}(\mu_0) < \hat{\mu}$. This is true for both $a = h$ and $a = l$ if

$$T_h^{1,1} \circ T_h^{1,0}(\mu_0) < \hat{\mu} . \tag{14}$$

Under this condition, following a similar argument as in the baseline model, we can see that when government 1 takes action h after seeing signal s, its expected payoff is

$$\pi_{s,h} = 1 - p_{s,h}p_{s,l}\left(1 - \mathbb{I}_{T_l^{0,0} \circ T_h^{1,0}(\mu_0) \geq \hat{\mu}}\right) ;$$

when it takes action l after seeing signal s, its expected payoff is

$$\pi_{s,l} = p_{s,l}^2 \mathbb{I}_{T_l^{0,0} \circ T_l^{1,0}(\mu_0) < \hat{\mu}} .$$

Notice that $T_h^{1,1} > T_l^{0,0}$ and $T_h^{1,0} > T_l^{1,0}$, and so (14) implies $T_l^{0,0} \circ T_l^{1,0}(\mu_0) < T_l^{0,0} \circ T_h^{1,0}(\mu_0) <$

Covid Economics 67, 4 February 2021: 53-93

$\hat{\mu}$. Therefore, $\pi_{b,h} > \pi_{b,l}$ if $p_{b,l}(p_{b,h} + p_{b,l}) < 1$, and $\pi_{g,h} < \pi_{g,l}$ if $p_{g,l}(p_{g,h} + p_{g,l}) > 1$. □

The intuition of no separating equilibrium with $\sigma_b = 1$ and $\sigma_g = 0$ in the single-society case is easy to see in the case when $\delta < 1$ is sufficiently close to 1. Suppose that the citizen holds the belief that the government is playing the separating strategy. If the government takes action h, its expected payoff is 1 regardless of the signal it receives, since the citizen will infer the state is B very likely and so will approve the action even if a good outcome is realized. If the government takes action l, however, its expected payoff must be strictly below 1. This is because no matter what signal it receives, the government is never perfectly sure that the state is G given $\delta < 1$ and so there is always a chance that the state is B and a bad outcome arises, in which case its low action will be disapproved. In other words, action h is always a safer option for the government. This contradicts the separating equilibrium.

The conditions in result (ii) are qualitatively similar to those in Proposition 2 in the baseline model. The first condition $T_h^{1,1} \circ T_h^{1,0}(\mu_0) < \hat{\mu}$, which holds if μ_0 is sufficiently low, ensures that after seeing a high action and a good outcome in society 1, people in society 2 will be optimistic enough so that their government will take action l. The second condition $p_{b,l}(p_{b,h} + p_{b,l}) < 1 < p_{g,l}(p_{g,h} + p_{g,l})$ holds when q_l is sufficiently low, and ν_b (ν_g) is sufficiently high (low), which is the case if δ is sufficiently high. It ensures that government 1 will take the efficient strategy, anticipating a good outcome will induce a low action in society 2. Intuitively, when government 1 is sufficiently confident that the state is bad (i.e., ν_b is high), it believes that an induced low action in society 2 will tend to generate a bad outcome, which will help justify its choice of high action; in contrast, when government 1 is sufficiently confident that the state is good (i.e., ν_g is low), it believes that even a low action will tend to generate a good outcome, and together with the same likely outcome in society 2 this will justify its choice of low action.

Discussion. This extended model with signaling is related to Brandenburger and Polak (1996) (BP thereafter). They study how a firm may make decisions the market wants to see. In their model, the firm receives a private signal of the state and then takes an action (e.g., an investment decision) which generates a profit if it matches the state. After seeing the firm's action (but not the resulting outcome), the market updates its belief on the state and then assesses the firm. The market assessment determines the firm's share price which the firm aims to maximize. BP show that if the prior is skewed to one state, there is no equilibrium in which the firm plays a separating strategy and maximizes its own expected profit. Instead in any equilibrium the firm's decision panders to the market's prior to some extent. This remains true even in the case with multiple firms which observe independent signals and

Covid Economics 67, 4 February 2021: 53-93

CEPR PRESS

make sequential decisions and are all evaluated by the market in the end.

Our model shares some features with BP: the market (the public) assesses a firm (a government) based on its posterior of the state instead of some underlying fundamental (e.g., the manager/government's ability), and the actions taken by early firms (governments) influence later firms' (governments') information and decisions. Nevertheless, the two papers differ in several important aspects. First, in BP both states and actions are symmetric (i.e., they can be relabelled), while in our model they are asymmetric. This asymmetry is natural in our context of crisis prevention (e.g., regardless of the state the high action prevents a crisis more likely than the low action). Second, in BP the market does not observe the outcome of the action and it only infers the state from the firm's action, while the observable outcome plays an important role in our model. Third, the above two differences imply that the policy-making dilemma in our single-society model does not occur in BP, and the result that having another society can restore the first government's incentive to take the efficient action does not arise in BP either.

B.4 A reputation model

As we discussed in the main text, a more conventional approach to model political accountability is to introduce a government's private type that is payoff relevant to citizens. In this section, we explore a modelling approach in this vein which can generate similar main results but with somewhat different economics and empirical implications.

There are two societies, where each government can be either *competent* or *incompetent*. The competence type is independent across the two governments. A competent government is a strategic player who chooses an action $a \in \{l, h\}$ to maximize its payoff as specified below given its information on the state, while an incompetent government is a "behavioral" player who mechanically commits to action h. This behavioral-type approach is standard in the reputation literature. See Kreps and Wilson (1982) for classic examples and Mailath and Samuelson (2015) for a comprehensive survey. In our crisis management context, the assumption for the behavioral type can be justified if an incompetent government is unable to efficiently acquire the state information and its enforcement ability is extremely poor. If it takes the low action, a third catastrophic outcome will take place when the state is severe, causing massive damage to both the society and itself. Consequently, provided it believes there is a chance that the true state is severe, an incompetent government always takes the high action.

Covid Economics 67, 4 February 2021: 53-93

Each government privately observes its competence type, and if it is competent it also observes a private signal of the true state. For simplicity we assume the signal perfectly reveals the true state, but no government can creditably reveal its information to its citizen. Each citizen's prior is that a government is competent with probability λ_0 and the state is severe with probability μ_0, and they know that their government, if competent, observes a perfect signal.[22]

The other aspects of the model remain the same as before, except for each government's payoff structure. Let λ denote a citizen's posterior belief that her government is competent, i.e., the government's *reputation*. Her government's payoff is then

$$\lambda + \gamma u(a, x)$$

for some constant $\gamma > 0$, where $u(a, x)$ is the citizen's payoff defined in (2) when her government's action is a and the outcome is x.[23] As standard in the political economy literature, the reputation concern can be justified by introducing a post-crisis reelection in each society: the citizen prefers a competent government and chooses between the incumbent government and a challenger whose reputation is uniformly distributed on $[0, 1]$. This specification implies that each government is motivated by both its citizen's welfare and the perks of office.

The strategy of a government specifies a competent government's policy choice in each state, conditional on the action and the outcome in the previous society (if any). Citizens observe actions and outcomes in both societies and form their beliefs about the state and the types of governments. A Perfect Bayesian Equilibrium consists of governments' strategies and citizens' beliefs that satisfy the following properties. First, citizens' beliefs are consistent with governments' strategies in the sense that they are generated by Bayesian updating wherever possible. Second, each government's strategy is optimal given citizens' beliefs.

Let us first consider the single-society case. When the state is mild, a competent government will choose action l. This is because the low action is a perfect signal of competence, and it is also the best policy for the citizen given the outcome is always good under a mild state. What needs to be pinned down is a competent government's strategy when the state is severe. Let $\sigma \in [0, 1]$ be the probability that it chooses action h. The government's trade-off

[22] The feature that the citizen is uncertain about both an underlying state and the policy maker's type is similar to, for example, Coate and Morris (1995) and Maskin and Tirole (2004).

[23] Notice that if $\gamma = 0$ and each government only cares about its reputation, then action l becomes their dominant strategy as it perfectly signals competence.

Covid Economics 67, 4 February 2021: 53-93

is between its desire to separate itself from an incompetent type (which favors action l) and the citizen's welfare (which favors action h).

Let $\lambda^{\sigma}_{a,x}$ denote the citizen's posterior of the government's type after seeing action a and outcome x given the competent government's policy strategy σ when the state is severe. When $a = l$, the posterior $\lambda^{\sigma}_{l,x}$ is always 1. When $a = h$ and $x = 1$, the citizen learns that the state must be severe, and so

$$\lambda^{\sigma}_{h,1} = \frac{\lambda_0 \sigma (1 - q_h)}{\lambda_0 \sigma (1 - q_h) + (1 - \lambda_0)(1 - q_h)} = \frac{1}{1 + \frac{1-\lambda_0}{\lambda_0} \frac{1}{\sigma}}; \tag{15}$$

when $a = h$ and $x = 0$, we have

$$\lambda^{\sigma}_{h,0} = \frac{\lambda_0 \mu_0 \sigma q_h}{\lambda_0 \mu_0 \sigma q_h + (1 - \lambda_0)(\mu_0 q_h + 1 - \mu_0)} = \frac{1}{1 + \frac{1-\lambda_0}{\lambda_0} \frac{1}{\sigma} \left(1 + \frac{1-\mu_0}{\mu_0} \frac{1}{q_h}\right)}. \tag{16}$$

(We stipulate $1/0 = \infty$ so that $\sigma = 0$ is permitted.) Note that the government will take action h only if it is competent and the state is severe or if it is incompetent.

The following two observations are important for both our subsequent analysis and the key insights in this reputation model: First, we have $\lambda^{\sigma}_{h,0} \leq \lambda^{\sigma}_{h,1} \leq \lambda_0$. Given an incompetent government always takes the high action, h is a signal of incompetence, and that is why both posteriors become smaller than λ_0. Meanwhile, when $x = 1$, the citizen learns the state is severe, in which case h is less a signal of incompetence given the competent government is more likely to take h in the severe state than in the mild state. Second, both posteriors are increasing in λ_0, μ_0 and σ. In particular, when the citizen believes the state is more likely to be severe or when she believes the competent government takes action h more often in the severe state, she regards h less as a signal of incompetence. When $x = 1$ and $\sigma = 1$, we have $\lambda^{\sigma}_{h,1} = \lambda_0$, i.e., the high action causes no reputation damage.

If the government takes action h, its expected payoff is $q_h \lambda^{\sigma}_{h,0} + (1 - q_h)\lambda^{\sigma}_{h,1} - \gamma(1 - q_h + c)$. In this case it bears the reputation cost and also imposes a cost c on the citizen, but the citizen is less likely to suffer from a bad outcome. If the government chooses action l, its expected payoff is $1 - \gamma(1 - q_l)$. In this case it bears no reputation cost, but the citizen is more likely to suffer from a bad outcome. (From the reputation perspective, there is no the feature of "damned if you do, damned if you don't" in this model, but it remains from the

Covid Economics 67, 4 February 2021: 53-93

CEPR PRESS

perspective of the government's payoff.) The first payoff is higher if and only if

$$q_h \lambda_{h,0}^{\sigma} + (1 - q_h)\lambda_{h,1}^{\sigma} \geq 1 - \gamma(q_h - q_l - c). \tag{17}$$

Notice that the left-hand side strictly increases in σ. With this observation we can characterize a unique (stable) equilibrium in the single-society case as reported in Proposition 5 below.

In the two-society case, a competent government 2 will act similarly as in the single-society case except that its citizen has an updated interim belief on the state after seeing what has happened in society 1. Then by backward induction we can similarly analyze a competent government 1's decision.

Proposition 5. *In the single-society case, there is a unique (stable) equilibrium in which a competent government takes the high action in the severe state if and only if (λ_0, μ_0) satisfies (17) at $\sigma = 1$; in the two-society case, a similar result holds for a competent government 1 but for a larger set of (λ_0, μ_0).*

Proof. Single society. Note that the left-hand side of (17) strictly increases in σ. If the opposite of (17) holds at $\sigma = 1$, the competent government always takes the low action in the severe state. Then we must have $\sigma = 0$ in equilibrium. In contrast, if (17) holds at $\sigma = 1$, it is an equilibrium that the competent government always takes the high action in the severe state, i.e., $\sigma = 1$. If the right-hand side of (17) is positive, there is also another equilibrium where the competent government plays a mixed strategy with $\sigma \in (0, 1)$ which solves the equality of (17). (Such an interior solution of σ always exists in this case since the left-hand side of (17) equals zero at $\sigma = 0$.) However, this equilibrium is unstable in the sense that if the citizen expects a slightly different σ, the competent government will take either the high or the low action for sure.

Two societies. Suppose both citizens expect a competent government 1 to take action h with probability $\sigma \in [0, 1]$ in the severe state. If the competent government 1 takes l in the severe state, its type is revealed perfectly. Then its expected payoff is independent of society 2 and is exactly the same as in the single-society case, i.e., $1 - \gamma(1 - q_l)$.

If the competent government 1 takes h in the severe state and if $x_1 = 1$, then its payoff is also independent of society 2 since the bad outcome already reveals the true severe state. In this case, its reputation is $\lambda_{h,1}^{\sigma}$ as defined in (15). If $x_1 = 0$, however, government 1's expected payoff will depend on government 2's policy and its outcome. An incompetent government 2 will always take action h; a competent government 2 will take a deterministic action a_2

Covid Economics 67, 4 February 2021: 53-93

Covid Economics 67, 4 February 2021: 53-93

as already shown in the single-society case. If $x_2 = 1$, the severe state is revealed, and then government 1's reputation is $\lambda^{\sigma}_{h,1}$; if $x_2 = 0$, let $\lambda^{\sigma}_{h,0;a_2,0}$ be government 1's reputation, which will be specified later. Therefore, government 1's expected payoff is $q_h[\lambda_0\Lambda^{\sigma}_{a_2} + (1 - \lambda_0)\Lambda^{\sigma}_{h}] + (1 - q_h)\lambda^{\sigma}_{h,1} - \gamma(1 - q_h + c)$, where

$$\Lambda^{\sigma}_{a} \equiv q_a\lambda^{\sigma}_{h,0;a,0} + (1 - q_a)\lambda^{\sigma}_{h,1}$$

is government 1's expected reputation when government 2 takes action a conditional on $a_1 = h$ and $x = 0$. Therefore, a competent government 1 prefers h if and only if

$$q_h\left[\lambda_0\Lambda^{\sigma}_{a_2} + (1 - \lambda_0)\Lambda^{\sigma}_{h}\right] + (1 - q_h)\lambda^{\sigma}_{h,1} > 1 - \gamma(q_h - q_l - c)\,. \tag{18}$$

Compared to condition (17) in the single-society case, the difference is the square-bracket term (which was simply $\lambda^{\sigma}_{h,0}$ in the single-society case), and it reflects how the presence of society 2 affects government 1's payoff.

Notice that given $a_1 = h$ and $x_1 = 0$, a competent government 2 will act as in the single-society case with primitives $(\lambda_0, T_h(\mu_0))$, where $T_h(\mu_0)$ is citizen 2's posterior of the state given she believes that government 1's strategy is σ.[24] If $(\lambda_0, T_h(\mu_0))$ is in the light blue area in Figure 4a, a competent government 2 will choose $a_2 = l$ for sure. In this case, if $x_2 = 0$, citizen 1's posterior of government 1's type is

$$\lambda^{\sigma}_{h,0;l,0} = \frac{\lambda_0\mu_0\sigma q_h\lambda_0 q_l}{\lambda_0\mu_0\sigma q_h\lambda_0 q_l + (1-\lambda_0)[\mu_0 q_h\lambda_0 q_l + (1-\mu_0)\lambda_0]} = \frac{1}{1 + \frac{1-\lambda_0}{\lambda_0}\frac{1}{\sigma}\left(1 + \frac{1-\mu_0}{\mu_0}\frac{1}{q_h q_l}\right)}\,.$$

If $(\lambda_0, T_h(\mu_0))$ is in the dark-blue area in Figure 4a, a competent government 2 will choose $a_2 = h$ for sure. In this case, if $x_2 = 0$, citizen 1's posterior of government 1's type is

$$\lambda^{\sigma}_{h,0;h,0} = \frac{\lambda_0\mu_0\sigma q_h q_h}{\lambda_0\mu_0\sigma q_h q_h + (1-\lambda_0)[\mu_0 q_h q_h + (1-\mu_0)(1-\lambda_0)]} = \frac{1}{1 + \frac{1-\lambda_0}{\lambda_0}\frac{1}{\sigma}\left(1 + \frac{1-\mu_0}{\mu_0}\frac{1-\lambda_0}{q_h^2}\right)}\,.$$

(It is ready to see that $\lambda^{\sigma}_{h,0;l,0} < \lambda^{\sigma}_{h,0;h,0}$ given $\frac{1}{q_l} > \frac{1-\lambda_0}{q_h}$ and both are less than λ_0 as expected.) When government 2 is incompetent and its high action leads to $x_2 = 0$, citizen 1's posterior

[24] More precisely,

$$T_h(\mu_0) = \frac{\mu_0\sigma q_h}{\mu_0\sigma q_h + (1-\mu_0)(1-\lambda_0)} = \frac{1}{1 + \frac{1-\mu_0}{\mu_0}\frac{1-\lambda_0}{\sigma q_h}}\,.$$

Covid Economics 67, 4 February 2021: 53-93

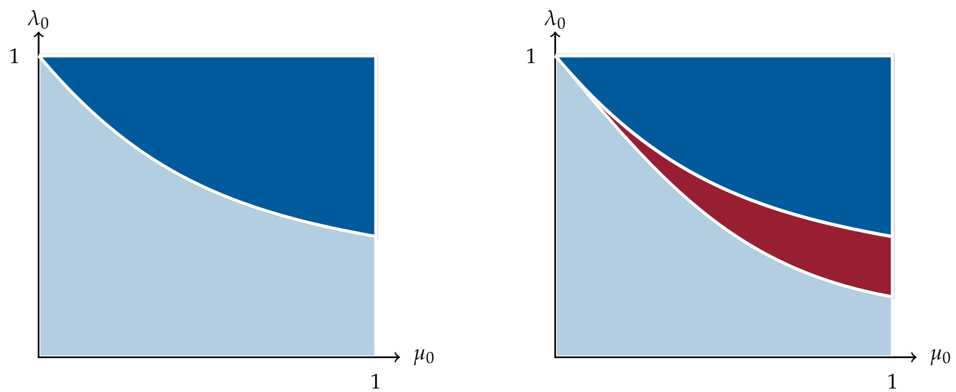
of its government's type is also $\lambda^\sigma_{h,0;h,0}$.

Given the left-hand side of (18) strictly increases in σ, the same argument as in the single-society case implies that there is a unique (stable) equilibrium where a competent government 1 takes h in the severe state if and only if (18) holds at $\sigma = 1$.

We now show that $\lambda_0 \Lambda^\sigma_{a_2} + (1 - \lambda_0)\Lambda^\sigma_h > \lambda^\sigma_{h,0}$, so that (18) holds at $\sigma = 1$ for a larger set of (λ_0, μ_0) than that for (17) at $\sigma = 1$. This is true if

$$q_{a_2} \lambda^\sigma_{h,0;a_2,0} + (1 - q_{a_2}) \lambda^\sigma_{h,1} > \lambda^\sigma_{h,0}$$

for both $a_2 = l$ and h. This is immediate once one notices that $q_l / \lambda^\sigma_{h,0;l,0} + (1 - q_l)/\lambda^\sigma_{h,1} = 1/\lambda^\sigma_{h,0}$ and $q_h / \lambda^\sigma_{h,0;h,0} + (1 - q_h)/\lambda^\sigma_{h,1} < 1/\lambda^\sigma_{h,0}$ and then apply the Jessen's inequality.[25] $\square$



(a) Government's decision in the single-society case (b) Government 1's decision in the two-society case

Figure 4: Illustration of a competent government's decision in the reputation model: The dark-blue area indicates the prior pairs (λ_0, μ_0) under which h is the government's optimal action, while the light-blue area corresponds to the prior pairs under which l is the optimal action. The red area corresponds to the extra prior pairs under which h becomes the optimal action for government 1 in the two-society case.

Figure 4a illustrates a competent government's optimal policy in the severe state in the single-society case: it takes the first-best high action if and only if both λ_0 and μ_0 are sufficiently high (so that the reputation damage caused by the high action is small enough), where the boundary is determined by the equality of (17) at $\sigma = 1$. (The boundary is decreasing because both $\lambda^\sigma_{h,0}$ and $\lambda^\sigma_{h,1}$ are increasing in λ_0 and μ_0.) In particular, for a given λ_0

[25]This is actually a consequence of a more general martingale property in our setup: given $\lambda^\sigma_{h,1} = \lambda^\sigma_{h,0;a_2,1}$, we have $\mathbb{E}[\lambda^\sigma_{h,0;a_2,x_2} | \text{severe state}] > \mathbb{E}[\lambda^\sigma_{h,0;a_2,x_2}] = \lambda^\sigma_{h,0}$.

which is not too small, the competent government takes the high action if and only if μ_0 is greater than some threshold as in our baseline model. The underlying economics, though, is different: in our baseline model, what discourages the government from taking the high action in the severe state is the prospect of being criticized for overreacting when a good outcome is realized; here in this reputation model, it is because taking a high action is regarded as a signal of incompetence.

Figure 4b illustrates a competent government 1's optimal policy in the severe state in the two-society case: the presence of the second society expands the range of λ_0 and μ_0 in which it takes the first-best high action. The intuition is as follows: Each government's reputation is now influenced by the action and outcome in both societies. A good outcome in society 1 leads to a lower updated μ_0 in society 2, which tends to induce a low action and so likely a bad outcome there. A bad outcome in society 2 helps reveal the severe state. Once citizen 1 is eventually convinced that the state is severe, she will regard its government's high action less as a signal of incompetence. This mitigates the reputation concern and encourages a competent government 1 to adopt the high action in the severe state. This result is qualitatively similar to what we saw in our baseline model.[26]

[26] A subtle difference here is that the negative sampling effect (which arises when a good outcome is also realized in society 2) is always dominated jointly by the positive sampling and the strategic effect. This is due to the payoff-structure difference for the government.

Covid Economics 67, 4 February 2021: 53-93

Benefit-cost analysis of COVID-19 policy intervention at the state and national level[1]

James L. Doti[2]

Date submitted: 26 January 2021; Date accepted: 28 January 2021

This study analyzes the benefits of statewide policy intervention in reducing COVID-19 deaths and the costs of that intervention in lost jobs and lower real gross state product (RGSP). Policy interventions are measured by the Oxford stringency index which places a daily numerical value on the level of a state's policy intervention. Empirical evidence is provided that shows policy interventions have reduced COVID-19 deaths in the U.S. by 358,000 lives in 2020. On the cost side, it was found that policy intervention resulted in a loss of 7.3 million jobs and a decline of $410 billion in RGSP. The study concludes by integrating the findings related to the benefits and costs of policy interventions to the economic cost per life saved for every state, as well as an estimate of the national average cost per life of $1.1 million. That figure is compared to an age-adjusted value of statistical life (VSL) calculated in the study of $4.2 million for COVID-19 fatalities.

Covid Economics 67, 4 February 2021: 94-127

1 The author is indebted to my Chapman colleagues, Lynne Doti, Fadel Lawandy, and Raymond Sfeir, who provided valuable advice and useful feedback. The excellent research assistance of my associate, Dorothy Farol, and research assistant, Laura Neis, and students is also gratefully acknowledged. I also wish to express appreciation for the financial support provided by the Robert Day Endowment for Research in Economic Analysis. I accept full responsibility for any errors.

2 President Emeritus and Professor of Economics, George L. Argyros School of Business & Economics, A.Gary Anderson Center for Economic Research, Chapman University.

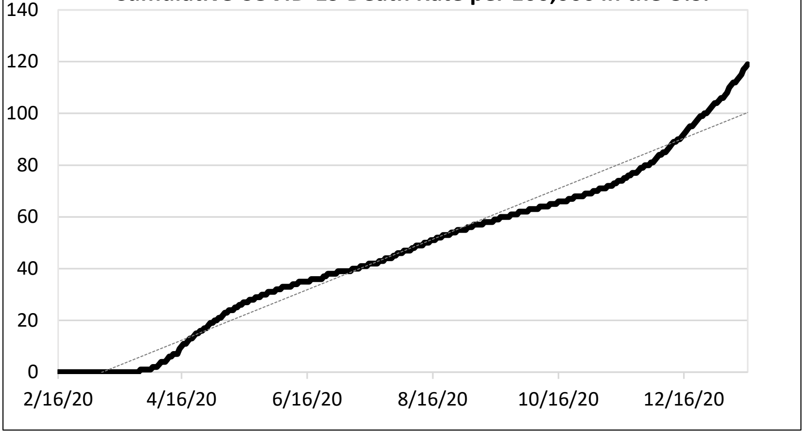
CEPR PRESS

1. Introduction

Understanding the benefits and costs associated with policy interventions designed to reduce the infection and death rates of COVID-19 is critically important. COVID-19 is the most significant health threat of our time. As shown below in Figure 1, the COVID-19 death rate in the U.S. continues to increase and towards the end of 2020 is increasing at a faster rate.

FIGURE 1

Cumulative COVID-19 Death Rate per 100,000 in the U.S.



Several academic studies have attempted to study the benefits and costs related to policy interventions to contain the spread of the COVID-19 virus and reduce its death rate. Unfortunately, most of these studies were conducted during the early months of the pandemic. Even these early studies, though, do not address the impact at the state level or examine the economic impact of policy interventions on jobs or spending.

In a study by Robinson, Sullivan, and Shogren, for example, the inquiry focuses on the relationship between age and the value of a statistical life (VSL) (Robinson, Sullivan, and Shogren, 2020). They use various approaches in measuring VSL to examine the empirical findings cited in other studies, but they do not independently measure the benefits and costs related to policy intervention.

One of the studies they cite is "The Benefits and Costs of Using Social Distancing to Flatten the Curve for COVID-19" (Thunstrom et al., 2020). The authors of this study use estimates of the impact of social distancing used by Australia in controlling the spread of the 1918 Spanish flu to measure the impact of social distancing in reducing the mortality risk of COVID-19. Not only is the use of data relating to the Spanish flu suspect, but these data relate only to social distancing rather than the full range of policy interventions. As they conclude, "While there may be other combinations of policies that could be adopted for this pandemic or in the future, we leave those for future work" (Thunstrom et al., 2020, page 193).

Covid Economics 67, 4 February 2021: 94-127

Greenstone and Nigam also focus their investigation on the impact of social distancing on COVID-19 deaths. No other policy interventions are considered. There is also no analysis relating to the cost side of the equation.

Dave et al. examine how shelter-in-place orders affect COVID-19 during the early months of the pandemic. The focus is on measuring the effectiveness of the timing of the orders on the virus, not to the costs and benefits of policy intervention (Dave et al., 2020).

In "A Cost-Benefit Analysis of the COVID-19 Disease," Rowthorn and Maciejowski's interest is "in the cost-benefit analysis of large-scale interventions such as lockdowns" (Rowthorn and Maciejowski, 2020, page 539). The only intervention evaluated is that of lockdowns, and the analysis relates to Britain – not the U.S.

Spiegel and Tookes create their own measure relating to business restrictions for every county in the U.S. and use those measures to forecast the impact on COVID-19 deaths (Spiegel and Toookes, 2020). They state, "We focus on fatalities rather than cases because of substantial variation on testing capacity over time and region." The authors find that policy intervention at the county level predicts lower 4 to 6 weeks ahead fatality growth. This study, however, as impressive as it is in attempting to measure the extent of policy intervention at the county level, does not analyze the costs of the interventions.

In the study to follow, the emphasis will be on measuring the benefits and costs of statewide policy interventions in reducing the rate of COVID-19 deaths. Policy interventions are measured by using the Oxford stringency index. The costs of policy intervention will measure the impact on each state's jobs and real gross state product. The period of analysis will be the full calendar year 2020.

There are several important areas of benefits and costs that will not be addressed in this study. It will not examine the benefits that might occur if policy interventions help prevent the health care system from being overwhelmed with COVID-19 patients. Neither does it consider the costs relating to increasing death rates, mental health, or other health problems associated with people not getting needed health care because they are discouraged from seeking medical treatment.

While these benefits and costs are relevant and important, this study's aim is to focus on how policy interventions at the state level benefit society by reducing death rates but, in doing so, incur costs relating to lost jobs and income. The study will conclude by estimating the economic cost per life saved for each state resulting from policy interventions and compare that cost to an age-adjusted value of statistical life (VSL).

Covid Economics 67, 4 February 2021: 94-127

2. Theoretical Model

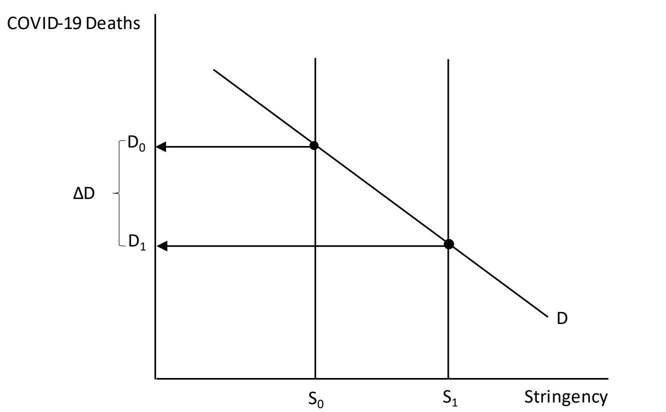
2.1 Benefits from Policy Intervention

The benefits from policy intervention are depicted graphically in Figure 2, where the downward sloping, D, points to an inverse relationship between COVID-19 deaths and stringency, where stringency measures the degree to which individuals protect themselves from being infected by the virus.

Even in a world with no policy intervention, it is reasonable to assume that individuals would voluntarily self-protect themselves from infection. Self-protection might include wearing a mask, distancing themselves from others, and avoiding crowds. Such voluntary levels of stringency where there is no policy intervention can be depicted in Figure 2 at an average stringency level of S_0. At that level, the intersection of S_0 and D points to COVID-19 deaths of D_0.

If public policy intervention results in a shift to a higher level of stringency, S_1, the intersection of S_1 and D points to a decline in the death rate from D_0 to D_1.

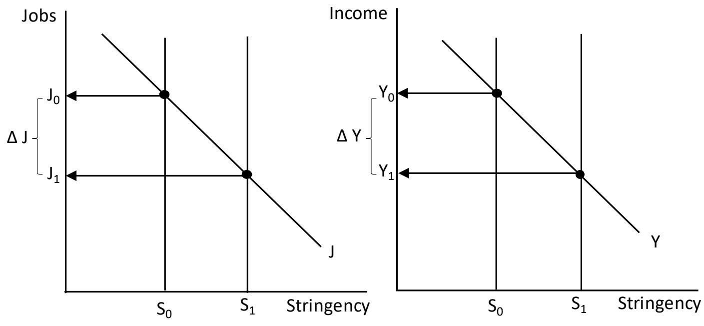
FIGURE 2
Benefits of Policy Intervention



The costs of policy intervention on jobs (J) and income (Y) are graphically shown in the two graphs in Figure 3. As in Figure 2, S_0 represents the average voluntary level of stringency with no public intervention. As stringency increases from S_0 to S_1, as a result of policy intervention, the costs to the economy are reflected by a decline in jobs from J_0 to J_1 and a decline in RGSP from Y_0 to Y_1.

Covid Economics 67, 4 February 2021: 94-127

FIGURE 3
Costs of Policy Intervention



In the study to follow, Section 3 will address how an increase in policy intervention such as that shown in the above figures by the shift from S_0 to S_1 can be measured. Section 3 will also present an empirical model for estimating the change in the number of deaths, ΔD, from policy intervention (see Figure 2). Section 4 will examine how greater stringency as shown by S_0 to S_1 results in lower jobs, ΔJ, while section 5 shows how it results in lower income, ΔY (see Figure 3). Before concluding, Section 6 will construct an age-adjusted dollar value of a statistical life for a person dying from COVID-19 and compare that value to the cost per life saved as estimated in this study.

3. Measuring the Benefits – Changes in Deaths, Δ D, Resulting from Policy Intervention

3.1 Empirical Model

The cumulative COVID-19 death rate per 100,000 people by state from January 1, 2020, to January 1, 2021, serves as the dependent variable in a cross-section model tested in this study. These death rates by state in alphabetical and rank order from highest to lowest are shown in Table 1. Note that the unweighted average COVID-19 death rate of all states is different from the death rate for the U.S. shown in Figure 1.

Policy interventions are measured by the Oxford daily government stringency index. Using a scale from 1 to 100, the ordinal daily measures that comprise the Oxford index include the following eleven government policy interventions relating to COVID-19:

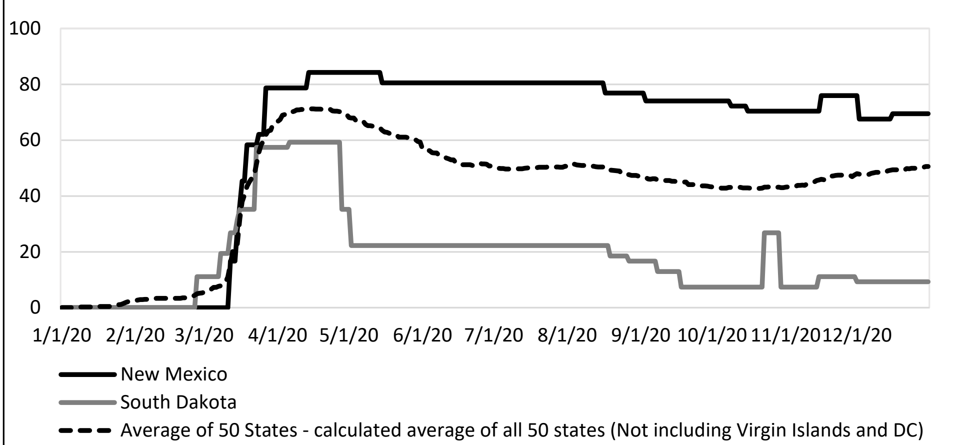
Covid Economics 67, 4 February 2021: 94-127

— School closings
— Workplace closings
— Cancellation of public event
— Restrictions on gathering size
— Closures of public transit
— Stay at home requirements
— Restrictions on internal movements
— Restrictions on international travel
— Public information campaign
— Testing polling
— Contact tracing

The daily Oxford stringency index in this study was derived by calculating an annual average from the daily index values for each state during the 1/1/20 to 12/31/20 period. The average Oxford stringency index values for all states in alphabetical order and rank order from highest to lowest over the 1/1/20 to 12/31/20 period are shown in Table 2. Since the average stringency index, $\overline{S}$, equals 42.12 in calendar year 2020, the shift from S_0 to S_1 shown graphically in Figures 2 to 3 can be represented numerically as a shift from 0 to 42.12.

Figure 4 shows the daily Oxford stringency index values for the U.S., and for comparison, it also shows the state with the highest average index (New Mexico) and the state with the lowest (South Dakota).

FIGURE 4
Oxford Stringency Index for the U.S., New Mexico and South Dakota



CEPR PRESS

The annual average of the Oxford daily stringency index will serve in this study as a proxy for each state's policy interventions. But in measuring the explanatory impact of policy interventions, it will be necessary to control and test for other demographic and socioeconomic variables that may significantly affect COVID-19 death rates.

Following a functional form similar to that used by Doti (Doti, 2021) Equation (1) shown below was tested.

$$d_i = b_o + b_m s_i + \sum_{d=1}^{3} b_{d,} \text{ Density}_i + \sum_{y=1}^{2} b_y \text{ Income}_i + \sum_{r=1}^{3} b_r \text{ Racial/Ethnic}_i + \sum_{h=1}^{4} b_h \text{ Age/Health}_i \quad (1)$$

All the dependent and independent variables are defined in Table 3.

The subscript i refers to state i.

b_o, b_m, b_d, b_y, b_r, b_h = Parameters to be estimated

Note: Displays of error terms are suppressed.

Covid Economics 67, 4 February 2021: 94-127

TABLE 1
COVID Death Rates in the U.S. by State
Per 100,000 people

Alphabetical order		Rank Order	
State	**1/1/2021**	**State**	**1/1/2021**
Alabama	99	New Jersey	216
Alaska	29	New York	197
Arizona	124	Massachusetts	183
Arkansas	124	North Dakota	172
California	67	Connecticut	171
Colorado	86	South Dakota	171
Connecticut	171	Rhode Island	168
Delaware	96	Mississippi	164
Florida	102	Louisiana	162
Georgia	103	Illinois	145
Hawaii	20	Michigan	133
Idaho	81	Pennsylvania	127
Illinois	145	Indiana	126
Indiana	126	Iowa	125
Iowa	125	Arizona	124
Kansas	99	Arkansas	124
Kentucky	61	New Mexico	122
Louisiana	162	South Carolina	106
Maine	27	Georgia	103
Maryland	99	Nevada	103
Massachusetts	183	Tennessee	103
Michigan	133	Florida	102
Minnesota	97	Alabama	99
Mississippi	164	Kansas	99
Missouri	93	Maryland	99
Montana	91	Texas	98
Nebraska	86	Minnesota	97
Nevada	103	Delaware	96
New Hampshire	57	Missouri	93
New Jersey	216	Montana	91
New Mexico	122	Wisconsin	90
New York	197	Colorado	86
North Carolina	66	Nebraska	86
North Dakota	172	Idaho	81
Ohio	78	Ohio	78
Oklahoma	64	West Virginia	77
Oregon	36	Wyoming	76
Pennsylvania	127	California	67
Rhode Island	168	North Carolina	66
South Carolina	106	Oklahoma	64
South Dakota	171	Kentucky	61
Tennessee	103	Virginia	60
Texas	98	New Hampshire	57
Utah	41	Washington	45
Vermont	22	Utah	41
Virginia	60	Oregon	36
Washington	45	Alaska	29
West Virginia	77	Maine	27
Wisconsin	90	Vermont	22
Wyoming	76	Hawaii	20
Average	101.76	Average	101.76

Covid Economics 67, 4 February 2021: 94-127

TABLE 2
Average Oxford Stringency Index Values from 1/1/20 to 12/31/20

Alphabetical Order		Rank Order	
State	Average Stringency Score Jan 1, 2020 - Dec 31, 2020	State	Average Stringency Score Jan 1, 2020 - Dec 31, 2020
Alabama	30.60	New Mexico	60.70
Alaska	44.69	Hawaii	58.55
Arizona	35.76	New York	58.26
Arkansas	36.09	Maine	55.35
California	51.29	Rhode Island	55.24
Colorado	45.25	California	51.29
Connecticut	50.76	Connecticut	50.76
Delaware	49.15	Vermont	50.03
Florida	40.99	Delaware	49.15
Georgia	39.96	Kentucky	48.96
Hawaii	58.55	Maryland	48.25
Idaho	39.75	Ohio	47.54
Illinois	45.04	Massachusetts	47.44
Indiana	37.86	North Carolina	46.90
Iowa	26.39	Minnesota	46.53
Kansas	38.27	Washington	46.25
Kentucky	48.96	Colorado	45.25
Louisiana	41.41	Illinois	45.04
Maine	55.35	Alaska	44.69
Maryland	48.25	Oregon	43.98
Massachusetts	47.44	West Virginia	43.49
Michigan	42.14	Texas	42.73
Minnesota	46.53	Pennsylvania	42.47
Mississippi	36.54	Michigan	42.14
Missouri	36.08	New Jersey	41.95
Montana	40.38	Virginia	41.63
Nebraska	35.88	Louisiana	41.41
Nevada	38.17	Florida	40.99
New Hampshire	40.22	Montana	40.38
New Jersey	41.95	New Hampshire	40.22
New Mexico	60.70	Georgia	39.96
New York	58.26	Idaho	39.75
North Carolina	46.90	Wyoming	38.78
North Dakota	28.30	Tennessee	38.49
Ohio	47.54	Kansas	38.27
Oklahoma	29.61	Nevada	38.17
Oregon	43.98	Indiana	37.86
Pennsylvania	42.47	Wisconsin	36.89
Rhode Island	55.24	Mississippi	36.54
South Carolina	34.18	Arkansas	36.09
South Dakota	18.38	Missouri	36.08
Tennessee	38.49	Nebraska	35.88
Texas	42.73	Arizona	35.76
Utah	32.34	South Carolina	34.18
Vermont	50.03	Utah	32.34
Virginia	41.63	Alabama	30.60
Washington	46.25	Oklahoma	29.61
West Virginia	43.49	North Dakota	28.30
Wisconsin	36.89	Iowa	26.39
Wyoming	38.78	South Dakota	18.38
Average	42.12	Average	42.12

Covid Economics 67, 4 February 2021: 94-127

Covid Economics 67, 4 February 2021: 94-127

TABLE 3. Dependent and independent variables used in Equation (1) and Equations 1 - 6, Table 4

Description	Name	Mean	SD	CV	Min	Max	Obs.	Source
Dependent variables								
COVID-19 cumulative death rates through 12/31/20	d	101.76	46.66	45.85	20.00	216.00	50	https://www.statista.com/statistics/1109011/coronavirus-covid19-death-rates-us-by-state/
Independent variables								
I. Policy Intervention								
Mean Oxford Stringency Index from 1/1/20 to 12/31/20	s	42.12	8.25	19.61	18.38	60.70	50	https://github.com/OxCGRT/USA-covid-policy/blob/master/data/OxCGRT_US_latest.csv
II. Density Variables								
Population density per square mile	density	202.65	266.24	131.38	1.30	1207.80	50	https://worldpopulationreview.com/state-rankings/state-densities
Super density per square mile	sdensity	342.98	1610.69	469.62	0.00	11076.00	50	https://en.wikipedia.org/wiki/List_of_United_States_cities_by_population_density
Urban population as a percentage of the total population	urbanpop	0.74	0.15	20.27	0.39	0.95	50	https://en.wikipedia.org/wiki/Urbanization_in_the_United_States
III. Income Variables								
Per Capita Personal Income (000)	py	54.50	8.80	16.15	39.36	79.09	50	https://fred.stlouisfed.org/release/tables?rid=151&eid=257197
Poverty rate, percent of persons in poverty	poverty	0.14	0.04	28.57	0.07	0.27	50	https://en.wikipedia.org/wiki/List_of_U.S._states_and_territories_by_poverty_rate
IV. Racial/Ethnic Variables								
Black or African American Population as a percentage of the total population	afram	10.51	9.55	90.87	0.40	37.60	50	https://worldpopulationreview.com/states/states-by-race
Hispanic population as a percentage of the total population	hispanic	11.74	10.34	88.07	1.50	48.54	50	https://worldpopulationreview.com/state-rankings/hispanic-population-by-state
Asian population as a percentage of the total population	asian	4.18	5.53	132.30	0.76	37.75	50	https://worldpopulationreview.com/state-rankings/asian-population
V. Age/Health Variables								
Percentage of population aged 65 or over	age65	16.49	1.88	11.40	11.10	20.60	50	https://www.prb.org/which-us-states-are-the-oldest/
Obesity rate	obesity	30.75	3.73	12.13	22.60	38.10	50	https://worldpopulationreview.com/state-rankings/obesity-rate-by-state
Diabetes mortality rate	diabetes	21.95	4.39	20.00	14.60	36.20	50	https://www.cdc.gov/nchs/pressroom/sosmap/diabetes_mortality/diabetes.htm
Smoking Rate	smokers	17.33	3.50	20.20	8.90	26.00	50	https://worldpopulationreview.com/state-rankings/smoking-rates-by-state

3.2 Empirical Findings

A step-wise regression model similar to that used by Doti (Doti, 2021) added explanatory variables in groupings from I to IV, as shown in Table 3. The regression results are presented in Equations 1 to 6, Table 4. Note that except for the policy intervention variable, s, in Equation 1, Table 4, other variables were removed if not significant at the $p < 0.10$ level (one-tailed). The rationale for retaining the policy intervention variable, s, in Equation 2, Table 4 is that the significance tests for s in Equation 1, Table 4 may be spurious since there are no other control variables in the equation. Indeed, when the density variables, density, and sdensity, were added to Equation 2, Table 4, the measured t statistic for s was significant at the $p < 0.01$ level (one-tailed).

Note also that the "best" fit equation, Equation 6, Table 4, is shown as shaded.

3.2.1 Policy Intervention Variable, s

Although a great deal of controversy has arisen over the efficacy of statewide policy interventions to control the spread of COVID-19 (*Boston Review*, 2020; *Healthline*, 2020; *Wall Street Journal*, 2020) more rigorous studies have shown that such interventions significantly reduce COVID-19 deaths (Doti, 2021).

The empirical results shown in Table 4, which extend the tests through the end of 2020, confirm Doti's earlier findings of a highly significant inverse relationship between policy interventions as measured by the Oxford stringency index and COVID-19 death rates by state (Doti, 2021). The measured t statistic of -4.30 for s in Equation 6, Table 4, is highly significant at $p < 0.01$ (one-tailed). Its estimated coefficient of -2.48 suggests that, on average, a state's COVID-19 death rate, d, decreases by 2.48 deaths per 100,000 for every increase of 1 point in a state's average Oxford stringency index, s.

In a regression equation (not reported here), the R^2 term for Equation 6, Table 4, when the policy intervention variable, s_i, is excluded from the equation, drops from 0.67 to 0.53. A scatter diagram that compares the residuals from the equation where s is excluded is shown in Figure 5.

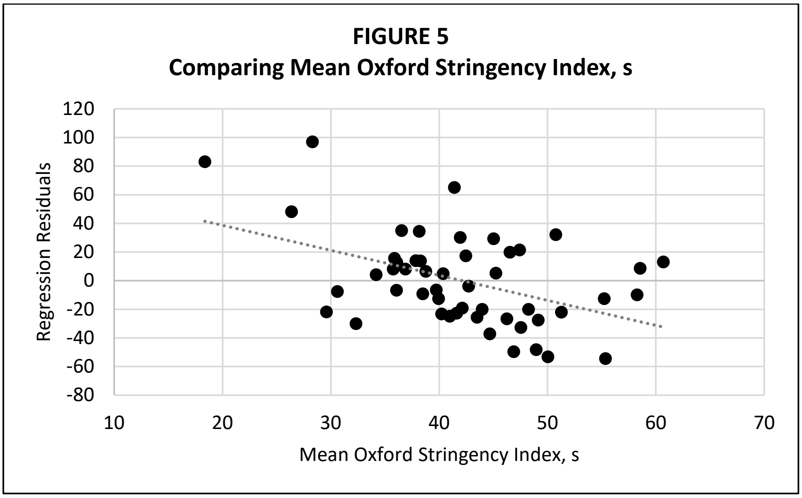
Covid Economics 67, 4 February 2021: 94-127

TABLE 4. Regression results, dependent variable definition: cumulative deathrate (COVID-19 deaths per 100,000 people by state) from 1/1/20 to 1/1/21, dependent variable name: d

	Equation 1	Equation 2	Equation 3	Equation 4	Equation 5	Equation 6
R-squared	0.02	0.54	0.66	0.68	0.67	0.67
Constant	136.29	198.07	91.31	131.45	157.81	126.27
	(-3.97) ***	(-5.59) ***	(-1.69) *	(-4.79) ***	(-2.30) **	(-4.68) ***
I. Policy Intervention						
s	-0.82	-2.77	-2.86	-2.64	-2.61	-2.48
	(-1.02)	(-4.36) ***	(-5.16) ***	(-4.42) ***	(-3.94) ***	(-4.30) ***
II. Density Variables						
density		0.11	0.11	0.12	0.12	0.12
		(5.23) ***	(5.44) ***	(6.75) ***	(6.34) ***	(7.27) ***
sdensity		0.01	0.01	0.01	0.01	0.01
		(3.65) **	(3.66) ***	(3.99) ***	(3.83) ***	(4.05) ***
urbanpop		-9.13				
		(-0.23)				
III. Income Variables						
py			0.66			
			(0.88)			
poverty			494.54	380.14	401.95	408.23
			(3.66) ***	(3.05) ***	(3.19) ***	(3.79) ***
III. Racial/Ethnic Variables						
afram				-0.01		
				(-0.01)		
hispanic				0.53		
				(1.20)		
Asian				-1.39	-1.27	-1.26
				(-1.68) **	(-1.40) *	(-1.55) *
V. Age/Health Variables						
age65$_i$					-0.39	
					(-0.16)	
obesity$_i$					-1.36	
					(-0.61)	
diabetes$_i$					-0.21	
					(-0.14)	
smoker$_i$					1.57	
					(-0.69)	

Notes: t statistics in parentheses. *p‹0.10, **p‹0.05, ***p‹0.01 (one-tailed test)

Covid Economics 67, 4 February 2021: 94-127



Although Figure 5 suggests a linear trendline, a double logarithmic form of Equation 6, Table 4 was tested. The empirical results of that test are presented below:

TABLE 5
Equation 6, Table 4 with All Variables Measured in Natural Logs (ln)

		Equation 6	
R-squared		0.45	
Constant		9.06	
		(-7.20)	***
I. Policy Intervention			
	s	-1.05	
		(-3.24)	***
II. Density Variables			
	density	0.17	
		(3.11)	***
	sdensity	0.06	
		(2.38)	***
III. Income Variables			
	poverty	0.66	
		(2.68)	***
III. Racial/Ethnic Variables			
	Asian	-0.13	
		(-1.43)	*

Notes: t statistics are in parentheses where *p‹0.10, **p‹0.05, ***p‹0.01 (one-tailed test)

Covid Economics 67, 4 February 2021: 94-127

Although the R^2 of 0.45 in the double logarithmic form of the Equation is lower than the R^2 of 0.62 in the linear form of the equation (Equation 6, Table 4), the measured t statistic for the ln of s is still significant at the $p < 0.01$ level. In spite of the lower R^2 value in the double logarithmic form of the equation, the coefficients have the desirable quality of representing constant elasticities across different values of the independent variables. That means that the -1.05 coefficient for the ln of s represents the constant elasticity of d with respect to s, which, in turn, suggests that a one percent increase in the Oxford stringency index, s, leads approximately to a one percent decline in COVID-19 deaths, d. For comparison purposes, the average elasticity for s in the linear form is shown in Equation (2).

$$\overline{E}_i = b_m \left[\frac{\overline{s}}{\overline{d}} \right] = -2.48 \left[\frac{42.12}{101.76} \right] = -1.03 \qquad (2)$$

Although the average elasticity of -1.03 in the linear form of the equation compares closely to the constant elasticity of -1.05 in the double logarithmic form of the equation, the elasticity of -1.03 in the linear form of the equation will change as s deviates from its mean value of 42.12.

3.2.2 Other Explanatory Variables

A super density variable, sdensity, was added as a variable to measure the impact on COVID-19 deaths for those states where a highly populated metropolitan area like New York City exhibits extremely high density. In those instances, the true nature of a metropolitan area's density is obscured when dividing by the entire land area of a state. To capture that impact, a sdensity variable was added as defined in Equation (3).

$$sdensity_{i,t} = \sum_{k=1}^{n_i} p_{k,i} \,/\, P_{i,t} \;\; * \; density_{i,t} \qquad (3)$$

where $p_{k,i}$ = Population of the kth city in state i with a population >300,000 and density >10,000 per sq. mile

n_i = Number of cities in state i with population >300,000 and density >10,000 per sq. mile

$P_{i,t}$ = Population of state i as of some period t

$density_{i,t}$ = Density of state i as of some period t

As shown in Equation 6, Table 3, both the sdensity and density variables were significant at the $p < 0.01$ level (one-tailed) and supportive of the theory that higher density facilitates virus transmission.

Covid Economics 67, 4 February 2021: 94-127

CEPR PRESS

The poverty variable in Equation 6, Table 3, was also highly significant. Its positive coefficient suggests that poverty is associated with higher rates of COVID-19 deaths. In the double logarithmic form of the equation reported in Table 5, the constant elasticity of 0.66 suggests that a one percent increase in a state's poverty rate leads to a 0.66 percent increase in its COVID-19 death rate.

The only Racial/Ethnic variable that tested as significant was that represented by the percentage of Asian-Americans (asian). Its negative coefficient of -1.26 suggests that an increase of one in the percentage of Asian-Americans living in a state is associated with a 1.26 percent decline in its COVID-19 death rate. While the relationship was significant, it was at a relatively low $p < 0.10$ level (one-tailed). As pointed out by Doti (Doti, 2021), a possible explanation for this is anecdotal evidence that Asian-Americans responded more quickly in adopting safe-distancing and mask-wearing before such preventive measures were mandated by governments (Magnier, 2020). This explanation received empirical support in the Doti study (Doti, 2021) that showed that the asian variable was only significant during the first half of 2020.

The fact that the percentage of African-Americans (afram) and Hispanics (hispanic) in a state was found to have no significant impact on COVID-19 deaths runs counter to other studies that suggest a positive causal relationship (Magnier, 2020, APM Research, 2020). It is likely, though, that those studies did not adequately control for the impact of other explanatory variables. When, for example, a variable measuring the poverty rate is omitted from Equation 6, Table 4, the coefficients for the African-American variable (afram) and Hispanic variable (hispanic) are both significant, as shown below in Table 6. These empirical results suggest that studies that have found a positive relationship between COVID-19 deaths and the percentage of African-Americans and Hispanics in a state or metropolitan area may be experiencing identification error.

Covid Economics 67, 4 February 2021: 94-127

TABLE 6
Equation 6, Table 4 with afram and hispanic added to the equation and poverty removed

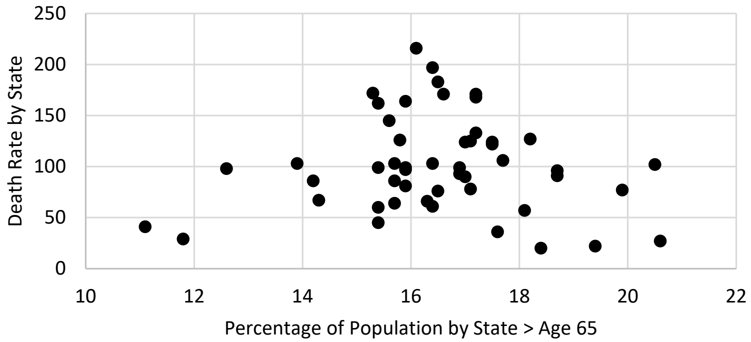
		Equation 6	
R-squared		0.61	
Constant		173.23	
		(6.69)	***
I. Policy Intervention			
	s	-2.57	
		(-3.95)	***
II. Density Variables			
	density	0.11	
		(5.66)	***
	sdensity	0.01	
		(3.69)	***
III. Income Variables			
	lpoverty	Removed form Equation 6, Table 4	
III. Racial/Ethnic Variables			
	afram	0.70	
		(1.41)	*
	hispanic	0.93	**
		(2.00)	
	asian	-1.60	**
		(-1.77)	

Notes: t statistics are in parentheses where *p‹0.10, **p‹0.05, ***p‹0.01 (one-tailed test)

None of the coefficients for the Age/Health variables were significant. Although these results may seem surprising, especially for the age65 variable, it is likely that there is not enough dispersion in the Age/Health variables for the regression equation to pick up any significant explanatory power at the state level. As shown in Figure 4, higher death rates at the state level occurred near the average of 16.49 for the percentage of a state's population older than 65 years old rather than at higher outlying values (Doti, 2021).

Covid Economics 67, 4 February 2021: 94-127

FIGURE 6
Death Rate for Age 65 or Over Population at the State Level



3.2.3 Impact of Policy Intervention on COVID-19 Lives Saved or Lost

The estimated coefficient for the stringency variable, sjanjul, can be used to estimate the change in the number of deaths (ΔD_i) as a result of a state having a stringency index above zero. Those estimates are presented in Table 7 and are based on Equation (4). The ΔD_i term in Equation (4) is represented by the ΔD term shown graphically in Figure 2 where $D_0 - D_1 < 0$.

$$\Delta D_i = \left[s_i \right] * \hat{b}_m * \left[P_i / 100{,}000 \right] \qquad (4)$$

where ΔD_i = Change in the number of COVID-19 deaths in 2020 in state i as a result of policy intervention

s_i = The average stringency index in 2020 for state i

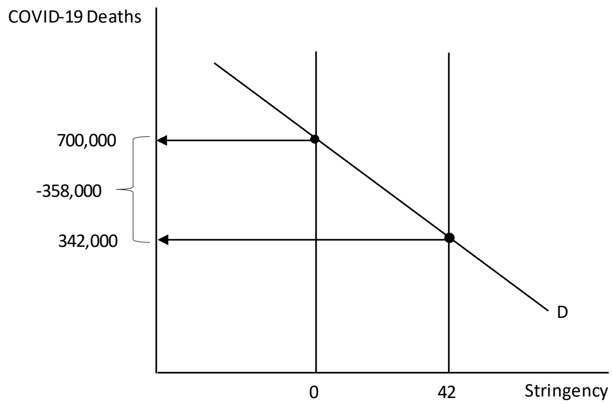
$\hat{b}_m$ = The estimated coefficient for the stringency index value (See Equation 6, Table 4)

P_i = The population of state i in 2020

Note that the above equation requires that the product include [P_i / 100,000] to convert death rates per 100,000 to the absolute number of lives saved or less.

As shown in Table 7, the estimated reduction in the total number of COVID-19 deaths in all states as a result of each state's policy intervention is -358,000. Since the total number of actual COVID-19 deaths in the U.S. in 2020 was 342,000, the estimated decrease of about 358,000 deaths suggests that the actual number of deaths would have been about double the actual level (342,000 + 358,000 = 700,000) had there been no intervention beyond $S_0 = 0$. These results are shown graphically in Figure 7.

FIGURE 7
Benefits of Policy Intervention



Section 4 that follows will examine economic costs associated with the impact of policy intervention on each state's jobs.

CEPR PRESS

TABLE 7
The impact on COVID-19 Llives Saved as a Result of Each State's Level of Policy Intervention

	State	Change in the Number of COVID-19 Deaths
1	Alabama	-3,721
2	Alaska	-811
3	Arizona	-6,455
4	Arkansas	-2,701
5	California	-50,258
6	Colorado	-6,463
7	Connecticut	-4,488
8	Delaware	-1,187
9	Florida	-21,831
10	Georgia	-10,522
11	Hawaii	-2,056
12	Idaho	-1,762
13	Illinois	-14,155
14	Indiana	-6,322
15	Iowa	-2,065
16	Kansas	-2,765
17	Kentucky	-5,425
18	Louisiana	-4,775
19	Maine	-1,845
20	Maryland	-7,234
21	Massachusetts	-8,110
22	Michigan	-10,438
23	Minnesota	-6,508
24	Mississippi	-2,697
25	Missouri	-5,492
26	Montana	-1,070
27	Nebraska	-1,721
28	Nevada	-2,915
29	New Hampshire	-1,356
30	New Jersey	-9,240
31	New Mexico	-3,157
32	New York	-28,109
33	North Carolina	-12,199
34	North Dakota	-535
35	Ohio	-13,781
36	Oklahoma	-2,905
37	Oregon	-4,600
38	Pennsylvania	-13,483
39	Rhode Island	-1,451
40	South Carolina	-4,365
41	South Dakota	-403
42	Tennessee	-6,519
43	Texas	-30,727
44	Utah	-2,571
45	Vermont	-774
46	Virginia	-8,812
47	Washington	-8,734
48	West Virginia	-1,933
49	Wisconsin	-5,327
50	Wyoming	-557
	Total	-358,000

Covid Economics 67, 4 February 2021: 94-127

Covid Economics 67, 4 February 2021: 94-127

4. Measuring the Costs – Change in Jobs, Δ J, Resulting from Policy Intervention

4.1 Empirical Model

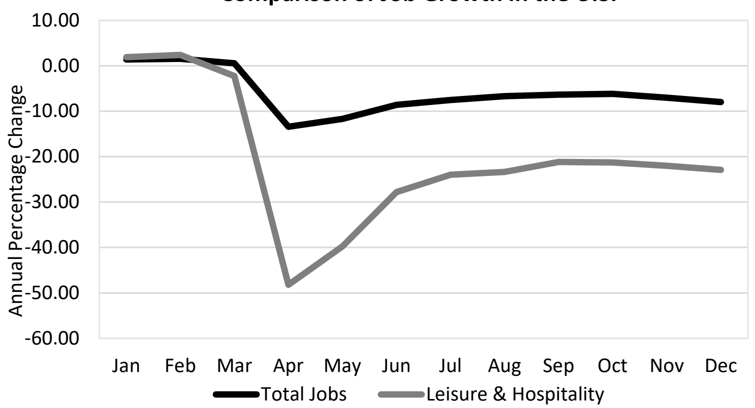
In order to measure the impact of policy intervention as measured by the Oxford stringency index on jobs, it will be necessary to hold constant other variables that exert an influence on job growth. Although more restrictive policy interventions to control the spread of COVID-19 would be expected to reduce jobs, the impact on each state's jobs will also depend on other factors.

To isolate the impact of policy interventions on jobs in 2020, one must hold constant each state's natural economic growth rate. Two states with the same stringency index but exhibiting different economic trends are likely to experience different rates of job loss. Unless those differing trends are accounted for in a regression test, the coefficients that measure the impact of differing levels of policy intervention will be biased.

A straightforward approach to account for each state's economic growth potential is to assume that annual job growth in 2020 would be similar to that which otherwise would have occurred in 2019 if COVID-19 had not occurred. West Virginia, for example, lost about 1 percent of its jobs in 2019. Because of that relatively weak economic performance, West Virginia would be expected to lose more jobs than other states in 2020, not necessarily because of its policy response to COVID-19 but because its economy is weaker than other states. Similarly, one would expect that Utah's relatively strong job growth of nearly 3 percent in 2019 will have a positive impact on its job performance in 2020.

Another state-specific economic factor that needs to be held constant is the proportion of its total jobs in leisure & hospitality. As shown in Figure 8, that sector took the brunt of the COVID-19 hit in the U.S., losing almost 50 percent of its jobs in April 2020. That compares to a much lower annual loss of about 13 percent for all jobs.

FIGURE 8
Comparison of Job Growth in the U.S.



The functional form of an equation that incorporates the impact of each state's policy intervention, its underlying economic strength, and its dependence on the leisure & hospitality job sector is shown below Equation (5).

$$pj_i = b_0 + b_j\,(s_i) + b_n\,(pj19_i) + b_h\,(jlh19_i) \tag{5}$$

where pj_i = Annual percentage change in jobs in 2020 in state i
s_i = Average Oxford stringency index in 2020 in state i
$pj19_i$ = Annual percentage change in jobs in 2019 in state i
$jlh19_i$ = Average proportion of total jobs in leisure & hospitality in 2019 in state i

b_o, b_j, b_n, b_h are parameters to be estimated

Note: Displays of error terms are suppressed.

The hypothesized signs of association in Equation (5) are shown in Equation (6):

$$pj_i = f(\overset{-}{s_i};\ \overset{+}{pj19_i};\ \overset{-}{jlh19_i}) \tag{6}$$

4.2 Empirical Findings

Table 8 presents the empirical results for the regression tests of Equation (5). Note that all of the coefficients for the above variables have the hypothesized signs of association shown in Equation (6) and are all significant at either the $p < 0.1$ or $p < 0.01$.

TABLE 8
Regression Results for Equation 5

Dependent Variable			
	pj_i		
R-squared		0.58	
Constant		-1.30	
		(-1.17)	
Independent Variables			
	s_i	-0.11	
		(-5.62)	***
	$pj19_i$	1.01	
		(4.88)	***
	$jlh19_i$	-12.02	
		(-1.62)	*

Notes: t statistics are in parentheses where *p‹0.10, **p‹0.05, ***p‹0.01 (one-tailed test)

CEPR PRESS

The coefficient of -0.11 for s suggests that a one point increase (decrease) in the stringency index, s, leads to a 0.11 decrease (increase) in job growth in 2020 (pj).

4.2.1 Impact of Policy Interventions on the Number of Jobs (ΔJ_i)

As in this study's analysis of the impact of policy intervention on COVID-19 deaths presented in Section II, a similar methodology can be used to measure the impact of policy intervention on jobs. The number of jobs saved by having stringency index values above zero is given by Equation (7). The ΔJ_i term in Equation (7) is represented by the ΔJ term shown graphically in Figure 3 where $J_0 - J_1 < 0$.

$$\Delta J_{i,} = \left[s_i \right] * \left[\hat{b}_j / 100 \right] * j19_i \qquad (7)$$

where ΔJ_i = Number of jobs lost (-) or saved (+) in 2020 in state i
s_i = The average stringency index in 2020 for state i
$\hat{b}_j$ = The estimated coefficient of -0.11 for the policy intervention variable, s_i, as shown in Table 8
$J19_i$ = Average number of jobs in 2019 in state i

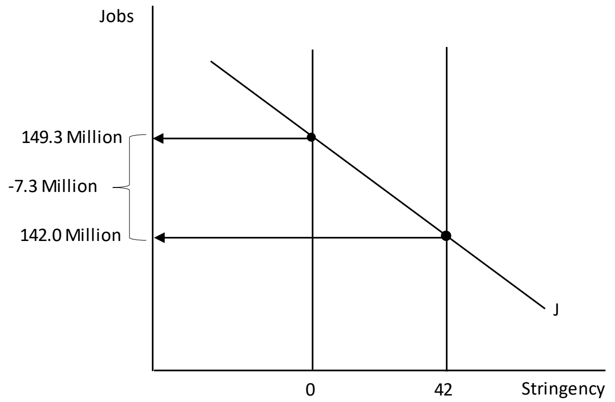
Note that the above equation requires that the estimated coefficient, $\hat{b}_j$, be divided by 100 to convert from percentage to decimal changes. The estimates based on Equation (7) above are presented in Table 9.

As shown in Table 9, the estimated loss in jobs in all states as a result of each state's policy intervention is about -7.3 million. Since the average number of jobs in 2020 was 142 million, the estimated loss of 7.3 million jobs suggests that the actual number of jobs would have been 149.3 million (142 million + 7.3 million) had there been no policy intervention beyond S_0. These results are shown graphically in the following Figure 9.

In percentage terms, the loss of 7.3 million jobs represents a decline of 4.8 percent from the job total in 2019. That compares to an actual decline in jobs of 6.3 percent. The ratio of the 4.8 decline in jobs resulting from policy intervention to the actual total decline of 6.3 percent is 0.75. That, in turn, suggests that the increase in stringency from S_0 to S_1 or 0 to 42 accounts for 75 percent of the total loss of jobs in 2020.

Covid Economics 67, 4 February 2021: 94-127

FIGURE 9
Costs of Policy Intervention



Covid Economics 67, 4 February 2021: 94-127

TABLE 9
The Impact on Jobs Lost as a Result of Each State's Level of Policy Intervention

	State	Δj_i (Change in the Number of Jobs)
1	Alabama	-70,241
2	Alaska	-16,302
3	Arizona	-116,315
4	Arkansas	-51,010
5	California	-989,672
6	Colorado	-139,590
7	Connecticut	-94,812
8	Delaware	-25,345
9	Florida	-406,322
10	Georgia	-204,163
11	Hawaii	-42,511
12	Idaho	-33,417
13	Illinois	-305,163
14	Indiana	-132,755
15	Iowa	-46,346
16	Kansas	-60,309
17	Kentucky	-105,122
18	Louisiana	-91,207
19	Maine	-38,948
20	Maryland	-147,928
21	Massachusetts	-193,853
22	Michigan	-206,868
23	Minnesota	-153,432
24	Mississippi	-46,877
25	Missouri	-115,937
26	Montana	-21,629
27	Nebraska	-40,808
28	Nevada	-59,923
29	New Hampshire	-30,476
30	New Jersey	-194,866
31	New Mexico	-57,597
32	New York	-631,344
33	North Carolina	-237,572
34	North Dakota	-13,764
35	Ohio	-294,117
36	Oklahoma	-55,844
37	Oregon	-94,511
38	Pennsylvania	-285,164
39	Rhode Island	-30,806
40	South Carolina	-82,875
41	South Dakota	-8,966
42	Tennessee	-133,082
43	Texas	-605,738
44	Utah	-55,906
45	Vermont	-17,514
46	Virginia	-187,102
47	Washington	-177,675
48	West Virginia	-34,655
49	Wisconsin	-121,806
50	Wyoming	-12,433
	Total	-7,320,623

To measure the impact of policy intervention on total spending, the following Section IV focuses on changes in real gross state product (RGSP). That analysis will allow for estimating the dollar cost of each life saved or lost, resulting from a state's policy intervention.

5. Measuring the Costs – Change in Income, Δ Y, Resulting from Policy Intervention

5.1 Empirical Model

A version of the model presented in Section 4 for measuring the impact of policy intervention on jobs can be used in this section to measure the impact on real gross state product (RGSP). As in Section 4, differences in a state's Oxford average stringency index in 2020 is used to measure the impact of policy intervention. Instead of using percentage changes in jobs in 2019 to measure the underlying job-producing strength of a state before COVID-19 hit, percentage changes in RGSP in 2019, py19, serve as a proxy for the income-producing potential of a state's economy.

In the national income accounts, an "Art, Entertainment, Accommodations and Food Services" category is used to measure spending in leisure & hospitality. Similar to Section 4, where the proportion of leisure & hospitality jobs is used to measure a state's dependence on the job sector hardest hit by COVID-19, the proportion of RGSP in "Art, Entertainment, Accommodation and Food Services" will serve as a proxy for that variable.

The functional form of an equation explaining each state's RGSP as a function of policy intervention, a state's underlying economic strength, and its dependence on the Arts, Entertainment, Accommodation, and Food Services sector of the economy is shown in Equation (8).

$$py_i = b_0 + b_g\,(s_i) + b_y\,(py19_i) + b_a\,(ae19_i) \tag{8}$$

where py_i = Annual percentage change in RGSP in 2020 in state i
s_i = Average Oxford stringency index in 2020 in state i
$py19_i$ = Annual percentage change in RGSP in 2019 in state i
$ae19_i$ = Average proportion of total RGSP in arts, entertainment, accommodation and food services in 2019 in state i

b_o, b_g, b_y, b_a are parameters to be estimated.

Note: Displays of error terms are suppressed.

The hypothesized signs of association in Equation (8) are shown below in Equation (9):

$$py_i = f\,(\overset{-}{s_i};\ \overset{+}{py19_i};\ \overset{-}{ae19_i}) \tag{9}$$

Covid Economics 67, 4 February 2021: 94-127

5.2 Empirical Findings

Table 10 presents the empirical results for the regression test of Equation (8). Note that all of the coefficients for the variables in Equation (8) have the hypothesized signs of association shown in Equation (9) and are all significant at the $p < 0.01$ (one-tailed test).

TABLE 10
Regression Results for Equation 8

Dependent Variable			
	py_i		
R-squared		0.48	
Constant		-1.70	
		(-2.56)	***
Independent Variables			
	s_i	-0.05	
		(-2.99)	***
	$py19_i$	0.64	
		(5.60)	***
	$ae19_i$	-14.45	
		(-2.31)	***

Notes: t statistics are in parentheses where *p‹0.10, *p‹0.05, ***p‹0.01 (one-tailed test)

The estimated coefficient of -0.05 for s suggests that a one-point increase (decrease) in the stringency index (s) leads to a 0.05 decrease (increase) in RGSP growth in 2020 (py). This result is about half the -0.11 estimated coefficient for s in Section 3, explaining percentage changes in jobs, pj (see Table 8). These findings are intuitively plausible since changes in stringency are likely to have a greater percentage impact on jobs than income. Jobs in leisure-related activities have a lower value-added than other job categories. As a result, the impact of disproportionately large leisure-related job losses will be muted when measuring the income effect.

5.2.1 Impact of Policy Intervention on the level of RGSP

The increase or decrease in a state's RGSP by having stringency index values lower or higher than average is given by Equation (10).

$$\Delta Y_i = \left[s_i \right] * \left[\hat{b}_m / 100 \right] * Y19_i \tag{10}$$

where ΔY_i = Change in the level of RGSP in 2020 in state i
s_i = The average stringency index in 2020 for state i
$\hat{b}_m$ = The estimated coefficient of -0.05 for the policy intervention variable as shown in Table 10
$Y19_i$ = Average RGSP in 2019 in state i

and all other variables are as defined in Equation 10.

Note that the above equation requires that the estimated coefficient, $\hat{b}_m$, be divided by 100 to convert from percentage to decimal changes. The estimates for ΔY_i based on Equation (10) above are presented in Table 11.

As shown in Table 11, the estimated loss in RGSP for all states as a result of each state's policy intervention is about $410 billion. Since RGSP in 2020 was about $18,500 billion, the estimated loss of $410 billion suggests that RGSP would have been about $18,900 (18,500 billion + 410 billion) had there been no policy intervention beyond S_0. These results are shown graphically in Figure 10.

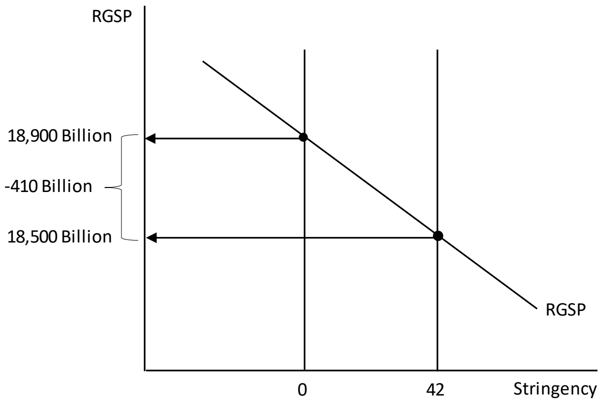
In percentage terms, the loss of $410 billion represents a decline of 2.2 percent in RGSP in 2020. As expected, given that the negative impact of the COVID-19 recession will be greater on jobs than income, the 2.2 percent decline in RGSP is roughly half the decline of 4.8 percent in jobs as estimated in Section 4.2.1.

Recall that policy intervention was also shown in Section 4.2.1 to account for 75 percent of the total loss in jobs in 2020. Similarly, the 2.2 percent decline in RGSP resulting from policy intervention is about 75 percent of the actual decline of 3 percent in 2020.

Covid Economics 67, 4 February 2021: 94-127

CEPR PRESS

FIGURE 10
Costs of Policy Intervention



Covid Economics 67, 4 February 2021: 94-127

TABLE 11
The Impact on RGSP as a Result of Each State's Level of Policy Intervention

	State	Δy_i Change in RGSP (In Millions)
1	Alabama	-2,998
2	Alaska	-1,141
3	Arizona	-5,737
4	Arkansas	-2,069
5	California	-70,325
6	Colorado	-7,961
7	Connecticut	-6,150
8	Delaware	-1,526
9	Florida	-19,274
10	Georgia	-10,684
11	Hawaii	-2,270
12	Idaho	-1,472
13	Illinois	-16,807
14	Indiana	-6,214
15	Iowa	-2,234
16	Kansas	-2,984
17	Kentucky	-4,524
18	Louisiana	-4,752
19	Maine	-1,574
20	Maryland	-8,822
21	Massachusetts	-11,933
22	Michigan	-9,505
23	Minnesota	-7,685
24	Mississippi	-1,828
25	Missouri	-5,026
26	Montana	-945
27	Nebraska	-2,070
28	Nevada	-2,823
29	New Hampshire	-1,490
30	New Jersey	-11,280
31	New Mexico	-2,931
32	New York	-41,399
33	North Carolina	-11,729
34	North Dakota	-740
35	Ohio	-14,134
36	Oklahoma	-2,785
37	Oregon	-4,845
38	Pennsylvania	-14,864
39	Rhode Island	-1,425
40	South Carolina	-3,549
41	South Dakota	-429
42	Tennessee	-6,054
43	Texas	-36,551
44	Utah	-2,715
45	Vermont	-712
46	Virginia	-9,966
47	Washington	-12,588
48	West Virginia	-1,497
49	Wisconsin	-5,468
50	Wyoming	-720
	Total	-410,000

Covid Economics 67, 4 February 2021: 94-127

Covid Economics 67, 4 February 2021: 94-127

6. Estimated Economic Cost Per Life Saved

Table 12 presents an estimated economic cost per life saved based on the total loss in RGSP presented in Table 11 and the total number of lives saved (fewer deaths) in Table 7 in Section 3.2.3. These findings, as shown in Table 12, point to an average loss in RGSP of $1,145,000 per life saved because of policy interventions. That cost per life saved ranges from a low of $677,813 in Mississippi to a high of $1,472,821 in New York state. A question that arises is whether the per capita costs in Table 12 are reasonable or not. That question turns on the challenging problem regarding the value of a human life.

A great deal of empirical research has been conducted regarding the value of a statistical life (VSL) (Robinson, Sullivan, and Shogren, 2020; Murphy and Topel, 2006). Both the U.S. Environmental Protection Agency (U.S. EPA, 2016 update) and the U.S. Department of Health and Human Services (U.S. HHS, 2016) include VSL estimates in their benefit-cost analyses.

As a standard tool in analyzing benefits and costs, VSL estimates are generally based on the values economists measure for the willingness of people to pay for a slight reduction in the probability of death (Murphy and Topel, 2006). For example, if a person is willing to pay $8,000 to reduce the probability of death by 0.1 percent, the resulting VSL for that person is $8,000/0.001 or $8 million. Note that this empirical approach captures not only the potential lifetime earnings of an individual but the consumption of non-market goods like leisure time.

VSL is sometimes held at a constant value that does not vary with age (Robinson, Sullivan, and Shogren; 2020). Although most governmental agencies follow that approach, as noted by Robinson, Sullivan, and Shogren, "… the HHS (U.S. HHS, 2016) guidance recommends adjustments in sensitivity analysis when the risk changes disproportionately to the old or the very young." (Robinson, Sullivan, and Shogren, 2020, page 3).

That is certainly the case in terms of COVID-19 deaths. As shown below in Table 13, roughly 80 percent of the deaths through year-end 2020 occurred at ages 65 years and above. The grouped median age of a COVID-19 death was 78.4. Using age-adjusted VSL (Greenstone and Nigam, 2020) and adjusting the age intervals to conform with the age groupings shown in Table 13 makes it possible to calculate a weighted average age-adjusted VSL of $4.2 million, as shown in Table 14.

The age-adjusted VSL estimate of $4.2 million presented in Table 14 compares closely with the $4.47 million estimated by Robinson, Sullivan, and Shogren (2020, page 7) using a similar approach.

The fact that the $4.2 million calculated in Table 14 is significantly above the estimated average cost per life saved of $1.15 million, as shown in Table 12, suggests that the cost of policy intervention is not excessive, at least when using a VSL methodology to place a dollar value on a human life.

TABLE 12
The Total Estimated Cost in RGSP Per Life Saved Resulting from a Stringency Index Above or Below the Mean Index

State	$\Delta RGSP20_i$ In Millions (See Table 11)	Change in Deaths Resulting from Policy Interventions Above or Below the Mean Index (See Table 7)	Economic Cost per Life Saved
Alabama	1,128	1,400	805,617
Alaska	-66	-47	1,407,729
Arizona	1,020	1,148	888,784
Arkansas	346	451	766,027
California	-12,574	-8,986	1,399,269
Colorado	-551	-448	1,231,730
Connecticut	-1,047	-764	1,370,242
Delaware	-218	-170	1,285,549
Florida	533	604	882,907
Georgia	577	569	1,015,454
Hawaii	-637	-577	1,104,075
Idaho	88	105	835,728
Illinois	-1,091	-919	1,187,318
Indiana	698	710	982,987
Iowa	1,331	1,230	1,081,879
Kansas	300	278	1,078,972
Kentucky	-633	-758	833,917
Louisiana	81	81	995,240
Maine	-376	-441	853,037
Maryland	-1,120	-919	1,219,652
Massachusetts	-1,339	-910	1,471,493
Michigan	-6	-6	910,576
Minnesota	-729	-617	1,180,852
Mississippi	279	411	677,813
Missouri	841	919	915,129
Montana	41	46	883,085
Nebraska	360	299	1,202,480
Nevada	292	302	968,257
New Hampshire	70	64	1,098,238
New Jersey	46	37	1,220,731
New Mexico	-897	-966	928,688
New York	-11,471	-7,788	1,472,821
North Carolina	-1,196	-1,244	961,454
North Dakota	361	261	1,383,264
Ohio	-1,612	-1,572	1,025,586
Oklahoma	1,177	1,228	958,670
Oregon	-205	-195	1,053,076
Pennsylvania	-122	-111	1,102,387
Rhode Island	-339	-345	982,144
South Carolina	824	1,013	813,137
South Dakota	555	521	1,064,902
Tennessee	570	614	928,625
Texas	-523	-440	1,189,531
Utah	821	777	1,055,714
Vermont	-113	-122	919,446
Virginia	117	103	1,130,883
Washington	-1,124	-780	1,441,195
West Virginia	-47	-61	774,593
Wisconsin	774	755	1,026,325
Wyoming	62	48	1,293,556
Average	-410,000	-358,000	1,145,000

Covid Economics 67, 4 February 2021: 94-127

TABLE 13
Deaths Associated with COVID-19 by Age Group in the U.S.
December 30, 2020

Age Group	No. of Deaths	Percent of Deaths	Death rate per 100,000 people
Under 1	32	0.01	0.85
1 - 4	19	0.01	0.12
5 - 14	51	0.02	0.12
15 - 24	483	0.16	1.13
25 - 34	2,087	0.69	4.54
35 - 44	5,398	1.79	12.96
45 - 54	14,496	4.81	35.46
55 - 64	35,981	11.93	84.76
65 - 74	64,355	21.33	204.41
75 - 84	82,646	27.40	517.51
85 and over	96,131	31.87	1,455.44
Total	301,679	100	91.91

TABLE 14
Calculating an Age-Adjusted VSL of COVID-19 Deaths

Age Group	VSL (In Millions)	Percent of Deaths (See Table 13)	VSL * Percent of Deaths
Under 1	14.70	0.01	0.15
1 - 4	14.70	0.01	0.15
5 - 14	15.00	0.02	0.30
15 - 24	15.70	0.17	2.51
25 - 34	15.90	0.73	10.97
35 - 44	14.80	1.88	26.49
45 - 54	12.00	5.00	57.72
55 - 64	8.50	12.23	101.40
65 - 74	4.80	21.41	102.39
75 - 84	2.60	27.08	71.24
85 and over	1.50	31.47	47.80
		Sum =	421.11

Age-adjusted VSL = 421.11/100 = $4.2 million

Covid Economics 67, 4 February 2021: 94-127

7. Conclusion

Although there has been much controversy over the efficacy of policy interventions taken to reduce the infection and death rates of COVID-19, no studies have systematically measured their benefits and costs at the state level. This study fills that gap by presenting cross-section regression analyses that measure how policy interventions, as measured by the Oxford stringency index, reduce COVID-19 death rates. It also examines how those interventions increase costs in terms of greater job losses and lower RGSP.

The study provides empirical support for the belief that policy interventions have resulted in lower COVID-19 death rates. It does this by measuring the impact of policy interventions while holding other explanatory variables constant. The findings suggest that the COVID-19 death rate decreases by 2.48 deaths per 100,000 in population for every increase of 1 point in the Oxford stringency index. That relationship is used to estimate that COVID-19 deaths decreased by 358,000 lives (Table 7) as a result of each state's level of policy intervention.

On the cost side of the equation, various economic factors are held constant in order to measure the impact of policy intervention on jobs and RGSP for every state. It was found that policy intervention resulted in a loss of about 7.3 million jobs (Table 9) and a decline of $410 billion in RGSP for all 50 states (see Table 11).

Because this study measures lives saved or lost as well as the gains or losses to RGSP, it was possible to derive an average cost per life saved in the U.S. of $1,145,000, a cost that ranges from a high of $1,473,000 in New York state to a low of $678,000 for Mississippi.

The study concluded by producing a weighted average age-adjusted value of a statistical life (VSL) of $4.2 million, a value significantly above the estimated $1.145 million average cost per U.S. life saved.

Future research should be directed at updating the empirical finding in this study as more data become available. This will be particularly valuable in light of both the recent surge in infection and death rates as well as the timing of future decreases in infection and death rates as more vaccinations take place. The findings of this study would also be more complete by confronting the empirical challenges involved in removing the assumptions laid out in the introduction of this study.

Covid Economics 67, 4 February 2021: 94-127

References

Centers for Disease Control and Prevention (CDC). (2020c*)***.** *Coronavirus disease 2019 (COVID-19): Cases in the U.S.* https://www.cdc.gov/coronavirus/2019-ncov/cases-updates/ cases-in-us.html

Dave, D., Friedson, A., Matsuzawa, K., Sabia, J. (2020). When Do Shelter-in-Place Orders Fight COVID-19 Best? Policy Heterogeneity Across States and Adoption Time. NBER Working Paper No. 27091. https://www.nber.org/system/files/working_papers/w27091/w27091.pdf

Doti, J. (2021). Examining the Impact of Socioeconomic Variables on COVID-19 Death Rates at the State Level. *Journal of Bioeconomics.* JBIO-D-20-00031R2

Doti, J. (2020). *A Model to Explain Statewide Differences in COVID-19 Death Rates*. Available at SSRN:https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3731803

Gottlieb, Scott (2020). The States Are Laboratories for Covid Control. *Wall Street Journal.* https://www.wsj.com/articles/the-states-are-laboratories-for-covid-control-11604867730

Greenstone, M., and Nigam, V. (2020). Does Social Distancing Matter?. *Journal of Political Economy* 114(5): 871-904. The University of Chicago, Becker Friedman Institute for Economics Working Paper No. 2020-26. https://ssrn.com/abstract=3561244 or http://dx.doi.org/10.2139/ssrn.3561244

Lebano, A. (2020, May 8). Sweden's Relaxed Approach to COVID-19 Isn't Working. *Boston Review*. http://bostonreview.net/politics/adele-lebano-sweden%E2%80%99s-relaxed-approach-covid-19-isn%E2%80%99t-working

Magnier, Mark (2020). Asians in the U.S. least likely to get coronavirus infection despite racist assumptions of many, data suggests. *South China Morning Post.* https://www.scmp.com/news/china/article/3084947/asians-us-least-likely-get-coronavirus-infection-data-suggests

Murphy, K.M., and Topel, R. H. (2006). The Value of Health and Longevity. *Journal of Political Economy* 114(5): 871-904.

Petherick, A., Kira, B., Hale, T., Phillips, T. (2020, August 6). Variation in U.S. States' Responses to COVID-19. Blavatnik School of Working Paper.https://www.bsg.ox.ac.uk/research/publications/variation-us-states-responses-covid-19

Radcliffe, S. (2020, June 4). Why Sweden's COVID-19 Strategy Can't Work in the U.S. *Healthline*. https://www.healthline.com/health-news/heres-what-happened-in-sweden-and-you-cant-compare-it-to-u-s

Robinson, L.A., Sullivan, R., Shogren, J. (2020). Do the Benefits of COVID-19 Policies Exceed the Costs? Exploring Uncertainties in the Age-VSL Relationship, *Risk Analysis,* Early View. https://doi.org/10.1111/risa.13561

Rowthorn, R., Maciejowski, J. (2020). A Cost-Benefit Analysis of the COVID-19 Disease. *Oxford Review of Economic Policy*. https://doi.org/10.17863/CAM.59021

Spiegel, M., Tookes, H. (2020). Business Restrictions and COVID Fatalities. https://ssrn.com/abstract=3725015

Thunstrom, L., Newbold, S., Finnoff, D., Ashworth, M., Shogren, J. (2020). The Benefits and Costs of Using Social Distancing to Flatten the Curve for COVID-19. Cambridge University *Journal of Benefit-Cost Analysis.* https://doi.org/10.1017/bca.2020.12

U.S. Department of Health and Human Services (2016). Guidelines for regulatory impact analysis. Washington, DC. https://aspe.hhs.gov/pdf-report/guidelines-regulatory-impact-analysis

U.S. Environmental Protection Agency (2016 update). Guidelines for preparing economic analyses. Washington, DC. https://www.epa.gov/environmental-economics/guidelines-preparing-economic-analyses

Covid Economics 67, 4 February 2021: 94-127

CEPR PRESS

128

Covid Economics Issue 67, 4 February 2021

The benefits of Coronavirus suppression: A cost-benefit analysis of the response to the first wave of COVID-19 in the United States[1]

James Broughel[2] and Michael Kotrous[3]

Date submitted: 25 January 2021; Date accepted: 27 January 2021

This paper estimates the benefits and costs of state suppression policies to "bend the curve" during the initial outbreak of COVID-19 in the United States. We employ a value-of-production approach that values benefits and costs in terms of additions or subtractions to total production. Relative to a baseline in which only the infected and at-risk populations mitigate the spread of coronavirus, we estimate that total benefits of suppression policies are between $605.9 billion and $841.1 billion from early March 2020 to August 1, 2020. Relative to private mitigation, the costs of suppression policies are estimated to be between $214.2 billion and $331.5 billion. The cost estimate is based on the duration of nonessential business closures and stay-at-home orders, which were enforced between 42 and 65 days. Our results indicate that the net benefits of suppression policies to slow the spread of COVID-19 are positive and may be substantial.

Covid Economics 67, 4 February 2021: 128-171

1 The authors thank Tracy Miller and Walter Valdivia for insightful comments, as well as Connor Haaland for helpful research assistance.
2 Senior Research Fellow, Mercatus Center at George Mason University.
3 Program Manager, Innovation and Governance, Mercatus Center at George Mason University.

Covid Economics 67, 4 February 2021: 128-171

1. Introduction

During the spring and summer months of 2020, many U.S. states enforced non-pharmaceutical interventions (NPIs) that sought to suppress COVID-19 transmission among the general population, namely by closing nonessential businesses and enforcing stay-at-home orders for all residents. According to the Institute for Health Metrics and Evaluation (IHME), between April 4, 2020 and April 24, 2020, 38 U.S. states and the District of Columbia actively enforced "stay-at-home" orders for their residents (IHME, 2020). During this time, almost 90 percent of the total U.S. population was required to stay at home unless engaged in "essential" activities. These policies, and the pandemic generally, had substantial impacts on economic output and production, causing a recession in the United States and raising the prospect of a prolonged economic downturn.

In this paper, we offer a cost-benefit analysis (CBA) for the legal orders implemented across the United States to address the first wave of the coronavirus. We calculate the impacts of suppression policies on economic output and total production from March 2020 up to the week ending August 1, 2020. On the costs side, this includes losses to gross domestic product (GDP) associated with the enforcement of nonessential business closure and stay-at-home orders, as well as indirect costs stemming from increased mortality risks associated with losses to income. On the benefits side, we value prevented COVID-19 deaths in terms of total lifetime production gained by extending lives. We also consider the economic cost savings associated with preventing COVID-19 illnesses and health-care utilization.

This paper proceeds as follows. Section 2 describes the methodology for this CBA. Section 3 outlines a theory for why total production is the appropriate measure of long-run efficiency for CBA, both in the context of COVID-19 and in general. Section 4 presents our

CEPR PRESS

calculations of benefits, costs, and net benefits. Section 5 discusses the key contributions of this article, as well as limitations of our analysis and remaining areas of uncertainty. Section 6 concludes.

2. Methods

We estimate the net benefits of U.S. state policies to slow the spread of COVID-19 in terms of their estimated effects on economic output and production. To calculate total benefits, we compare the observed impacts of the COVID-19 pandemic in the United States between early March 2020 and August 1, 2020 (a period during which "suppression" policies were enforced by most U.S. states) against a counterfactual scenario in which only targeted "mitigation" was practiced during that time span.

Suppression policies aim to reduce virus transmission among the general population and keep case numbers low, and most U.S. states enforced some version of these policies for at least several weeks between March and August 2020. During this time, many state governors declared states of emergency and issued public health directives that required residents to stay-at-home and for public schools, higher educational facilities, and nonessential businesses to close. Between March 17, 2020 and August 1, 2020, 39 states (including Washington, D.C.) enacted stay-at-home orders, and 35 states required all nonessential businesses to close for a period of time. As of April 4, 2020, all 50 states and Washington, D.C. had closed educational facilities. Appendix B shows a full list of state policies and their dates of enforcement, as reported by IHME (2020).

Meanwhile, mitigation strategies seek to reduce the health impact of an epidemic by reducing the exposure of at-risk populations (Ferguson et al., 2020, p. 3). We use Ferguson et al.'s (2020) forecast under its "most effective" mitigation strategies as our counterfactual

Covid Economics 67, 4 February 2021: 128-171

progression of the COVID-19 disease from March to August 2020. Under this mitigation scenario, Ferguson et al. (2020, p. 16) estimates that the United States would see "a single, relatively short epidemic," in which 1.1 to 1.2 million deaths would occur, almost all of them before August 2020. In that model, most of the sick isolate, other members of their households voluntarily quarantine, and elderly individuals and other high-risk populations practice social distancing behaviors. The authors assume that a significant share (though not all) of the affected population voluntarily comply with case isolation and household quarantines for three months, roughly from April through June, while elderly individuals maintain social distancing for a fourth month (July) as well (Ferguson et al., 2020, pp. 6, 8). While the authors assume that social distancing of elderly individuals will be ordered by governments, we believe it is reasonable to assume that elderly and other high-risk populations would engage in social distancing behaviors even without government enforcement. Accordingly, this scenario reflects what may have happened during the first wave of COVID-19 cases if state governments across the United States had allowed private businesses and individuals to respond to the coronavirus pandemic as they saw fit, instead of enforcing COVID-19 suppression policies during these months, as they did.

When calculating benefits of suppression measures, we consider the factors that have the largest incremental effects on productive output. Our approach to calculating benefits is "bottom-up" analysis in the sense that we estimate COVID-19 deaths, lung damage, hospitalizations—including intensive care unit (ICU) stays and mechanical ventilation—and symptomatic infections under suppression policies as well as under the baseline scenario of private mitigation. We then calculate the impact of these events on U.S. production and aggregate them. We do not estimate an additional impact of suppression policies on the future path of GDP since most of the

Covid Economics 67, 4 February 2021: 128-171

factors included in our benefits estimate should contribute to GDP, and we seek to avoid double-counting benefits.

When estimating the health benefits of suppressing COVID-19, our analysis focuses only on the impacts of COVID-19 on adults, specifically people ages 18 and older. The U.S. Centers for Disease Control and Prevention (CDC) reports that, as of August 1, 2020, 98.7 percent of COVID-19 hospitalizations in its COVID-NET Network of hospitals were for adults 18 years or older (CDC, 2020a, 2020c). Meanwhile, the total number of COVID-19 deaths observed among children younger than 15 years old was under 0.04 percent of all COVID-19 deaths as of August 1, 2020 (CDC, 2020d). The fact that so few children have died of COVID-19 makes inferences about the impact of COVID-19 on children in the U.S. subject to substantial uncertainty. For this reason, we focus our benefits estimates on U.S. adults.

To calculate total costs of coronavirus suppression, we take a "top down" approach by multiplying the incremental daily costs to GDP of enforcing suppression policies by the duration of suppression policies, measured in days, that were enforced between March 2020 and August 1, 2020. We also consider the indirect effect that forgone national income has on mortality, as described by Broughel and Viscusi (in press).

3. Theory

The most consequential benefit of government coronavirus suppression orders is likely preventing deaths from COVID-19. We value prevented COVID-19 deaths according to individuals' expected remaining contributions to societal production (what we call a "value-of-production" approach). This approach distinguishes our study from some other analyses of the benefits and costs of slowing the spread of COVID-19 that use the "value of a statistical life", or VSL (Thunström et al., 2020; Greenstone and Nigam, 2020).

Covid Economics 67, 4 February 2021: 128-171

CEPR PRESS

The VSL incorporates nonpecuniary benefits such as “leisure, time with friends and family, and consumption of goods and services” (Greenstone and Nigam, 2020, p. 12). However, we believe it is a mistake to use the VSL in the COVID-19 context for several reasons. First, COVID-19 poses significant mortality risks to identifiable at-risk populations. The U.S. Office of Management and Budget (2003), Cameron (2010), and Pindyck (2020) all note that the VSL is appropriate for valuing only *small* risk reductions among *unidentifiable* individuals. The VSL is not fit for use when valuing changes in large, out-of-sample mortality risks like those associated with COVID-19 (Adler, 2020). Moreover, the VSL can lead to absurd policy conclusions. For example, Pindyck (2020) observes that an $11 million VSL applied to the entire U.S. population exceeds the total net wealth of U.S. households by 37 times.

Many CBAs, including those evaluating the effects of social distancing in a COVID-19 context, also take a static perspective that only considers the impacts of policy on *current* wellbeing. Use of the VSL actually exacerbates this issue because the metric fails to account for significant benefits of extended life that accrue in the future. Figure 1 below illustrates the value of extending life using both the VSL approach and the value-of-production approach used in this paper. On the x-axis is time, and on the y-axis is the value of extended life. Time t_0 is the time ascribed to death. A policy intervention extends life to time t_1.

Covid Economics 67, 4 February 2021: 128-171

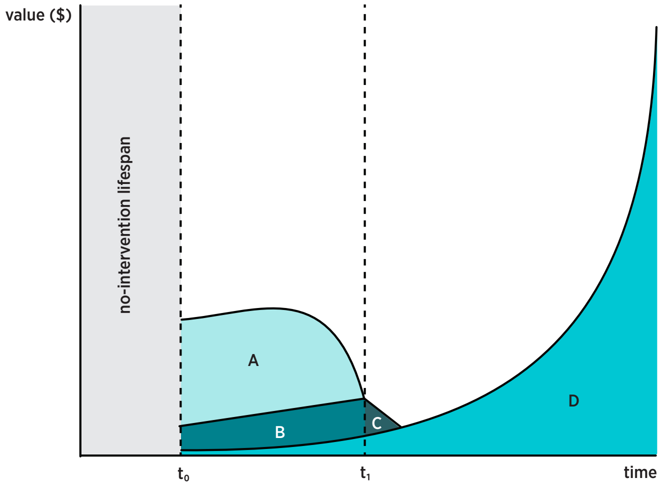


Fig. 1. The Value of Extended Life.
Source: Author's illustration.

What is the value of this extension of life? When life is extended, the benefit comes in two forms: nonpecuniary consumption A and consumption out of the accrual of pecuniary income B. The VSL is represented by the areas A and B in Figure 1. In other words, part of what people are willing to pay for to reduce mortality risk is expected nonpecuniary benefits like those described in Greenstone and Nigam (2020), and part of what people are willing to pay for is expected benefits deriving from financial income in the future. Empirically, A is usually thought to be much larger than B, perhaps an order of magnitude larger (Viscusi, 2018).

The VSL may also include an area like C, which represents the value to current consumers of leaving a moderately larger bequest to one's heirs. In the figure, heirs consume their additional inheritance beginning at the new time of death, t_1, until the bequest is either exhausted or is far enough in the future that it is no longer of importance to the individual(s) whose valuation process is portrayed in the figure.

CEPR PRESS

Critically, the VSL ignores D—the value of returns to invested capital that are not reflected in an individual's willingness to pay for the capital asset. These are social returns not accounted for in individual decision-making owing to time preference. In other words, individual willingness-to-pay values generally deviate from what society would be willing to pay for resources because individuals' discount rates deviate from the social discount rate. As a result, the VSL "reflects individual preferences, not the preferences of society" (Pindyck, 2020, p. 19), since individual preferences do not fully account for the long-run opportunity cost of capital. Moreover, the divergence between private benefits and social benefits increases with time, owing to the positive social rate of return to capital.

The VSL may represent the implicit value an individual places on his or her own life, or similarly, the value a group of individuals today places on extending the life of one member of the group. But from a comprehensive social perspective, what matters in Figure 1 is A, B, C, *and* D. The cumulative area of all four regions reflects what society should be willing to pay for the reduction in mortality, not the VSL. While the value of D, the production value of life, is generally lower than the VSL in present value terms, when combined with the practice of discounting, the value-of-production amount projects how returns to invested output can be expected to grow without bound in the future. The value-of-production amount is higher than the VSL in future value terms, since the VSL simply represents a fixed, static bundle of consumption that is not likely to earn a rate of return.

We acknowledge that the value-of-production approach does not explicitly account for nonpecuniary consumption, however, nonpecuniary consumption is not what determines the efficiency of projects *in the limit*. An approach to CBA based on the value of benefits and costs in the limit is described in Cowen (2007). Such an approach emphasizes total production, which

Covid Economics 67, 4 February 2021: 128-171

is the approach taken here. Focusing on production and output is more appropriate for assessing the long-run effects of policy on productive efficiency than is an approach grounded in what a subset of individuals alive today are willing to pay for transitory benefits.

4. Results

4.1. Benefits analysis

4.1.1. Reduced mortality

The CDC reports that 159,683 people ages 15 and older had died of COVID-19 in the U.S. up to the week ending August 1, 2020 (CDC, 2020d). The CDC (2020d) does not report the number of deaths specific to ages 18 to 24, so we use the total number of deaths for ages 15 to 24 to represent that age group. (Given the small number of deaths among those 15 to 24 years old, the resulting overcount is small.) Meanwhile, Ferguson et al. (2020) estimate that the United States would see 1.1 to 1.2 million deaths before August 2020 under the "most effective" mitigation strategy. That model assumes that the infection fatality rate (IFR) increases significantly with age, so most of these deaths would be among adults (Ferguson et al., 2020, p. 5). Comparing observed deaths in the U.S. against the counterfactual mitigation scenario, we estimate between 940,000 and 1.04 million deaths among U.S. adults were prevented by the enforcement of state suppression policies.

To put a monetary value on the social benefit of each life saved, we use the present value of workers' remaining lifetime production (as discussed in Section 3). Our estimates of lifetime production come from Grosse et al. (2009, p. S100) and are adjusted for inflation and productivity growth since that study's publication (see Table A.1 in Appendix A). That study calculated the present value of total worker production, including nonmarket production such as

Covid Economics 67, 4 February 2021: 128-171

household production, for the American population, broken down by age group. Because the study includes nonmarket production, it is unlikely to discriminate against those who, for example, choose to stay at home to raise children rather than seek employment. Moreover, because the study includes a detailed breakdown of production value by age, it provides a more precise estimate of the value of reduced mortality than does the common practice of relying on population-average values of life (Adler, 2020).

According to the estimates in Grosse et al. (2009), expected lifetime production varies substantially with age, with prime-working-age people having higher expected lifetime production remaining than elderly and very young individuals, when a 5 percent discount rate is applied. Accordingly, we compute a weighted average of lifetime production according to the age distribution of COVID-19 deaths in the United States, shown in Table 1. We calculate an expected benefit of approximately $338,000 in lifetime production per life saved from death by COVID-19.

To calculate the estimated benefit value of suppression measures, we simply multiply our estimate of the expected social benefits from each prevented COVID-19 death by the projected number of prevented deaths. Multiplying $338,000 by the range of estimates of lives saved—940,000 on the low end and approximately 1.04 million on the high end—yields a gross estimate of $317.7 billion to $351.5 billion in benefits from reductions in mortality alone. To be clear, this is a gross estimate of the benefits of prevented mortality. In Section 4.2.2, we estimate costs associated with countervailing increases in mortality risk owing to the effects of depressed economic activity and income loss.

Covid Economics 67, 4 February 2021: 128-171

Table 1. Expected lifetime production lost to COVID-19 deaths.

Age	Present value of lifetime production, 2020 USD	Number of COVID-19 deaths	Approx. share of COVID-19 deaths	Expected lifetime production lost
18 to 24	$1,700,684	289	0.2%	$3,078
25 to 34	$1,743,368	1,288	0.8%	$14,062
35 to 44	$1,511,338	3,278	2.1%	$31,025
45 to 54	$1,102,485	8,544	5.4%	$58,990
55 to 64	$626,928	20,194	12.6%	$79,283
65 to 74	$305,058	34,015	21.3%	$64,982
75 to 84	$163,013	41,898	26.2%	$42,772
85 plus	$137,889	50,177	31.4%	$43,329
All	—	159,683	100.0%	**$337,521**

Sources: CDC (2020d); Grosse et al. (2009, p. S100); authors' calculations.

4.1.2. Reduced illness, health-care utilization, hospitalizations, and ICU stays

The coronavirus will not kill most people it infects, yet many of those infected will bear the cost of health-care services, which may be considerable in the aggregate if a significant number are hospitalized, are admitted to an ICU, or, in the most extreme cases, require mechanical ventilation. Many adults will also develop symptoms of COVID-19 that may not require hospitalization but that will require them to miss work. In this section, we estimate the net effect of suppression policies in terms of reducing symptomatic infections, hospitalizations, ICU stays, and mechanical ventilation.

In order to estimate the total expected number of symptomatic infections among U.S. adults under suppression measures, we consider estimates of the IFR and the share of COVID-19 cases that are asymptomatic. First, we estimate the IFR for each age group reported in the CDC's death data (2020d) by using a metaregression equation that estimates a log-linear relationship

Covid Economics 67, 4 February 2021: 128-171

between age and IFR (Levin et al., 2020, p. 7). Dividing the number of deaths observed in each age group by each age group's estimated IFR allows for estimation of the total number of infections in the U.S. as of the week ending August 1, 2020.

We estimate that 25.4 million U.S. adults were infected with COVID-19 as of that week, which is approximately 10.2 percent of the U.S. adult population (U.S. Census Bureau, 2019). This is comparable to the result of a U.S. seroprevalence study that finds that approximately 9.3 percent of all U.S. adults, or 23.6 million adults, had been infected by COVID-19 as of July 2020 (Anand et al., 2020). Our calculations are presented in Table 2. Notably, our results imply an adult population IFR of 0.6 percent, which is within one-tenth of a percent of IFR estimates reported in Russell et al. (2020) and Meyerowitz-Katz and Merone (2020).

Table 2. Estimated COVID-19 infections among U.S. adult population, week ending August 1, 2020.

Age	Midpoint of Age Group	Deaths	Predicted IFR	Estimated Infections
18 to 24	21.0	289	>0.0%	4,270,688
25 to 34	29.5	1,288	>0.0%	6,825,208
35 to 44	39.5	3,278	0.1%	5,197,673
45 to 54	49.5	8,544	0.2%	4,053,790
55 to 64	59.5	20,194	0.7%	2,866,965
65 to 74	69.5	34,015	2.4%	1,445,009
75 to 84	79.5	41,898	7.9%	532,590
85 plus	89.5	50,177	26.3%	190,856
Total	—	**159,683**	**0.6%**	**25,382,778**

Sources: CDC (2020d); Levin et al. (2020); authors' calculations.

A significant share of COVID-19 infections are believed to be asymptomatic, though there is substantial uncertainty about what share of COVID-19 cases never show symptoms. Mizumoto et al. (2020) estimate that about 18 percent of passengers aboard the *Diamond Princess* cruise ship who had confirmed COVID-19 infections were asymptomatic. Meanwhile, the CDC (2020b) estimates that 40 percent of people infected by coronavirus in the United States may never develop symptoms. These estimates of the share of infections that are asymptomatic imply that between 60 percent and 82 percent of infections are symptomatic. As such, we estimate that, in total, between 15.2 million and 20.8 million U.S. adults experienced symptomatic COVID-19 infections as of August 1, 2020.

With respect to hospitalizations, through the week ending August 1, 2020, CDC (2020c) estimates that cumulatively 181.1 adults aged 18 and older were hospitalized due to COVID-19 for every 100,000 adults in the U.S. population. Multiplying 181.1 per 100,000 adults by the total U.S. adult population yields approximately 452,000 total hospitalizations for U.S. adults (U.S. Census Bureau, 2019). According to the CDC (2020c), 46,041 adults were hospitalized with coronavirus in the COVID-NET Network between the week ending March 7, 2020, and the week ending August 1, 2020. Assuming each age group's share of hospitalizations in the COVID-NET Network is the same as its share of total hospitalizations across the country, we estimate the total number of COVID-19 patients hospitalized in the United States during that time period by age group. Those estimates are shown in Table 3. The CDC (2020b) also estimates that 23.8 percent of 18 to 49 year-olds, 36.1 percent of 50 to 64 year-olds, and 35.3 percent of people 65 and older of those who are hospitalized for COVID-19 are admitted to the ICU. Similarly, CDC (2020b) estimates the percentage of hospitalized COVID-19 patients that require mechanical ventilation for the same three adult age groups. Its estimates are: 12.0 percent

Covid Economics 67, 4 February 2021: 128-171

of hospitalized 18 to 49 year-olds; 22.1 percent of 50 to 64 year-olds; and 21.1 percent of those 65 and older. Table 3 presents our calculation of the total number of adults hospitalized, admitted to ICU, and requiring mechanical ventilation in the U.S., broken down by the CDC's age groups.

Table 3. Estimated COVID-19 hospitalizations for U.S. adults, week ending August 1, 2020.

Age	Number of COVID-19 hospitalizations, COVID-NET	Share of COVID-19 hospitalizations, COVID-NET	Estimated total hospitalized, by age group	Estimated total ICU admissions, by age group	Estimated mechanical ventilation, by age group
18 to 49	13,726	29.8%	134,625	32,041	16,155
50 to 64	13,368	29.0%	131,114	47,332	28,976
65 plus	18,947	41.2%	185,833	65,599	39,211
Total	**46,041**	**100.0%**	**451,572**	**144,972**	**84,342**

Sources: CDC (2020b, 2020d); U.S. Census Bureau (2019); authors' calculations.

The above estimates reflect our best approximation of what occurred under government suppression policies. To estimate the number of symptomatic infections, hospitalizations, ICU admissions, and uses of mechanical ventilation under our counterfactual scenario, we assume the relationships among these factors in the suppression scenario hold in the counterfactual scenario. We infer the number of adults that have symptomatic cases of COVID-19 under the counterfactual scenario by dividing the estimated number of deaths by the infection fatality rate for symptomatic cases (IFR-S) for U.S. adults. We estimate the IFR-S for U.S. adults by dividing the observed number of COVID-19 deaths among adults by our estimated range of total symptomatic infections (15.2 to 20.8 million), which yields an IFR-S of between 0.8 percent and 1.1 percent. Ferguson et al. (2020) projected 1.1 million to 1.2 million COVID-19 deaths in the United States under its "most effective" mitigation scenario. Dividing 1.1 million deaths by the upper-bound IFR-S estimate (1.1 percent) and 1.2 million by the lower-bound IFR-S estimate

Covid Economics 67, 4 February 2021: 128-171

(0.8 percent), we estimate that between 100 million and 150 million people in the United States would need to have been infected and developed symptoms of COVID-19 in order for that number of deaths to occur.

To infer the number of hospitalizations, ICU admissions, and mechanically ventilated patients in the mitigation scenario, we observe that approximately 3.0 percent of the 15.2 million adults who had symptomatic cases of COVID-19 are hospitalized, and about 32.1 percent and 18.7 percent of hospitalizations result in ICU admission and mechanical ventilation, respectively (see the figures in Table 3). If 100 million to 150 million adults have symptomatic cases, then between 3 million and 4.5 million adults would be expected to be hospitalized in the U.S. Of those hospitalized, between 960,000 and 1.4 million would be admitted to the ICU, and between 560,000 and 840,000 COVID-19 patients would require mechanical ventilation.

Table 4 summarizes our health-care utilization estimates under the counterfactual private mitigation scenario and the observed suppression scenario. Calculating the difference between our estimates under these scenarios allows us to estimate the net effect of suppression policies.

Covid Economics 67, 4 February 2021: 128-171

Table 4. Estimates of the net effects of COVID-19 suppression measures on health-care utilization among U.S. adults, as of the week ending August 1, 2020.

Category	Private mitigation scenario	Government suppression scenario	Net effect of suppression measures
COVID-19 symptomatic infections	100–150 million	15.2–20.8 million	79–135 million
Hospitalizations	3.0–4.5 million	452,000	2.5–4.0 million
ICU admissions	960,000–1.4 million	145,000	820,000–1.3 million
Mechanical ventilation	560,000–840,000	84,000	480,000–760,000

Sources: CDC (2020b, 2020c, 2020d); Ferguson et al. (2020); Levin et al. (2020); Mizumoto et al. (2020); authors' calculations.
Note: Differences or sums may not be exact owing to rounding.

4.1.3. Estimated cost of health-care utilization

Many adults who contract COVID-19 will not be hospitalized but will bear the cost of lost wages. The CDC (2020e) advises those with COVID-19 to isolate for at least 10 days, and to remain isolated until fever and other symptoms improve. We calculate the cost of a case of COVID-19 treated at home to be approximately equal to two weeks of lost earnings, which, on average, is just over $1,900. We calculate this by multiplying the average hourly wage in January 2020, $28.43 (U.S. Bureau of Labor Statistics, 2020), by the average number of hours worked by an "engaged person" in two weeks during 2017, which was about 68 hours (University of Groningen and University of California, Davis, 2020).

For those who develop more serious symptoms or develop complications, hospitalization may be necessary. To approximate the cost of a hospitalization from COVID-19, we use the estimate from Torio and Moore (2016) for the average cost of a hospitalization for pneumonia. Like COVID-19, pneumonia is a respiratory condition, and it is common for COVID-19 patients to develop pneumonia in mild and severe cases (Zhou, Yang, et al., 2020). Adjusted to 2020

Covid Economics 67, 4 February 2021: 128-171

dollars, the average cost of a pneumonia hospitalization was just over $11,000. This estimate likely overestimates the costs of non-ICU hospitalizations because it may include those patients who spend time in the ICU. That said, we will use this number since it is the best estimate available, with the understanding that it might overestimate the average cost of non-ICU hospitalizations, since ICU stays have substantially higher costs than a standard hospitalization, especially on the first day.

We break down other health-care utilization costs according to how many hospitalized patients require an ICU stay and how many require mechanical ventilation. We use estimates from Dasta et al. (2005) on average costs for ICU patients and for patients needing mechanical ventilation. We source estimates of median ICU length of stays and median number of days of mechanical ventilation for COVID-19 patients from CDC (2020b), which presents estimates of the median number of days of hospitalization for patients admitted to the ICU by the same three adult age groups—11 days for those 18 to 49, 14 days for those 50 to 64, and 12 days for those 65 and older. Calculating an average of the three median estimates weighted by the number of observed hospitalized patients in each age group (see Table 3), we estimate that an adult admitted to the ICU will have an expected length of stay of just over 12 days. Dasta et al. (2005) estimate, all in 2002 dollars, that the first day in the ICU costs about $6,700, the second day costs about $3,500, and each ICU day thereafter costs about $3,000. Taking our estimate of a median stay of 12 days for ICU patients, average ICU costs are $40,200 in 2002 dollars, or about $58,500 in 2020 dollars.

For the 18.7 percent of hospitalized COVID-19 patients that we estimate will require mechanical ventilation, they are expected to require 6 days of mechanical ventilation. Dasta et al. (2005) estimate that the first day of mechanical ventilation costs about $11,000, the second day

Covid Economics 67, 4 February 2021: 128-171

CEPR PRESS

about $5,000, and $4,000 thereafter, again in 2002 dollars. We estimate costs for six days of mechanical ventilation during a stay that lasts 12 days. For the six days without mechanical ventilation, we assume daily costs of $3,000, which is the daily cost of a standard ICU day. Altogether, we estimate average ICU costs of $50,000 (in 2002 dollars), which is about $72,800 in 2020 dollars.

Above, we presented estimates of the effects of suppression measures relative to the baseline scenario of more targeted mitigation practices, in terms of the expected reductions in COVID-19 infections in which symptoms are present, hospitalizations, ICU admissions, and mechanical ventilation. We calculate the financial value of these benefits by simply multiplying the number of people predicted to be relieved of each medical service by the average economic cost of that service. Results are presented in Table 6 in Section 4.3. We find that the benefits associated with reduced health-care utilization are between $260.5 billion and $431.9 billion.

4.1.4. Reduced incidence of permanent lung damage

Some patients who have recovered from COVID-19 develop acute respiratory distress syndrome (ARDS) and may have permanent lung damage and decreased lung capacity. Zhou, Yu, et al. (2020, p. 1058) finds that 9 of 137 (6.6 percent) COVID-19 survivors in Wuhan who were ultimately discharged from the hospital developed ARDS.

To estimate the number of people who will be impacted by ARDS as a result of COVID-19, we assume that 6.6 percent of those who are hospitalized and recover will develop ARDS. We simply subtract the number of expected deaths from the range of estimates of expected total hospital admissions from above, and then multiply that number by 6.6 percent. Doing so, we estimate that between 119,000 and 224,000 ARDS cases would emerge under a targeted mitigation strategy, while only about 19,000 are expected to be seen under suppression policies.

Covid Economics 67, 4 February 2021: 128-171

This means suppression measures may reduce ARDS cases resulting from COVID-19 by between 100,000 and 205,000.

A 2017 study of ARDS patients in the United States measured their use of inpatient and outpatient services within the first year of their diagnosis of ARDS. Ruhl et al. (2017, pp. 983, 986) finds that 55 percent of the ARDS patient cohort in the study sought inpatient services (e.g., hospitalization or skilled nursing facility) at a median cost of $16,800, in 2014 dollars. Meanwhile, 88 percent of the cohort sought outpatient services from a primary care physician or specialists, such as a pulmonologist, at a median cost of $6,761, also in 2014 dollars. In expected-value terms, an ARDS patient will bear approximately $16,700 in inpatient and outpatient costs within the first year, after adjustment to 2020 dollars.

Considering only first-year health-care costs likely understates the expected total health-care costs for those who develop ARDS as a result of COVID-19. Further, permanent lung damage also likely has a significant effect on recovered patients' productivity for the remainder of their life. As such, we assume those who develop ARDS will see their lifetime total production decrease by 30 percent. Using the same Grosse et al. (2009, p. S100) estimates of total lifetime production by age, we calculate the expected lifetime production lost for those hospitalized with COVID-19 who develop ARDS (see Table A.2 in Appendix A). We weight this average by the distribution of age among 46,041 adults hospitalized in the COVID-Net Network (CDC, 2020c). Results are presented in Table 5.

Covid Economics 67, 4 February 2021: 128-171

Table 5. Expected lifetime production lost to lung damage resulting from COVID-19.

Age	Lifetime production, 2020 USD	Number of COVID-19 hospitalizations, COVID-NET	Approx. share of COVID-19 hospitalizations	Expected lifetime production lost (30% reduction)
18 to 49	$1,571,597	13,726	29.8%	$140,560
50 to 64	$746,446	13,368	29.0%	$65,019
65 plus	$234,035	18,947	41.2%	$28,893
Total	—	**46,041**	**100.0%**	**$234,472**

Sources: Grosse et al. (2009, p. S100); CDC (2020c); authors' calculations.

Covid Economics 67, 4 February 2021: 128-171

We estimate that a patient who recovers from COVID-19 but develops ARDS will, on average, see a loss of just over $234,000 to his or her lifetime production. Combined with the expected cost of care in the first 12 months ($16,700), we estimate the present value of total costs of lung damage to be just over $251,000. Multiplying that cost estimate by the 100,000 to 205,000 people who we expect won't develop ARDS as a result of suppression measures, we estimate the economic benefit of reduced permanent lung damage from suppression measures to be between $25.1 billion and $51.5 billion.

4.1.5. Aggregate gross benefits of COVID-19 suppression measures

To summarize, we expect that the primary benefits of policies that slow the spread of the novel coronavirus will be reduced mortality, reduced symptomatic infections leading to lost earnings, reduced health-care utilization in the form of hospitalizations, ICU stays, and mechanical ventilation, and reduced permanent lung damage among a subset of those who contract and recover from COVID-19. Compared with the outcomes projected under Ferguson et al.'s (2020) model of the most effective mitigation practices (the no-suppression policy counterfactual), including case isolation, household quarantine, and social distancing among elderly individuals and high-risk populations, we estimate total gross benefits in the range of

CEPR PRESS

$603.3 billion to $834.9 billion. Note that the mortality reduction benefits associated with suppression measures are gross estimates and do not yet account for any increases in mortality risk that accompany economic dislocations. We return to this issue shortly.

4.2 Cost Analysis

4.2.1. Forgone output

A shock to economic output would be expected regardless of what policies the government enacts in response to the outbreak of COVID-19. Relative to a baseline of continued pre-pandemic economic activity, Mulligan (2020, p. 7) estimates that the impacts of shutting down nonessential activities during the pandemic have total welfare costs of $1,768 billion on a quarterly basis. An even more pessimistic forecast from Makridis and Hartley (2020) estimates total losses in GDP of just over $2 trillion during the first two months of the COVID-19 outbreak in the United States (April and May). However, both estimates are of the total economic costs of private and public measures to slow the spread of COVID-19. The key challenge in calculating the costs of suppression measures is isolating the costs of policy from the costs of private action undertaken to mitigate risks during the pandemic.

Scherbina (2020) estimates that the incremental cost of suppression policies, relative to Ferguson et al.'s (2020) mitigation scenario, is approximately $35.8 billion per week, or about $5.1 billion per day, on average. According to this estimate, suppression policies alone may impose economic costs of $143 billion every four weeks and $465 billion every quarter, which are equivalent to 8.7 percent of GDP on an annual basis.

To estimate the aggregate costs of state-level suppression polices, we calculate the number of days during which the U.S. states enforced stay-at-home orders and nonessential business closures. Requiring residents to stay at home and requiring nonessential businesses to

Covid Economics 67, 4 February 2021: 128-171

close are not the only suppression policies, but they likely imposed the most costs on economic output among the NPIs that were widely enforced during the initial outbreak of COVID-19. The start and end dates of these orders for each state are sourced from IHME (2020) and listed in Table B.1 in Appendix B.

We weight the number of days that each state enforced stay-at-home orders and nonessential business closures by each state's GDP relative to U.S. GDP (Bureau of Economic Analysis, 2020). Weighting the number of suppression days by GDP reflects the fact that a day of suppression in larger states, such as California, causes more lost output than a day of suppression in smaller states, such as Maine. We then sum across states to calculate a weighted average of the number of days nonessential business closures and stay-at-home orders were in place.

Distinguishing the incremental costs specific to a stay-at-home order from the incremental costs of a nonessential business closure order (as well as distinguishing the incremental costs of when these policies are enforced jointly) is a difficult task. Accordingly, we calculate two weighted averages to produce lower- and upper-bound estimates of the number of days in which suppression policies were enforced in the United States.

First, we calculate the number of days that both a stay-at-home order and a nonessential business closure order were enforced at the same time. For the 22 states that did not enforce both types of legal orders jointly, we set the number of days of suppression equal to zero. In this lower-bound scenario, we estimate that U.S. states will enforce suppression, on average, for 42 days, equal to 6 weeks. That calculation is shown in Table B.2 in Appendix B.

Second, we calculate the number of days that *either* a stay-at-home order or a nonessential business closure order was enforced by states. For the six states that did not enforce either measure, we set the number of days of suppression policies equal to zero. In this upper-

Covid Economics 67, 4 February 2021: 128-171

bound case, we estimate that suppression policies were enforced for an average of 65 days, which is just over 9 weeks. That calculation is shown in Table B.3 in Appendix B.

Multiplying the range of the estimated number of days in which the U.S. states enforced suppression policies (42 – 65 days) by the estimated daily incremental costs of suppression policies ($5.1 billion), we estimate that state policies resulted in losses to economic output between $214.2 billion and $331.5 billion.

4.2.2 Countervailing risks from lost income

As a result of the COVID-19 pandemic, the United States faces the prospect of a prolonged economic downturn. Economic dislocation can impose costs not just on household finances, but also on health and safety. While the effects of the business cycle on mortality can be positive or negative, depending on the risk being considered, the effects of lost income over the long term tend to have unambiguous detrimental effects on health. When incomes fall enough, deaths can be expected. Recent estimates suggest that for every $111 million (in 2020 dollars) in reduced income, one expected death will occur (Broughel & Viscusi, in press). The mechanism driving this effect is that economic costs reduce expenditures made by households to reduce risks privately.

However, countervailing changes in mortality risks owing to income shocks can be positive or negative, depending on whether policies on balance impose costs or are cost-saving. The total cost estimate of suppression policies above ranges from about $214.2 billion to $331.5 billion. Costs of $214.2 billion to $331.5 billion would correspond to an initial 1,900 to 3,000 additional expected deaths. However, total gross benefits are estimated to be in the range of $603.3 billion to $834.9 billion. Because these benefits come in the form of cost savings or prevention of lost production (and by extension prevention of lost income), they result in

Covid Economics 67, 4 February 2021: 128-171

offsetting countervailing risk *reductions*, estimated at 5,400 to 7,500 initial lives saved. The net effect, therefore, of these countervailing risks ranges from 2,400 additional expected lives saved to 5,600 additional expected lives saved.

Assuming these changes in risk are spread equally across the population, the age distribution of which is different from the age distribution of COVID-19 deaths, the gains to production associated with 2,400 additional prevented deaths would be approximately $2.6 billion, assuming a production value of the average American of approximately $1.1 million (see Table A.3 in Appendix A). The benefit associated with 5,600 fewer expected deaths is therefore $6.2 billion.

Taken together, the countervailing mortality risks associated with lost income may actually produce initial benefits between $2.6 billion and $6.2 billion. Whether the countervailing mortality risks are, on balance, beneficial will depend on whether suppression policies are cost-saving. Combining these estimates with the gross mortality benefits estimated in the section on reduced mortality ($317.7 billion to $351.5 billion), we estimate net mortality benefits between $320.3 billion and $357.7 billion.

4.3 Net Benefits

We estimate the net benefits of COVID-19 suppression policies in the United States enforced between March and August 2020 are between $274.4 billion and $626.9 billion. Table 6 shows our estimates of net effects, per person prevented costs, and aggregate benefits presented in Section 4.1, as well as our estimate of forgone GDP due to stay-at-home orders and nonessential business closures from Section 4.2.1. The most significant factor in our estimate of benefits is reduced mortality. In fact, the lower bound of our estimate of the net mortality benefits almost surpasses the upper-bound estimate of total costs. Considering the benefits of reduced mortality

Covid Economics 67, 4 February 2021: 128-171

CEPR PRESS

alone, suppression policies as they were enforced during the summer months of 2020 in the United States likely pass a cost-benefit test. That said, the other factors for which we estimate the total benefits of suppression policies also produce significant benefits.

Table 6. Net benefit estimates of COVID-19 suppression measures enforced from early March 2020 to August 1, 2020.

Category	**Effect relative to baseline**	**Value per person, 2020 USD**	**Value, 2020 USD**
Net reductions in mortality	940,000–1.04 million	—	$320.3–$357.7 billion
Prevented COVID-19 deaths	940,000–1.04 million	$338,000	$317.7–$351.5 billion
Initial deaths from lost income	(5,600)–(2,400)	$1.1 million	($6.2)–($2.6 billion)
COVID-19 symptomatic infections	79–135 million	$1,900	$150.1–$256.5 billion
Hospitalizations	2.5–4.0 million	$11,000	$27.5–$44 billion
ICU admissions	820,000–1.3 million	$58,500	$48–$76.1 billion
Mechanical ventilation	480,000–760,000	$72,800	$34.9–$55.3 billion
ARDS cases	100,000–205,000	$251,000	$25.1–$51.5 billion
Total benefits	—	—	**$605.9–$841.1 billion**
Total costs	—	—	**$214.2–$331.5 billion**
Net benefits	—	—	**$274.4–$626.9 billion**

Source: Authors' calculations.
Note: Sums may not be exact, owing to rounding.

5. Discussion

Our analysis makes several notable contributions to the literature on CBA during the COVID-19 pandemic. Our finding of positive net benefits is consistent with some other cost-benefit analyses of social distancing, though our net benefit estimates are smaller in magnitude

Covid Economics 67, 4 February 2021: 128-171

(Thunström et al., 2020; Greenstone & Nigam, 2020). The distinction in our findings is attributable to two key contributions of our article to this literature. First, we attempt to estimate the costs and benefits associated with the *policy response* to COVID-19, not the costs and benefits associated with social distancing more generally (which includes public and private actions that reduce the health and economic impacts of COVID-19). Second, our analysis focuses on the costs and benefits of COVID-19 suppression in terms of its effects on economic output and production. While our approach excludes nonpecuniary factors that affect the short-run costs and benefits of public policy, we believe excluding nonpecuniary factors and focusing on total production better aligns our CBA with an analysis of long-run efficiency. Moreover, our focus on production is similar to other CBAs in the literature, such as one evaluating COVID-19 screening tests (Atkeson et al., 2020).

Another novel contribution of our CBA is that it explicitly accounts for potential increases in mortality risks, owing to the economic costs associated with income losses imposed by public policies (Broughel and Viscusi, in press). Because we find that suppression policies are, on net, cost-saving, we find that these policies prevent deaths through this income-saving channel, in addition to preventing COVID-19 deaths directly. An important additional point is that the change in countervailing mortality risks is not static. Because some fraction of the net benefits associated with suppression measures will be reinvested and earn interest, countervailing changes in risk will tend to grow as income grows with returns to invested capital.

Our analysis also has certain limitations. The most significant is uncertainty regarding the number of COVID-19 deaths that would have occurred in the counterfactual scenario in which suppression policies were not enforced, including what the IFR would be under such a scenario. Our use of the IFR implied by the number of deaths and infections under suppression policy

Covid Economics 67, 4 February 2021: 128-171

enforcement may understate the age and population IFR that would occur under mitigation given capacity constraints in the health-care system, such as the limited number of ICU beds and mechanical ventilators. Underestimating the IFR in the counterfactual scenario would imply that our estimated number of symptomatic infections among U.S. adults in the counterfactual scenario are overestimated, which would bias our benefits estimates upward.

More generally, our bottom-up approach of aggregating factors that have incremental effects on production inevitably omits certain factors. For instance, we consider the potential long-term effects of lung damage among recovered COVID-19 patients. We assume a permanent loss in remaining lifetime total production, but a cohort study of Severe Acute Respiratory Disorder (SARS) patients found that one year after hospital discharge, over half showed no signs of lung impairment (Ong, 2005). Other potential chronic conditions have been observed following recovery from COVID-19 infection, such as myocarditis (Siripanthong et al., 2020) and neurological effects (Kaseda & Levine, 2020; Nordvig et al., in press), but estimating the prevalence of these conditions and their long-term effects is difficult only a few months after the coronavirus began spreading in the U.S. Moreover, NPIs have resulted in certain unintended consequences. Studies have identified upticks in domestic violence as a potential result of sheltering at home (Bright et al., 2020), as well as reductions in traffic accidents (Qureshi et al., 2020).

While we do not expect those factors would dramatically change our conclusions, even the factors accounted for in our study may not be measured precisely. Declines in some forms of market production, such as childcare or restaurant dining, could be made up for by nonmarket production in the household, such as homeschooling or making dinner at home. In this sense, estimates of changes in output could overestimate the costs of suppression policies. On the other

Covid Economics 67, 4 February 2021: 128-171

CEPR PRESS

hand, declines in research and development expenditures or investments in human capital may impose total costs that exceed short-term losses to output. For instance, closing schools for only a few months could result in reduced earnings over the entire lifetimes of affected children (Azevedo et al., 2020). In spite of these challenges, we have done our best to include what we believe are the most direct, impactful, and predictable effects of suppression policies.

Another potential limitation of our analysis is that our estimates attribute most social distancing behaviors that reduce infections, health-care utilization, and deaths to public policy interventions. This might be reasonable if the costs of infection are not fully internalized by U.S. adults. However, studies of geographic mobility data have found that major changes in mobility preceded the implementation of stay-at-home policies (Goolsbee & Syverson, 2020; Luther, 2020). If the private response to COVID-19 more closely resembles population-wide social distancing than targeted private mitigation, then the incremental costs and benefits of suppression policies reported in this article are likely both overstated.

6. Conclusion

We estimate that suppression policies enforced by the U.S. states in the spring and early summer months of 2020 had substantial net benefits, in terms of preventing losses to economic output. Relative to targeted mitigation strategies that would likely have been adopted instead of suppression policies, we estimate that the benefits of suppression policies that bent the curve of COVID-19 are between $606 billion and $841 billion through August 1, 2020 during the first wave of cases. However, we find that suppression policies resulted in substantial losses to GDP, too, between $214 billion and $332 billion. Our results suggest that the net benefits of suppression policies are positive and likely substantial, possibly as high as $627 billion.

Covid Economics 67, 4 February 2021: 128-171

These estimates assume that the bending of the curve in the United States is largely attributable to suppression policies that were implemented in most U.S. states. However, if the American public would have engaged in social distancing irrespective of state-enforced NPIs, then the benefits and costs of these policies may be much lower. In that case, then our estimates can be thought of as estimates of the costs and benefits of social distancing broadly, which includes private actions. To gain a better understanding of the effectiveness of NPIs to address COVID-19, further research that estimates the efficacy of specific policies would be beneficial.

Covid Economics 67, 4 February 2021: 128-171

References

Adler, M. (2020). What should we spend to save lives in a pandemic? A critique of the value of statistical life. *Covid Economics Vetted and Real-Time Papers,* (33), 1-45.

Anand S., Montez-Rath, M., Han, J., Bozeman, J., Kerschmann, R., Beyer, P., Parsonnet, J., & Chertow, G.M. (2020). Prevalence of SARS-CoV-2 antibodies in a large nationwide sample of patients on dialysis in the USA: A cross-sectional study. *The Lancet* 396(10259), 1335-44.

Atkeson, A., Droste, M. & Stock, J.H. (2020). Economic benefits of COVID-19 screening tests. Unpublished manuscript, medRxiv preprint 2020.10.22.20217984.

Azevedo, J.P., Hasan, A., Goldemberg, D., Iqbal, S.A., & Geven, K. (2020). Simulating the potential impacts of COVID-19 school closures on schooling and learning outcomes: A set of global estimates. Policy Research Working Papers. Washington, D.C.: The World Bank.

Broughel, J., & Viscusi, W.K. (in press). The mortality cost of expenditures. *Contemporary Economic Policy*.

Bright, C.F., Burton, C., & Kosky, M. (2020) Considerations of the impacts of COVID-19 on domestic violence in the United States. *Social Sciences and Humanities Open,* 2(1), 100069.

Cameron, T. (2010). Euthanizing the value of a statistical life. *Review of Environmental Economics and Policy*, 4, 161–178.

Cowen, T. (2007). Caring about the distant future: Why it matters and what it means. *The University of Chicago Law Review*, 74(1), 5–40.

Dasta, J.F., McLaughlin, T.P., Mody, S.H., & Piech, C.T. (2005). Daily cost of an intensive care unit day: The contribution of mechanical ventilation. *Critical Care Medicine*, 33, 1266–1271.

Ferguson, N., Laydon, D., Nedjati Gilani, G., Imai, N., Ainslie, K., Baguelin, M., … Ghani, A. (2020). Impact of non-pharmaceutical interventions (NPIs) to reduce COVID19 mortality and healthcare demand. COVID Response Team. Imperial College London.

Goolsbee, A. & Syverson, C. (2020, June). Fear, lockdown, and diversion: Comparing drivers of pandemic economic decline 2020. BFI Working Paper No. 2020-80. Chicago: Becker Friedman Institute for Economics at the University of Chicago.

Greenstone, M., & Nigam, V. (2020). Does social distancing matter? *Covid Economics Vetted and Real-Time Papers,* (7), 1-23.

Grosse, S.D., Krueger, K.V., & Mvundura, M. (2009). Economic productivity by age and sex: 2007 estimates for the United States. *Medical Care*, 47, S94–S103.

Institute for Health Metrics and Evaluation (IHME). (2020, Oct 29). COVID-19 hospital needs and death projections. Retrieved Oct 31, 2020, from http://www.healthdata.org/covid/data-downloads.

Kaseda, E.T., & Levine, A.J. (2020). Post-traumatic stress disorder: A differential diagnostic consideration for COVID-19 survivors. *The Clinical Neuropsychologist*, 34(7-8), 1498-1514.

Levin, A.T., Hanage, W.P., Owusu-Boaitey, N., Cochran, K.B., Walsh, S.P., & Meyerowitz-Katz, G. (2020, Oct 30). Assessing the age specificity of infection fatality rates for COVID-19: Systematic review, meta-analysis, and public policy implications. Unpublished manuscript, medRxiv preprint 2020.07.23.20160895.

Luther, W. (2020). Estimating the effect of state-level stay-at-home orders. AIER Sound Money Project Working Paper No. 2020-09. Great Barrington, MA: American Institute for Economic Research. Retrieved Nov. 4, 2020, from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3610503#.

Makridis, C., & Hartley, J. (2020). The cost of COVID-19: A rough estimate of the 2020 U.S. GDP impact. Arlington, VA: Mercatus Center at George Mason University. Retrieved from https://www.mercatus.org/publications/covid-19-policy-brief-series/cost-covid-19-rough-estimate-2020-us-gdp-impact.

Meyerowitz-Katz. G. & Merone L. (2020). A systematic review and meta-analysis of published research data on COVID-19 infection-fatality rates. *International Journal of Infectious Diseases*, 101, 138–148.

Mizumoto, K., Kagaya, K., Zarebski, A., & Chowell, G. (2020). Estimating the asymptomatic proportion of coronavirus disease 2019 (COVID-19) cases on board the Diamond Princess cruise ship, Yokohama, Japan, 2020. *Eurosurveillance,* 25, 2–6.

Mulligan, C.B. (2020). Economic activity and the value of medical innovation during a pandemic. BFI Working Paper No. 2020-48. Chicago: Becker Friedman Institute for Economics at the University of Chicago.

Nordvig, A.S., Rimmer, K.T., Willey, J.Z., Thakur, K.T., Boehme, A.K., Vargas, W.S., Smith, C.J., & Elkind, M.S.V. (in press). Potential neurological manifestations of COVID-19. *Neurology Clinical Practice.*

Ong, K.C., Wei-Keong, N.A., Soon-U, L.L, Gregory, K., Seow-Khee, K., Khee-Shing, L.M., Arul, E. (2005). 1-Year pulmonary function and health status in survivors of Severe Acute Respiratory Syndrome. *CHEST*, 128(3), 1393–1400.

Pindyck, R. (2020). COVID-19 and the welfare effects of reducing contagion. NBER Working Paper No. 27121. Cambridge, MA: National Bureau of Economic Research.

Qureshi A. I., Huang, W., Khan, S., Lobanova, I., Siddiq, F., Gomez, C.R., & Surid, M.F.K. (2020). Mandated societal lockdown and road traffic accidents. *Accident Analysis and Prevention,* 146, 105747.

Ruhl, A.P., Huang, M., Colantuoni, E., Karmarkar, T., Dinglas, V.D., Hopkins, R.O., & Needham, D.M. (2017). Healthcare utilization and costs in ARDS survivors: A 1-year longitudinal national U.S. multicenter study. *Intensive Care Medicine*, 43, 980–991.

Russell, T.W., Hellewell, J., Jarvis, C., van-Zandvoort, K., Abbott, S., & Ratnayake, R. (2020). Estimating the infection and case fatality ratio for coronavirus disease (COVID-19) using age-adjusted data from the outbreak on the Diamond Princess cruise ship, February 2020. *Eurosurveillance,* 25, 10–14.

Scherbina, A. (2020, May). Determining the optimal duration of the COVID-19 suppression policy: A cost-benefit analysis. AEI Economic Policy Working Paper Series. Washington, DC: American Enterprise Institute.

Siripanthong, B., Nazarian, S., Muser, D., Deo, R., Santangeli, P., Khanji, M.Y., Cooper, L.T., Jr., & Chahal, C.A.A. (2020). Recognizing COVID-19–related myocarditis: The possible pathophysiology and proposed guideline for diagnosis and management. *Heart Rhythm*, 17(9), 1463–1471.

Thunström, L., Newbold, S., Finnoff, D., Ashworth, M., & Shogren, J.F. (2020). The benefits and costs of flattening the curve for COVID-19. *Journal of Benefit-Cost Analysis,* 11(2), 179-195.

Torio, C., & Moore, B. (2016). National inpatient hospital costs: The most expensive conditions

Covid Economics 67, 4 February 2021: 128-171

by payer, 2013. HCUP Statistical Brief #204. Rockville, MD: Agency for Healthcare Research and Quality.
University of Groningen and University of California, Davis. (2020). Average annual hours worked by persons engaged for United States. Retrieved Nov 5, 2020, from https://fred.stlouisfed.org/series/AVHWPEUSA065NRUG.
U.S. Bureau of Economic Analysis. (2020, April). Gross domestic product by state, 4th quarter and annual 2019. Suitland, MD: Bureau of Economic Analysis. Retrieved June 1, 2020, from https://www.bea.gov/system/files/2020-04/qgdpstate0420.pdf.
U.S. Bureau of Labor Statistics. (2020). Average hourly earnings of all employees, total private. Retrieved Nov 6, 2020, from https://fred.stlouisfed.org/series/CES0500000003.
U.S. Census Bureau. (2019). 2018 American Community Survey 5-Year Estimates: Table S0101, Age and Sex. Suitland, MD: U.S. Census Bureau. Retrieved May 27, 2020, from https://data.census.gov/cedsci/table?q=Age%20and%20Sex&t=Age%20and%20Sex&hidePreview=false&tid=ACSST5Y2018.S0101&vintage=2018.
U.S. Centers for Disease Control and Prevention (CDC). (2020a, Aug 28). Coronavirus disease 2019 (COVID-19)-associated hospitalization surveillance network (COVID-NET). Atlanta, GA: U.S. Centers for Disease Control and Prevention. Retrieved Nov 4, 2020, from https://www.cdc.gov/coronavirus/2019-ncov/covid-data/covid-net/purpose-methods.html.
U.S. Centers for Disease Control and Prevention. (2020b, Sept 10). COVID-19 pandemic planning scenarios. Atlanta, GA: U.S. Centers for Disease Control and Prevention. Retrieved Oct 31, 2020, from https://www.cdc.gov/coronavirus/2019-ncov/hcp/planning-scenarios.html.
U.S. Centers for Disease Control and Prevention. (2020c, Oct 27). COVID-NET: COVID-19-associated hospitalization surveillance network. Atlanta, GA: U.S. Centers for Disease Control and Prevention. Retrieved Nov 3, 2020, from https://gis.cdc.gov/grasp/COVIDNet/COVID19_5.html.
U.S. Centers for Disease Control and Prevention. (2020d, Oct 28). Provisional COVID-19 death counts by sex, age, and week. Atlanta, GA: U.S. Centers for Disease Control and Prevention. Retrieved Oct 31, 2020, from https://data.cdc.gov/NCHS/Provisional-COVID-19-Death-Counts-by-Sex-Age-and-W/vsak-wrfu.
U.S. Centers for Disease Control and Prevention. (2020e, Nov 3). Isolate if you are sick. Atlanta, GA: U.S. Centers for Disease Control and Prevention. Retrieved Nov 3, 2020, from https://www.cdc.gov/coronavirus/2019-ncov/if-you-are-sick/isolation.html.
U.S. Office of Management and Budget. (2003, September 17). Circular A-4: Regulatory analysis. Washington, DC: U.S. Office of Management and Budget. Retrieved from https://obamawhitehouse.archives.gov/omb/circulars_a004_a-4/.
Viscusi, W.K. (2018). *Pricing lives: Guideposts for a safer society*. Princeton, NJ: Princeton University Press.
Zhou, F., Yu, T., Du, R., Fan, G., Liu, Y., Liu, Z., … Xiang, J. (2020). Clinical course and risk factors for mortality of adult inpatients with COVID-19 in Wuhan, China: A retrospective cohort study. *The Lancet*, 395, 1054–1062.
Zhou, P., Yang, X., Wang, X., Hu, B., Zhang, L., Zhang, W., … Shi, Z. (2020). A pneumonia outbreak associated with a new coronavirus of probable bat origin. *Nature*, 579, 270–273.

Covid Economics 67, 4 February 2021: 128-171

Covid Economics 67, 4 February 2021: 128-171

Appendix A. Production-value-of-life tables

Table A.1. Author calculations of the present value of lifetime production by age, adjusted to age groups in CDC COVID-19 deaths counts.

Age	Lifetime total production, 2007 USD	Lifetime total production, 2020 USD	CDC COVID-19 deaths age groups	Lifetime total production, 2020 USD
20 to 24	$1,119,137	$1,700,684	18 to 24	$1,700,684
25 to 29	$1,164,022	$1,768,893		
30 to 34	$1,130,428	$1,717,842	25 to 34	$1,743,368
35 to 39	$1,051,137	$1,597,348		
40 to 44	$937,939	$1,425,328	35 to 44	$1,511,338
45 to 49	$802,484	$1,219,486		
50 to 54	$648,498	$985,483	45 to 54	$1,102,485
55 to 59	$486,469	$739,257		
60 to 64	$338,632	$514,598	55 to 64	$626,928
65 to 69	$230,954	$350,967		
70 to 74	$170,533	$259,149	65 to 74	$305,058
75 to 79	$123,803	$188,136		
80 plus	$90,738	$137,889	75 to 84	$163,013
			85 plus	$137,889

Sources: Grosse et al. (2009, p. S100); CDC (2020d).
Note: We use estimates in Grosse et al. (2020, p. S100) that apply a 5 percent discount rate, and then we adjust for inflation using the CPI from January 2007 to January 2020. We also adjust for average annual labor productivity growth, measured in terms of real output per hour, from 2007 to the end of 2019, which was approximately 1.39 percent per year on an annualized basis. Lifetime total production values represent an average of the production values for the age groups from Grosse et al. (2009) that the CDC (2020d) age groups span.

Table A.2. Author calculations of the present value of lifetime production by age, adjusted to age groups in CDC hospitalized patient counts.

Age	Lifetime total production, 2007 USD	Lifetime total production, 2020 USD	CDC hospitalization age groups	Lifetime total production, 2020 USD
20 to 24	$1,119,137	$1,700,684		
25 to 29	$1,164,022	$1,768,893		
30 to 34	$1,130,428	$1,717,842		
35 to 39	$1,051,137	$1,597,348		
40 to 44	$937,939	$1,425,328		
45 to 49	$802,484	$1,219,486	18 to 49	$1,571,597
50 to 54	$648,498	$985,483		
55 to 59	$486,469	$739,257		
60 to 64	$338,632	$514,598	50 to 64	$746,446
65 to 69	$230,954	$350,967		
70 to 74	$170,533	$259,149		
75 to 79	$123,803	$188,136		
80 plus	$90,738	$137,889	65 plus	$234,035

Sources: Grosse et al. (2009, p. S100); CDC (2020c).
Note: We use estimates in Grosse et al. (2020, p. S100) that apply a 5 percent discount rate, and then we adjust for inflation using the CPI from January 2007 to January 2020. We also adjust for average annual labor productivity growth, measured in terms of real output per hour, from 2007 to the end of 2019, which was approximately 1.39 percent per year on an annualized basis. Lifetime total production values represent an average of the production values for the age groups from Grosse et al. (2009) that the CDC (2020c) age groups span.

Table A.3. Expected lifetime production lost to increased mortality from lost national income.

Age	Lifetime total production, 2020 USD	U.S. population (2018)	Approx. percentage of U.S. population (2018)	Expected lifetime production, 2020 USD
0 to 4	$864,396	19,836,850	6.1%	$53,102
5 to 9	$1,052,093	20,311,494	6.3%	$66,180
10 to 14	$1,278,457	20,817,419	6.4%	$82,422
15 to 19	$1,518,608	21,204,226	6.6%	$99,723
20 to 24	$1,700,684	22,286,970	6.9%	$117,382
25 to 29	$1,768,893	22,779,537	7.1%	$124,788
30 to 34	$1,717,842	21,788,439	6.7%	$115,914
35 to 39	$1,597,348	20,730,622	6.4%	$102,551
40 to 44	$1,425,328	20,032,588	6.2%	$88,426
45 to 49	$1,219,486	20,827,879	6.5%	$78,659
50 to 54	$985,483	21,761,694	6.7%	$66,416
55 to 59	$739,257	21,611,374	6.7%	$49,477
60 to 64	$514,598	19,675,357	6.1%	$31,356
65 to 69	$350,967	16,409,942	5.1%	$17,836
70 to 74	$259,149	12,125,477	3.8%	$9,731
75 to 79	$188,136	8,549,216	2.6%	$4,981
80 plus	$137,889	12,153,946	3.8%	$5,190
Total	**—**	**322,903,030**	**100.0%**	**$1,114,134**

Sources: Grosse et al. (2009, p. S100); U.S. Census Bureau (2019).
Note: Differences or sums may not be exact owing to rounding. Grosse et al. (2009, p. S100) present lifetime production by five-year increments between ages 0 and 80+. The U.S. Census Bureau (2019) reports population by age in the same five-year increments, except that it separates those who are 80–84 years old from those 85 or older, so we take the sum of those two groups to align them with the Grosse et al. (2009, p. S100) production estimates. Refer to Table A.1 and Table A.2 for adjustments of Grosse et al. (2009) for inflation and productivity growth.

Covid Economics 67, 4 February 2021: 128-171

Covid Economics 67, 4 February 2021: 128-171

Appendix B. U.S. state suppression policies to slow the first wave of COVID-19

The COVID-19 forecast produced by the IHME considers several state-level policies in its model (2020). While the details of each policy vary among the U.S. states, the IHME broadly groups public health interventions into five categories:

- *Stay-at-Home Orders:* 38 states and the District of Columbia enacted a stay-at-home order, 36 of which were lifted between the last week of April and the first week of July. As of August 1, 2020, only two orders remained in force, in California and Georgia.
- *Public School and University Closures:* All 50 states and the District of Columbia ordered educational facilities to be closed by April 4, 2020, and all these measures remain in force through August 1, 2020.
- *Any Restriction on Size of Gatherings:* 49 states and the District of Columbia placed some legal restriction on public or private gatherings, with the exception being North Dakota. Fifteen states had lifted their restrictions on gatherings entirely on or before August 1, 2020. In total, 34 states and the District of Columbia enforce some restriction on gathering size as of August 1, 2020.
- *Legally Ordered Closure of Any Business:* 49 states and the District of Columbia required at least one type of business (like bars, restaurants, or hair salons) to close starting in late March or early April. Only South Dakota did not actively legally enforce the closure of some businesses in their state. Fifteen states eased business restrictions on or before August 1, 2020, meaning 34 states and the District of Columbia were still enforcing business restrictions through August 1, 2020.
- *Legally Ordered Closure of All Nonessential Businesses:* More restrictive than the category above, 34 states and the District of Columbia ordered all businesses not deemed “essential” to be shut down starting in March or April. By July 3, 2020, all jurisdictions

had lifted their nonessential business closures except California, which enforced nonessential business closures as of August 1, 2020.

- *Severe Travel Restrictions:* As of May 26, only Alaska had issued a legal order significantly restricting the travel of its residents within the state, which took effect on March 28 and remained in effect through August 1, 2020.

The start and end dates of legal orders in each category (except "severe travel restrictions") are listed by state in Table B.1. If an order had not been lifted or if an end date had not been formally announced prior as of IHME's October 29, 2020 update, then the end date is set equal to "to be determined" (TBD), and we assume the policy was in force as of August 1, 2020.

Covid Economics 67, 4 February 2021: 128-171

CEPR PRESS

Table B.1. Start and end dates of most common policies to enforce social distancing, by state

	Stay-at-home order		School closures		Gathering size limits		Any business closure		Nonessential business closures	
State	**Start**	**End**	**Start**	**End**	**Start**	**End**	**Start**	**End**	**Start**	**End**
AL	4/4	4/30	3/19	TBD	3/19	TBD	3/19	6/15	3/28	4/30
AK	3/28	4/24	3/16	TBD	3/24	5/22	3/17	5/22	3/28	4/24
AZ	3/30	5/16	3/16	TBD	3/30	5/16	3/30	5/16	—	—
AR	—	—	3/17	8/24	3/27	6/18	3/19	TBD	—	—
CA	3/19	TBD	3/19	TBD	3/11	TBD	3/19	TBD	3/19	TBD
CO	3/26	5/9	3/23	TBD	3/19	TBD	3/17	TBD	3/26	5/9
CT	—	—	3/17	TBD	3/12	TBD	3/16	TBD	3/23	5/20
DE	3/24	6/1	3/16	TBD	3/16	TBD	3/16	TBD	3/24	5/8
DC	3/30	5/29	3/16	TBD	3/13	TBD	3/16	TBD	3/25	5/29
FL	4/3	5/18	3/17	TBD	4/3	6/5	3/17	9/25	—	—
GA	4/3	TBD	3/18	TBD	3/24	TBD	3/24	TBD	—	—
HI	3/25	6/10	3/19	TBD	3/17	TBD	3/17	TBD	3/25	5/1
ID	3/25	5/1	3/23	TBD	3/25	5/1	3/25	6/13	3/25	5/1
IL	3/21	5/29	3/17	TBD	3/13	TBD	3/16	TBD	3/21	5/1
IN	3/25	5/18	3/19	TBD	3/12	TBD	3/16	9/26	3/24	5/18
IA	—	—	4/4	TBD	3/17	6/12	3/17	10/16	3/17	5/8
KS	3/30	5/4	3/17	TBD	3/17	5/22	3/30	6/8	—	—
KY	—	—	3/20	TBD	3/19	TBD	3/16	6/29	3/26	5/11
LA	3/23	5/15	3/16	TBD	3/13	5/15	3/17	TBD	3/22	5/1
ME	4/2	5/31	3/16	TBD	3/18	TBD	3/18	TBD	3/25	5/1
MD	3/30	5/15	3/16	TBD	3/16	6/10	3/16	TBD	3/23	5/15
MA	—	—	3/17	TBD	3/13	TBD	3/17	TBD	3/24	5/18
MI	3/24	6/1	3/16	TBD	3/13	TBD	3/16	TBD	3/23	5/7

Covid Economics 67, 4 February 2021: 128-171

MN	3/28	5/18	3/18	TBD	3/28	TBD	3/17	6/10	—	—
MS	4/3	4/27	3/19	TBD	3/24	TBD	3/24	6/1	4/3	4/27
MO	4/6	5/15	3/23	TBD	3/23	5/4	3/23	6/16	—	—
MT	3/26	4/26	3/15	TBD	3/24	6/1	3/20	6/1	3/26	5/1
NE	—	—	4/2	TBD	3/16	TBD	3/19	7/6	—	—
NV	3/31	5/9	3/16	TBD	3/24	TBD	3/18	TBD	3/21	5/9
NH	3/27	6/16	3/16	TBD	3/16	TBD	3/16	6/29	3/28	5/11
NJ	3/21	6/9	3/18	TBD	3/16	TBD	3/16	TBD	3/21	5/2
NM	—	—	3/13	TBD	3/12	TBD	3/16	TBD	3/24	5/15
NY	3/22	6/8	3/18	TBD	3/12	TBD	3/16	TBD	3/22	6/8
NC	3/30	5/8	3/14	TBD	3/14	TBD	3/17	TBD	3/30	5/8
ND	—	—	3/16	TBD	—	—	3/20	TBD	—	—
OH	3/23	5/20	3/16	TBD	3/12	TBD	3/15	TBD	3/23	5/4
OK	—	—	3/17	TBD	3/24	5/24	4/1	6/1	4/1	4/24
OR	3/23	6/19	3/16	TBD	3/12	TBD	3/17	TBD	—	—
PA	4/1	6/5	3/17	TBD	4/1	9/14	3/18	7/3	3/23	5/8
RI	3/28	5/9	3/16	TBD	3/17	TBD	3/17	TBD	—	—
SC	4/7	5/4	3/16	TBD	3/18	TBD	3/18	8/3	—	—
SD	—	—	3/16	TBD	4/6	4/28	—	—	—	—
TN	4/2	5/26	3/20	TBD	3/23	TBD	3/23	TBD	4/1	5/26
TX	4/2	5/1	3/19	TBD	3/21	6/4	3/21	TBD	—	—
UT	—	—	3/16	TBD	3/19	5/1	3/19	TBD	—	—
VT	3/24	5/15	3/18	TBD	3/13	TBD	3/17	TBD	3/25	5/4
VA	3/30	6/5	3/16	TBD	3/15	TBD	3/17	TBD	3/24	5/15
WA	3/23	7/3	3/13	TBD	3/11	TBD	3/16	TBD	3/25	7/3
WV	3/25	5/4	3/14	TBD	3/24	TBD	3/18	TBD	3/24	5/4
WI	3/25	5/13	3/18	TBD	3/17	TBD	3/17	TBD	3/25	5/11

Covid Economics 67, 4 February 2021: 128-171

WY	—	—	3/19	TBD	3/20	TBD	3/19	5/15	—	—

Source: IHME (2020)
Note: State policy information as of October 29, 2020. "TBD" indicates that a state suppression policy has not been lifted as of IHME's October 29, 2020 update. Missing values, indicated by a dash, indicate that a state never enforced a particular suppression policy.

Table B.2. Number of days during which both stay-at-home and nonessential business closures were enforced, weighted by each state's share of U.S. GDP.

State	GDP, 2019Q4 (in millions of dollars)	Percent of GDP	First day both orders enforced	Last day both orders enforced	Number of Days	Expected Number of Days
AL	$234,054	1.1%	4/4	4/30	26	0
AK	$55,759	0.3%	3/28	4/24	27	0
AZ	$372,522	1.7%	—	—	0	0
AR	$135,225	0.6%	—	—	0	0
CA	$3,183,251	14.7%	3/19	8/1	135	20
CO	$396,367	1.8%	3/26	5/9	44	1
CT	$288,985	1.3%	—	—	0	0
DE	$76,410	0.4%	3/24	5/8	45	0
DC	$148,231	0.7%	3/30	5/29	60	0
FL	$1,111,378	5.1%	—	—	0	0
GA	$625,329	2.9%	—	—	0	0
HI	$98,536	0.5%	3/25	5/1	37	0
ID	$82,265	0.4%	3/25	5/1	37	0
IL	$908,913	4.2%	3/21	5/1	41	2
IN	$381,733	1.8%	3/25	5/18	54	1
IA	$197,172	0.9%	—	—	0	0
KS	$175,703	0.8%	—	—	0	0
KY	$217,564	1.0%	—	—	0	0

Covid Economics 67, 4 February 2021: 128-171

LA	$267,051	1.2%	3/23	5/1	39	0
ME	$68,441	0.3%	4/2	5/1	29	0
MD	$434,312	2.0%	3/30	5/15	46	1
MA	$604,208	2.8%	—	—	0	0
MI	$548,567	2.5%	3/24	5/7	44	1
MN	$385,907	1.8%	—	—	0	0
MS	$120,429	0.6%	4/3	4/27	24	0
MO	$336,816	1.6%	—	—	0	0
MT	$52,948	0.2%	3/26	4/26	31	0
NE	$129,098	0.6%	—	—	0	0
NV	$180,406	0.8%	3/31	5/9	39	0
NH	$89,836	0.4%	3/28	5/11	44	0
NJ	$652,412	3.0%	3/21	5/2	42	1
NM	$105,263	0.5%	—	—	0	0
NY	$1,751,674	8.1%	3/22	6/8	78	6
NC	$596,383	2.8%	3/30	5/8	39	1
ND	$57,400	0.3%	—	—	0	0
OH	$706,764	3.3%	3/23	5/4	42	1
OK	$207,381	1.0%	—	—	0	0
OR	$255,418	1.2%	—	—	0	0
PA	$824,603	3.8%	4/1	5/8	37	1
RI	$64,441	0.3%	—	—	0	0
SC	$249,958	1.2%	—	—	0	0
SD	$54,057	0.3%	—	—	0	0
TN	$385,741	1.8%	4/2	5/26	54	1
TX	$1,918,065	8.9%	—	—	0	0
UT	$192,013	0.9%	—	—	0	0

Covid Economics 67, 4 February 2021: 128-171

VT	$35,271	0.2%	3/25	5/4	40	0
VA	$561,846	2.6%	3/30	5/15	46	1
WA	$610,488	2.8%	3/25	7/3	100	3
WV	$78,507	0.4%	3/25	5/4	40	0
WI	$351,922	1.6%	3/25	5/11	47	1
WY	$39,794	0.2%	—	—	0	0
Total	**$21,606,817**	**100.0%**	—	—	—	**42**

Sources: U.S. Bureau of Economic Analysis (2020); IHME (2020); authors' calculations.
Note: We set the number of days of suppression policies equal to zero for the 22 states that did not enforce both a nonessential business closure and stay-at-home order. Refer to Table B.1 for the dates on which suppression policies were enacted and lifted in the U.S. states and the District of Columbia.

Covid Economics 67, 4 February 2021: 128-171

Table B.3. Number of days during which either a stay-at-home order or nonessential business closure order (inclusive) was enforced, weighted by each state's share of U.S. GDP.

State	GDP, 2019Q4 (in millions of dollars)	Percent of GDP	First day either order enforced	Last day either order enforced	Number of Days	Expected Number of Days
AL	$234,054	1.1%	3/28	4/30	33	0
AK	$55,759	0.3%	3/28	4/24	27	0
AZ	$372,522	1.7%	3/30	5/16	47	1
AR	$135,225	0.6%	—	—	0	0
CA	$3,183,251	14.7%	3/19	8/1	135	20
CO	$396,367	1.8%	3/26	5/9	44	1
CT	$288,985	1.3%	3/23	5/20	58	1
DE	$76,410	0.4%	3/24	6/1	69	0
DC	$148,231	0.7%	3/25	5/29	65	0
FL	$1,111,378	5.1%	4/3	5/18	45	2
GA	$625,329	2.9%	4/3	8/1	120	3
HI	$98,536	0.5%	3/25	6/10	77	0

ID	$82,265	0.4%	3/25	5/1	37	0
IL	$908,913	4.2%	3/21	5/29	69	3
IN	$381,733	1.8%	3/24	5/18	55	1
IA	$197,172	0.9%	3/17	5/8	52	0
KS	$175,703	0.8%	3/30	5/4	35	0
KY	$217,564	1.0%	3/26	5/11	46	0
LA	$267,051	1.2%	3/22	5/15	54	1
ME	$68,441	0.3%	3/25	5/31	67	0
MD	$434,312	2.0%	3/23	5/15	53	1
MA	$604,208	2.8%	3/24	5/18	55	2
MI	$548,567	2.5%	3/23	6/1	70	2
MN	$385,907	1.8%	3/28	5/18	51	1
MS	$120,429	0.6%	4/3	4/27	24	0
MO	$336,816	1.6%	4/6	5/15	39	1
MT	$52,948	0.2%	3/26	5/1	36	0
NE	$129,098	0.6%	—	—	0	0
NV	$180,406	0.8%	3/21	5/9	49	0
NH	$89,836	0.4%	3/27	6/16	81	0
NJ	$652,412	3.0%	3/21	6/9	80	2
NM	$105,263	0.5%	3/24	5/15	52	0
NY	$1,751,674	8.1%	3/22	6/8	78	6
NC	$596,383	2.8%	3/30	5/8	39	1
ND	$57,400	0.3%	—	—	0	0
OH	$706,764	3.3%	3/23	5/20	58	2
OK	$207,381	1.0%	4/1	4/24	23	0
OR	$255,418	1.2%	3/23	6/19	88	1
PA	$824,603	3.8%	3/23	6/5	74	3

RI	$64,441	0.3%	3/28	5/9	42	0
SC	$249,958	1.2%	4/7	5/4	27	0
SD	$54,057	0.3%	—	—	0	0
TN	$385,741	1.8%	4/1	5/26	55	1
TX	$1,918,065	8.9%	4/2	5/1	29	3
UT	$192,013	0.9%	—	—	0	0
VT	$35,271	0.2%	3/24	5/15	52	0
VA	$561,846	2.6%	3/24	6/5	73	2
WA	$610,488	2.8%	3/23	7/3	102	3
WV	$78,507	0.4%	3/24	5/4	41	0
WI	$351,922	1.6%	3/25	5/13	49	1
WY	$39,794	0.2%	—	—	0	0
Total	**$21,606,817**	**100.0%**	—	—	—	**65**

Sources: U.S. Bureau of Economic Analysis (2020); IHME (2020); authors' calculations.
Note: We set the number of days of suppression policies equal to zero for the 6 states that did not enforce either nonessential business closures or a stay-at-home order. Refer to Table B.1 for the dates on which suppression policies were enacted and lifted in the U.S. states and the District of Columbia.

Young lives, interrupted: Short-term effects of the COVID-19 pandemic on adolescents in low- and middle-income countries

Marta Favara,[1] Richard Freund,[2] Catherine Porter,[3] Alan Sánchez[4] and Douglas Scott[5]

Date submitted: 29 January 2021; Date accepted: 30 January 2021

Covid Economics 67, 4 February 2021: 172-198

We examine how the lives of adolescents in Low- and Middle- Income countries have been affected by the COVID-19 pandemic and related economic downturn using data from a large-scale phone survey conducted in four countries as a part of Young Lives, a 20-year longitudinal study. The phone survey asked detailed information about the COVID-19 pandemic e.xperiences as well as collecting welfare indicators that are comparable across rounds. This allows a unique opportunity to compare a cohort of young people born around the turn of the Millennium (Younger Cohort) with an Older Cohort born in 1994, measured at the same age but seven years previously; both cohorts have been surveyed by the project since 2002. We find that relative gains in multidimensional well-being of the Younger Cohort found in survey rounds up to 2016 had largely disappeared in 2020. The significant (absolute and relative) downturn in self-reported wellbeing and economic circumstances is apparent in India, Ethiopia, and Peru, though not in Vietnam, the country which has had the most success at controlling the virus. However, educational enrolment has been affected in all countries. We suggest that the consequences of education dropout and links to

1 Deputy Director, Young Lives, Oxford Department of International Development, University of Oxford.
2 Research Assistant, Young Lives, Oxford Department of International Development, University of Oxford
3 Senior Lecturer, Lancaster University Management School, Lancaster University.
4 Senior Researcher, Grupo de Análisis para el Desarrollo (GRADE) and Principal Investigator, Young Lives Peru
5 Research Officer, Young Lives, Oxford Department of International Development, University of Oxford

potential mental health issues may mean the effects are long lasting in the absence of interventions to support young people's wellbeing and livelihoods.

Covid Economics 67, 4 February 2021: 172-198

Covid Economics 67, 4 February 2021: 172-198

1. Introduction

Adolescence is a challenging period of life, but the COVID-19 pandemic has intensified the pressure on young people trying to complete an education and enter the labour market. Although medical research shows that the young in general are at lower risk in terms of the direct health effects of the virus, including hospitalization and death (Snape and Viner, 2020), the economic effects are likely to be long-lasting for those at the beginning of their adult life. The worldwide closure of schools and higher learning institutions has no historical precedent (United Nations, 2020). To minimize learning losses, many schools in developed as well as developing countries have offered online learning; however, this option is only accessible to some and typically excludes those with limited infrastructure or no access to internet. International organisations have warned about the potential of the pandemic to exacerbate existing inequalities and reduce the potential of an entire generation (International Labour Organisation, 2020a; United Nations 2020), to the extent that this group of young adults has been named as the "lockdown generation" (International Labour Organisation, 2020b) and "Generation COVID" (Major et al., 2020), given the risk of scarring that may continue throughout their working lives.

This study contributes to the understanding of how severely a cohort of adolescents have been impacted by the crisis, using comparable longitudinal data from four Low- and Middle- Income countries (LMICs) that have been very differently affected by the health crisis: Ethiopia, India (states of Andhra Pradesh and Telangana), Peru and Vietnam. In particular, Peru has experienced one of the highest rates of COVID-related deaths per population in the world, whilst Vietnam has been praised for its successful containment of the virus, though no country has escaped unscathed from the global economic slowdown. We conducted two phone surveys between June and October 2020, interviewing nearly 10,000 young people from two cohorts aged 19 and 25 in the four countries, who had been part of the Young Lives Survey (YLS) and had already participated in the survey five times (in person) since 2002. The data show that the young people in our sample live in households which have experienced food shortages, job losses and other economic shocks, and in some cases illness and higher health expenses since the crisis began. They are very worried about the future, have interrupted their education, taken on more responsibilities in their households, and their self-reported wellbeing has fallen significantly in all countries except Vietnam.

In this paper we investigate to what extent the pandemic might be halting progress made over the last two decades and may be reversing life chances and deepening inequalities for many young people, unless decisive action is taken. The two-cohort, longitudinal structure of the data allows us to compare the outcomes of young people aged 19-20 (Younger Cohort), who were living through the pandemic in 2020, to those of an Older Cohort when they were surveyed at the same ages in 2013. In previous rounds, the study has consistently shown a gap between outcomes of the two cohorts, with the younger-born cohort achieving higher educational attainment, working fewer hours whilst of school age, and having higher levels of self-reported wellbeing (see, for instance, Favara el al., 2018). Prior research shows that the younger cohort had performed better in cognitive tests, performed less child labour and felt higher life satisfaction at age 15. Using a difference-in-difference approach we investigate the cohort gap before and during the pandemic. We show that in the pandemic year 2020, in all countries except Vietnam, the gains in wellbeing had largely disappeared, while losses in perceived wealth are also observed, and enrollment was affected in all countries.

In light of the social distancing measures that have severely limited the use of face-to-face interviews, there has been an increase in the use of phone surveys to assess the socio-economic impact of COVID-19

Covid Economics 67, 4 February 2021: 172-198

in Low- and Middle-Income Countries (LMICs). However, most of those surveys are administered online, which limits the representativeness of the survey population, mainly reaching educated children and those with access to internet (International Labour Organisation, 2020a). For those under-represented in such surveys (usually the poor and those in rural areas) the impacts of COVID-19 may be more severe as they were already in a vulnerable position before the outbreak of the pandemic.

In contrast, the Young Lives original 2002 sample was broadly representative of poor children in the four countries, and the 2020 phone survey was able to reach the rural poor, even those without access to the internet or mobile phones. Reaching this group was achieved via local guides living in the sample villages, an approach which was especially important in Ethiopia where the poorest groups often live in isolated rural areas. Furthermore, given the long-lasting relationship with participants, the Young Lives phone survey has higher response rate than most phone surveys and lower attrition than many follow up surveys of developed country cohort studies.[1] The multi-cohort panel structure offers a unique opportunity to assess the impact that the pandemic has had on the lives of adolescents in developing countries.

We build on findings from other pre-existing longitudinal studies, such as the National Income Dynamics Study (NIDS) in South Africa, and the Gender and Adolescence: Global Evidence (GAGE) study, which have also pivoted their operations to carry out phone surveys of their participants, though none has the multi-cohort structure Young Lives has. Emerging results from these studies found adverse effects of the pandemic on household well-being – with consistent negative impacts on factors such as employment, food insecurity, education and mental health (e.g. Spaull et al., 2020; Wieser et al., 2020; Chikoti et al., 2020). Using evidence from qualitative phone surveys, Banati, et al. (2020) found that the pandemic has increased food insecurity, disrupted schooling, and amplified economic hardships among adolescents in Ethiopia, Côte d'Ivoire and Lebanon.

The paper proceeds as follows. In the next section we outline the heterogeneous country contexts in terms of background and COVID-19 experience. In section 3, we describe the dataset and methodology. In section 4, we provide some descriptive findings of the effects of the pandemic as reported by respondents in the 2020 phone survey. In section 5, we present the difference-in-difference (cross-cohort) analysis for pandemic outcomes. In section 6, we discuss some potential reasons for longer-term pessimism and then we briefly conclude with some policy recommendations.

2. Country context and COVID-19 experiences

2.1 Pre-2020 background

Over the last two decades up to 2020, all four Young Lives countries had seen significant economic growth. In Peru, the economy underwent high growth between 2002 and 2013 (GDP average annual growth rate of 6.2% during this period), with slower growth after that (3.1% average annual growth between 2014 and 2019).[2] India has consistently recorded strong economic growth, with an average annual GDP growth

[1] For example, the UK Millennium Cohort study began at a similar time to Young Lives with 18,818 participants, though only 2,645 participated in the COVID-19 survey (see https://cls.ucl.ac.uk/covid-19-survey/content-and-data/).

[2] Central Bank of Peru, Annual Review, 2020.

rate of over 6.5% between 2002 and 2019.[3] After decades of low-income levels and stagnant economic growth, since 2004 Ethiopia has exhibited a higher growth rate than most African countries, overtaking Kenya as East Africa's largest economy in 2017 (International Monetary Fund, 2017), albeit still classified as a low-income country. Vietnam, the most developed country out of the Young Lives sample countries, saw a drop in its growth between 2007 and 2012, but has displayed high growth since, with an average annual GDP growth rate of 6.3% between 2012 and 2019.[3]

Over the same time period, we have also witnessed substantial improvements in the living standards of the Young Lives families. Between 2002 and 2016 the proportion of Young Lives families with access to essential services increased in all four countries (Galab et al., 2017a; Sánchez and Pazos, 2017; Woldehanna et al., 2018; Espinoza et al., 2017a). By 2016, access to electricity was near universal in India, Vietnam and Peru, and access greatly improved over this period in Ethiopia (from 34% in 2002 to 64% in 2016). Ethiopia and Peru also saw large improvements in access to sanitation (74% in 2002 to 95% in 2016 in Peru, and 37% to 76% in Ethiopia), while Vietnam, India and Ethiopia all displayed marked improvements in access to clean drinking water (50% in 2002 to 89% in 2016 in Vietnam, and 33% to 69% in Ethiopia).

Whilst Young Lives families were generally better off in 2016, a number of substantial and statistically significant inequalities observed in 2002 remained, including in relation to access to basic services, but also in terms of school achievement notably school dropout rates and access to higher education. These disadvantages were particularly felt by children and young people living in rural areas, those from poorest households, and those with parents having low levels of education. There have been moderate improvements in overall labour market outcomes since we began following Young Lives families, including a reduction in unemployment, and an increase in the share of salaried jobs in these four countries (International Labour Organisation, 2020c). However, because improvements have been slow, most young people continue to work in low-skilled and informal jobs, which are typically vulnerable in times of crisis.

2.2 COVID-19 experiences

The four study countries have had very diverse experiences during the pandemic, both with regards to the number of cases and in their policy responses. Table 1 shows data on the impact of COVID-19 in the four Young Lives countries by the time that our survey was completed on 15th October. The number of COVID-19 cases differs dramatically by country, with Vietnam having been exceptionally successful at limiting the spread of the pandemic, and Peru being one of the worst affected countries in the world in terms of cases and deaths per capita. Relative to the country population, the number of deaths was more than 2500 times higher in Peru than in Vietnam at the end-date of our survey. The reported number of deaths were more than 12 times lower in India than Peru (though the situation has since worsened) and were also much lower in Ethiopia.

[3] The World Bank, World Development Indicators, GDP growth (annual %). Available: https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG?end=2019&start=2002

Covid Economics 67, 4 February 2021: 172-198

Table 1: Confirmed COVID-19 cases and deaths per million as at 15 October

Country	Number of COVID-19 cases per million people	Cumulative COVID-19 deaths per million people
Peru	26,075	1,019
India	5,341	82
Ethiopia	759	12
Vietnam	12	<1

Source: https://ourworldindata.org. 15th October is the end-date of fieldwork.

In terms of policy to control the spread of the virus, India, Peru, and Vietnam all implemented strict national lockdowns. The Oxford COVID-19 Government Response Tracker systematically collects information on several different common policy responses that governments have taken to respond to the pandemic - such as school closures, health system policies and travel restrictions (Thomas et al., 2020). The data is aggregated into, amongst others, a Government Response Stringency Index which records the strictness of lockdown policies that restrict people's behaviours. As of 15 October, out of our study countries, Peru was rated the most stringent, with a score of 82 out of 100. Ethiopia and India were ranked second and third respectively, with Vietnam recording the least strict measures (Roser et al., 2020).

Peru instituted a national lockdown in response to the pandemic on 15 March 2020 that through multiple extensions lasted until 31 July (Sánchez et al., 2020). During this period, people were only allowed to leave the house for essential activities, social gatherings were prohibited, an evening curfew was maintained, and education institutions were closed, although the government (and many private institutions) introduced emergency home-learning. From May, the government started gradually re-opening the economy. Between August and September, the country moved into a phase of local lockdowns at both the region and province levels. During this period and throughout October, schools (except some in rural areas) and higher education institutions remained closed for in-presence learning, those under 12 years old and above 65 years old were asked to stay at home, and other measures were maintained (including an evening curfew and prohibition of social gatherings.

India began a nationwide lockdown in response to the pandemic at the end of March 2020. Only essential services were allowed, educational institutions were closed, large gatherings outlawed, and campaigns launched emphasising social distance and hygiene responses. This national lockdown lasted for 75 days, until various restrictions were relaxed under Unlock 1.0 on 8 June 2020 (Favara et al., 2020).

Ethiopia did not impose a national lockdown; however, following the first reported cases in March 2020, the government closed schools and banned public meetings (Porter et al., 2020). The government gradually reopened educational institutions, with schools reopening since 20 October 2020, and eased restrictions on travel to encourage a resumption of business and tourism, aimed at reviving the economy.

In Vietnam, a series of early proactive measures, including a 15-day national lockdown in April, the closure of schools and nonessential businesses, a ban on large gatherings, and extensive contact tracing have been highly effective at limiting the spread of the virus (Scott et al., 2020).

Despite many common features in the four countries' responses to COVID-19, the economic consequences of the pandemic are somewhat different. Due to Vietnam's success in curbing the spread of COVID-19, the Vietnamese economy is predicted not only to record positive GDP growth, but to mark the highest growth in Southeast Asia in 2020 (Asian Development Bank, 2020; Onishi, 2020). The economy

Covid Economics 67, 4 February 2021: 172-198

has already shown signs of recovery, with GDP rising 2.6% year-on-year in the third quarter of 2020. However, even in Vietnam, the youth unemployment rate is estimated to have increased by between 56 to 91 per cent, with a greater impact on the unemployment of young people than adults (International Labour Organisation and Asian Development Bank, 2020). In contrast, Peru and India are projected to record large negative GDP growth rates in 2020 and are yet to show signs of recovery (International Monetary Fund, 2020); Peru's GDP contracted by 9.4 per cent in the third quarter of 2020 compared with the same period in 2019, while India's GDP contracted by 7.5 per cent year-on-year in the second quarter of 2020 (Central Reserve Bank of Peru, 2020; ENS Economic Bureau, 2020). According to a survey of three states in India (Bihar, Rajasthan and Uttar Pradesh), just over 11 per cent of 15-to-24-year-olds stated that their worries about getting a decent job had increased during the pandemic (Population Foundation of India, 2020).

3. Data and Methodology

3.1 Data and descriptive statistics

In the following section we show descriptively how the pandemic has affected young people's lives in the four study countries of the Young Lives based on responses to the COVID-19 phone surveys. The surveys were a continuation of the Young Lives study (YL), which has been conducted in Ethiopia, India (Andhra Pradesh and Telangana), Peru and Vietnam since 2002 with almost 12,000 participants. The original 2002 YL sample was selected to include a significant coverage of poorer areas (Escobal and Flores, 2008; Kumra, 2008; Nguyen, 2008; Outes-León and Sánchez, 2008). Two cohorts of approximately 1,000 children per country born in 1994-5 (Older Cohort) and 2,000 children born in the year 2001-2 (Younger Cohort) have been visited in person every three/four years, with five rounds having been completed by 2016. One unique aspect of the cohort age set up is that it allows a comparison between the Younger Cohort and the Older Cohort at the same ages, but at different points in time. For example, we can compare the two cohorts at the age of 15 using 2016 data (round 5) for the Younger cohort and 2009 data (round 3) for the Older.

The 'Listening to Young Lives at Work': COVID-19 Phone Survey (YL COVID-19 phone survey) consists of two phone calls with each of the two cohorts, and the attrition rates of the phone survey are very low relative to other follow-up surveys on cohorts, with 93% of the sample tracked in 2019/2020 participating in the survey.[4] The first call took place between June and July 2020, and the second call took place between August and October 2020.[5] The cohorts were aged approximately 18-19 and 25-26 years in 2020. The Younger Cohort were at the same age as the Older Cohort were in round 4 of the survey (2013), and this comparison is the key to our identification of the pandemic impacts.

The YL instruments are multi-disciplinary and extensive, including household and caregiver characteristics, anthropometrics, education, health and subjective wellbeing. The phone survey by necessity included a reduced version of the core YL instruments and included new questions on experiences of and behaviour during the pandemic. It also included measures of mental health (anxiety and depression).

We restrict the analysis to those indicators that are available for both cohorts in at least two survey rounds. In particular, we investigate to what extent the pandemic affects the subjective well-being, the

[4] After 19 years, this represents 82% of the original sample.
[5] A third call took place from November-December 2020, but data are not available yet.

economic situation of the household, as measured by subjective wealth (or wealth perception) and household livelihood loss, as well as individuals' school enrolment and labour market participation. Subjective well-being has been measured in all rounds using the Cantril (1965) Self-anchoring Scale (also known as the Cantril Ladder), which asks the respondent to visualise a ladder of nine steps, with the bottom step representing the worst life and the top step representing the best possible life. Respondents are asked to identify which step they presently stand on. The ladder has been used in several studies in developing countries (Howell and Howell, 2008; Kahneman and Deaton, 2010; Clark, 2018).

In rounds 2-5 the economic situation of the household was measured by consumption and a wealth index as well as subjective wealth. Given that the former are quite time-consuming to administer, the phone survey included only the subjective wealth measure.[6] This uses a Likert scale, with 1 representing 'destitute' and 6 representing 'very rich'. We asked young people about their perception of the current wealth ranking of their household, but also asked them to give an assessment of their wealth ranking just before the pandemic began. School enrolment takes the value 1 if the respondent is enrolled in education at the point of the interview, and household livelihood loss takes the value of 1 if anyone in household has lost their job, source of income and/or family enterprise.

Table 2 presents an overview of the variables measured for both the Younger Cohort and the Older Cohort at age 19 (2020, phone survey for the Younger Cohort and 2013, Round 4, for the Older Cohort). It also presents the results of a t-test for differences in means between the Younger Cohort and the Older Cohort.

Covid Economics 67, 4 February 2021: 172-198

[6] In Round 5 of the YLS, the subjective wealth measure was significantly positively correlated (at the 1% level) with wealth quintile in all four countries. Across the countries, the average correlation was 0.33.

Table 2: Descriptive statistics of Younger and Older Cohorts at age 19

	Ethiopia				India			
	Younger Cohort		*Older Cohort*		*Younger Cohort*		*Older Cohort*	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Age (years)	18.4	0.48	19.0***	0.33	18.4	0.49	19.0***	0.35
Female	0.47	0.50	0.46	0.50	0.46	0.50	0.51***	0.50
Livelihood loss in household	0.33	0.47	0.09***	0.28	0.63	0.48	0.02***	0.14
Subjective well-being	4.79	1.58	5.18***	1.55	4.54	1.73	4.97***	1.45
School enrolment	0.68	0.47	0.61***	0.49	0.66	0.48	0.51***	0.50
Subjective wealth (YC=during pandemic)	3.47	0.80	3.48	0.86	3.39	0.72	3.48***	0.91
Subjective wealth (YC=pre-pandemic)	3.62	0.79	3.48***	0.86	3.59	0.72	3.48***	0.91
Highest education grade (YC=pre-pandemic)	9.22	2.76	8.13***	2.91	13.73	1.77	10.41***	2.71
Observations	1,665		908		1,868		953	

	Peru				Vietnam			
	Younger Cohort		*Older Cohort*		*Younger Cohort*		*Older Cohort*	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Age (years)	18.4	0.49	18.9***	0.40	18.4	0.50	19.3***	0.35
Female	0.51	0.50	0.46**	0.50	0.50	0.50	0.52	0.50
Job loss in household	0.73	0.44	0.07***	0.01	0.26	0.44	0.05***	0.22
Subjective well-being	5.80	1.73	5.97**	1.57	6.35	1.58	5.36***	1.46
School enrolment	0.41	0.49	0.56***	0.50	0.52	0.50	0.47**	0.50
Subjective wealth (YC=during pandemic)	3.61	0.57	3.39***	0.72	3.86	0.51	3.56***	0.85
Subjective wealth (YC=pre-pandemic)	3.81	0.58	3.39***	0.72	3.91	0.45	3.56***	0.85
Highest education grade (YC=pre-pandemic)	11.95	1.84	10.89***	3.26	11.97	2.41	10.50***	2.49
Observations	1,561		635		1,691		887	

Note: Younger Cohort data come from the Listening to Young Lives at Work Second Call (2020). Older Cohort data come from Young Lives Survey Round 4 (2013). Subjective wealth at age 19 was measured twice for the Younger Cohort, once during the pandemic and once as a recall measure referring to the period directly before the pandemic. The question about household livelihood loss has as time horizon 'since the last visit' for the Older Cohort and 'since the pandemic' for the Younger Cohort. Stars relate to t-tests of equality between Younger and Older Cohort means. * denotes significant at 10%, ** significant at 5% and *** significant at 1%.

3.2 Empirical approach

To quantify the impact of the COVID-19 pandemic on the lives of our study cohorts, we exploit the multi-cohort nature of YL. We compare the Younger Cohort's outcomes at age 19 (in 2020) to the Older Cohort's outcomes measured at the same age but seven years earlier (in 2013). We can account for any pre-pandemic differences in outcomes by using a specification in the spirit of a difference-in-difference estimator. For the Younger Cohort, we utilize information from 2016 (Round 5) and 2020 (Phone Survey),

Covid Economics 67, 4 February 2021: 172-198

and for the Older Cohort, we use information from 2009 (Round 3) and 2013 (Round 4). In each case, the cohort members are aged approximately 15 and 19. The following model is estimated separately for each country:

$$Y_{ica} = \alpha + \gamma a + \lambda YC_i + \theta(a * YC_i) + \beta(COVID_c * YC_i) + \delta_s + e_{ia} \quad (1)$$

Y_{ica} is the outcome of child *i* in cohort *c* at age *a*. Outcomes are self-reported subjective wellbeing, subjective wealth, a dummy for whether the household experienced any livelihood loss, a wealth assessment for the household and a dummy for whether they are enrolled in school. YC_i is a dummy variable referring to the Younger Cohort born in 2001; *a* is a trend variable referring to the age of measurement and therefore captures the age trend rather than the year in time (i.e. age 12, 15, 19 but measured 7 years apart). To allow for differing trends between cohorts in different time periods we interact the time trend with the YC_i indicator variable. This also allows us to assess whether there have been inter-cohort changes over and above the existing underlying trends. The COVID effect β is the coefficient on a dummy variable that differentiates the Younger Cohort at age 19, during the COVID-19 pandemic. We include cluster (sentinel site) fixed effects from the first visit δ_s to reflect the sampling method of the study.

There are two main caveats to interpreting this difference-in-difference specification causally. First, the Round 5 (4) data were collected several years ago in 2016 (2013), and many events, other than COVID-19, have occurred since then, so we cannot completely attribute any differences to the pandemic. However, having two observations prior to these datapoints means that we can evaluate trends as well as compare across countries. We show below that the Younger Cohort have consistently been better off at every age, and just prior to the pandemic they were also better off in observable characteristics that were not changed by the pandemic (such as highest education grade completed by January 2020). Second, it is possible that the phone survey may not yield comparable answers to an in-person survey, even to the same questions, and the pandemic itself may have affected the way that respondents answered certain questions, for example their ability to recall events/gauge severity of shocks.

A key assumption for the validity of the standard difference-in-difference estimator is that of parallel trends. In this application, this implies that the change in outcomes from age 15 to age 19 in the Older Cohort is a good proxy for the counterfactual change in potential outcomes in the Younger Cohort in the absence of the pandemic. However, this fails to account for any cohort-level improvements that differentially affect the outcomes of the Younger Cohort at the same age as the Older Cohort. In general, up to Round 5 in 2016, YL findings had been showing a cohort-level improvement in most aspects of life (Penny, 2018; Cueto and Felipe, 2017; Espinoza-Revello and Porter, 2018). We discuss this in detail below, but in the empirical specification we follow the recommendation of Bilinski and Hatfield (2019) to allow for a differential pre-COVID trend.

Covid Economics 67, 4 February 2021: 172-198

Covid Economics 67, 4 February 2021: 172-198

4. Descriptive findings from COVID-19 Phone survey

Table 3 below presents an overview of the key variables collected in the second phone survey, when the Younger Cohort was aged 19.

Table 3: Descriptive statistics – impact of COVID-19 on Younger Cohort

	Ethiopia		India		Peru		Vietnam	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Tested for COVID-19	0.07	0.25	0.10	0.29	0.15	0.36	0.05	0.22
Proportion tested positive	0.01	0.09	0.04	0.21	0.14	0.35	0.00	0.00
Belief: No risk of COVID-19	0.09	0.29	0.23	0.42	0.13	0.33	0.40	0.49
Belief: Low risk of COVID-19	0.23	0.42	0.33	0.47	0.35	0.48	0.41	0.49
Belief: Medium risk of COVID-19	0.42	0.49	0.35	0.48	0.42	0.49	0.17	0.38
Belief: High risk of COVID-19	0.25	0.44	0.10	0.30	0.10	0.30	0.02	0.13
Household income decreased	0.57	0.50	0.82	0.38	0.77	0.42	0.57	0.50
Household expenses increased	0.72	0.45	0.83	0.38	0.64	0.48	0.11	0.31
Spent more time on childcare	0.33	0.47	0.38	0.49	0.34	0.47	0.41	0.49
Spent more time on household chores	0.52	0.50	0.47	0.50	0.78	0.42	0.52	0.50
Spent more time working in business	0.16	0.37	0.10	0.30	0.16	0.37	0.15	0.36
Attending or planning to attend classes	0.78	0.41	0.66	0.47	0.82	0.38	0.92	0.27
Enrolled but classes suspended	0.21	0.40	0.29	0.45	0.01	0.10	0.00	0.00
Not enrolled and not planning to enrol	0.01	0.11	0.05	0.22	0.16	0.37	0.08	0.27
Contact with teacher during lockdown	0.13	0.33	0.42	0.49	0.80	0.40	0.76	0.42
At least symptoms of mild anxiety	0.15	0.46	0.10	0.30	0.40	0.49	0.10	0.30
At least symptoms of mild depression	0.15	0.36	0.09	0.29	0.32	0.47	0.11	0.31

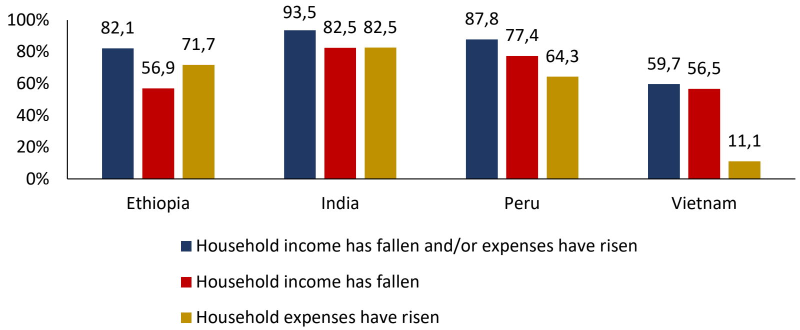
Note: Data come from the Listening to Young Lives at Work Second Call. Analysis is on the Younger Cohort only. Variables about COVID-19 risk are self-reported subjective assessments. Analysis on attending classes, enrolled but classes suspended, not enrolled, and contact with teacher are for sample who attended school sometime in 2020 only.

In three of the four study countries, the young people in our sample had largely been spared the direct health impacts of COVID-19. In Peru, the country that has been hardest hit by the pandemic, nearly 15 per cent of the Younger Cohort had been tested for the virus, with close to one-in-seven of these testing positive. In India, roughly one-in-ten of the Younger Cohort had been tested for the virus, with only 5 per cent of these testing positive. In Ethiopia and Vietnam, fewer than 10 per cent had been tested, with less than 1 per cent testing positive for the virus.

Despite the low prevalence of the virus among 19-year-olds, fears around contracting the virus were still high in Peru, Ethiopia and India. In Peru, half of the sample believed that they were at medium or high risk of contracting COVID-19, and in Ethiopia, this figure rises to nearly 7 in 10. In India, 45 per cent believed that they were at medium or high risk, while in Vietnam, given the lower spread of the virus, fears were not as high - with only one in five participants considering themselves at medium or high risk of contracting COVID-19.

One of the most common experiences across all countries was the negative impact that pandemic has had on the economic situations of households. Even in Vietnam, where the number of COVID-19 cases reported has been low, nearly 60 per cent of households report a fall in income and/or a rise in expenses. In Ethiopia, Peru, and India, these economic impacts were even more prevalent, with over 93 per cent of households in India experiencing an economic shock (Figure 1).

Figure 1: Economic shocks since the outbreak of COVID-19 on Younger Cohort



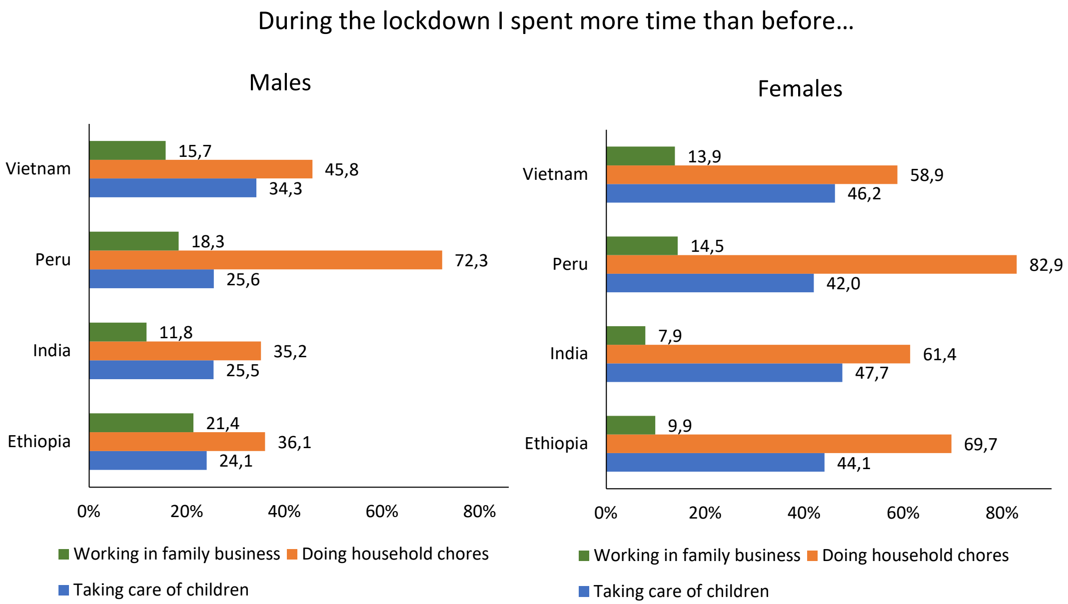
Note: Data come from the Listening to Young Lives at Work Second Call. Analysis is on the Younger Cohort only.

The degree to which those in education before the pandemic experienced interruptions has varied by country. In Peru, 16 per cent of the Younger Cohort who were engaged in formal education before the pandemic had dropped out or chosen not to enrol. One-in-four of these children dropped out as, due to quarantine, they could no longer pay the required fees. In Vietnam, the impact is only half as severe, with 8 per cent choosing not to enroll. In Ethiopia and India, the proportion who had dropped out is lower still; however, 21 and 29 per cent of those in education before the pandemic in Ethiopia and India receptively were still waiting for classes to resume. The extent of remote learning during lockdown has also varied by country. In Vietnam and Peru, nearly 8 in 10 of the 19-year-olds successfully engaged with their schoolteacher (through in-person or virtual classes, or assignments). However, in India, this dropped to 4 in 10 and, in Ethiopia, only 1 in 10 participants managed to engage in learning activities with their teacher.

The pandemic has also influenced the time use of the 19-year-olds. In all four countries, participants reported spending more time on childcare and performing more domestic work than before. Nearly 80 per cent of 19-year-old respondents in Peru reported an increase in domestic work, while in Vietnam roughly 40 per cent reported spending more time taking care of children. This increase in household and caring responsibilities fell disproportionately on females in all countries, while young men tended to work more in the family business (Figure 2). For example, in Ethiopia, 70 per cent of adolescent females reported spending more time on domestic work (compared to just 36 per cent of males) and 48 per cent of young women in India reported spending more time taking care of children (compared to 26 per cent of males). However, in Ethiopia and Peru, 21 and 18 per cent of adolescent males reported working more in the family business respectively (compared to 10 and 14 per cent of females).

Covid Economics 67, 4 February 2021: 172-198

Figure 2: Changes in time use and redistribution of household and caring responsibilities among 19-year-olds, by gender



Note: *Data come from the Listening to Young Lives at Work Second Call. Bars show the percentage of the Younger Cohort who agree or partially agree with the statements.*

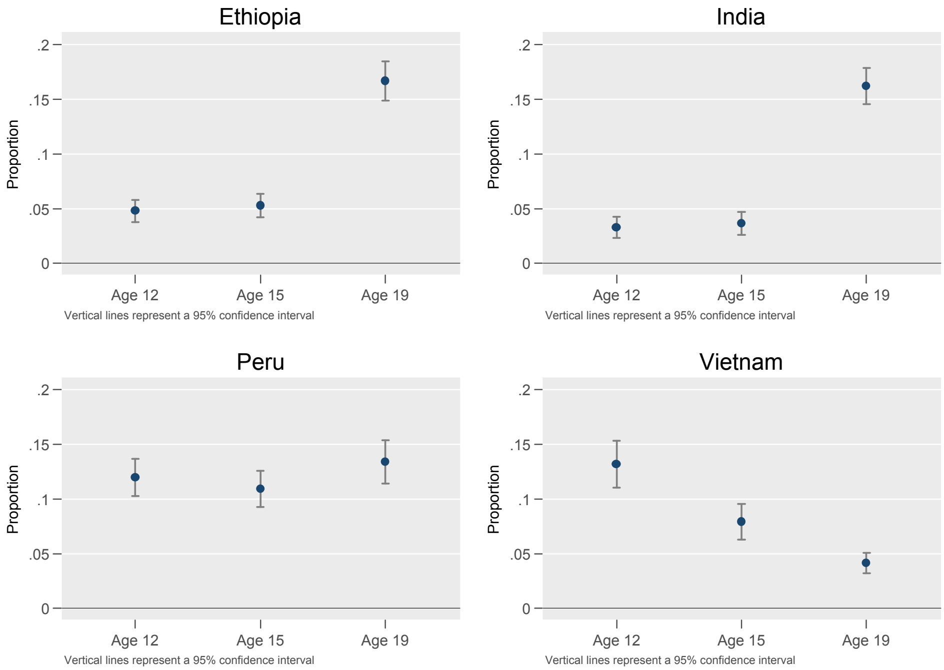
In all four countries, the pandemic resulted in adolescents entering the labour force. In Peru, one in three of those who were not working before the pandemic worked in the week before the second call. In Ethiopia, Vietnam and India, these figures were 13, 21 and 32 per cent respectively. In India and Ethiopia, the pandemic also resulted in an increase in working among school-enrolled adolescents; of those still enrolled in school in India, 18 per cent worked before the pandemic, whereas 42 per cent worked just before the second call (37 per cent and 40 per cent respectively for Ethiopia). However, in Peru and Vietnam, the pandemic resulted in fewer students working and studying; the proportion of 19-year-olds who were enrolled and working dropped from 56 and 44 per cent before the pandemic to 44 and 25 per cent, respectively.

Running out of food during the pandemic was a serious concern for respondents in at least three of the Young Lives countries. In Ethiopia and India, around 16 per cent of respondents reported that their household had run out of food since the beginning of the pandemic on one or more occasions. In Peru, this figure was around 13 per cent, while in Vietnam it was much lower – at around 4 per cent. In Ethiopia and India, this marked a significant movement away from the existing trend for this definition of food insecurity, with the proportion of households without food increasing by over 200 per cent since 2016 (Figure 3). Peru and Vietnam appear to have been less affected in terms of food security, with the increase in Peru since 2016 not statistically significant, and households in Vietnam continuing to experience

Covid Economics 67, 4 February 2021: 172-198

improvements in food security. Comparing the countries when the children were 12 years old, Peru and Vietnam had the highest incidence of running out of food, whereas at age 19 the situation is reversed.

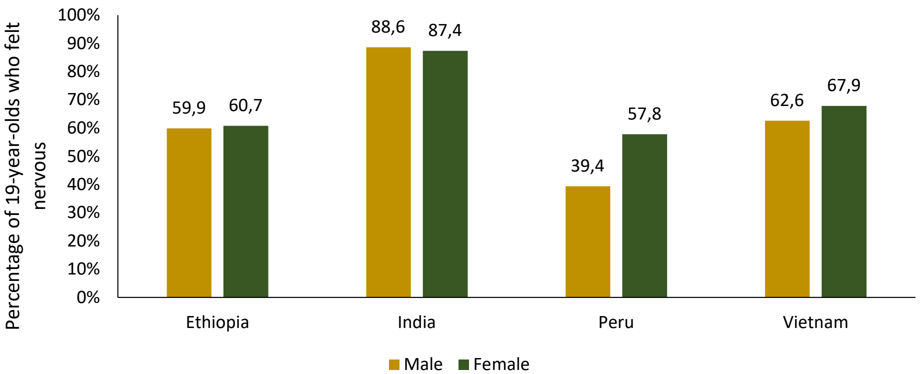
Figure 3: Proportion of households with no food to eat at ages 12, 15 and 19 (Younger Cohort only)



Note: Age 12 and Age 15 data come from YL while age 19 come from the Listening to Young Lives at Work Second Call. Analysis is on the Younger Cohort only.

The COVID-19 outbreak also increased the burden on the stress and wellbeing among the Younger Cohort. In the first call, in June/July 2020, a significant proportion of participants felt nervous about their circumstances at the time (Figure 4). We discuss the relationship between the drop in subjective wellbeing and the consequences of rising mental health issues in section 5.3 below.

Figure 4: Percentage of 19-year-olds that felt nervous about their circumstances at the time of call 1



Note: Data come from the Listening to Young Lives at Work First Call, Younger Cohort only.

It is clear that the COVID-19 pandemic has had pronounced impacts on the lives of 19-year-olds in the four study countries. The effective containment of the virus in Vietnam has paid off in terms of the wellbeing of young people in terms of their food security; however, even they have not been immune to the economic shocks and increased responsibilities that the pandemic has engendered.

In consequence, the subjective wellbeing of the cohort has fallen considerably in three of the four countries – on average, by almost a full point on a nine-point ladder scale. This finding is discussed further in section 5.2 below.

5. Cross-cohort comparison

We first document that the Younger Cohort were doing better before the pandemic, then show the loss in wellbeing during the pandemic, using the difference-in-difference framework outlined in section 3.2.

5.1 Pre-pandemic

Previous Young Lives research also shows significant inter-cohort improvements in critical aspects of human development. Comparing the two cohorts at the same age, we have seen a decline in the prevalence of stunting; in Peru, India, Ethiopia and Vietnam, stunting among the Older Cohort was 31%, 36%, 32% and 23% respectively at age 15 in 2009; among the Younger Cohort (at age 15 in 2016), these figures declined to 15%, 28%, 27% and 12% (Penny, 2018; Galab et al., 2017b; Woldehanna et al., 2017a; Espinoza et al., 2017b). In all four countries, the Younger Cohort also exhibited higher school enrolment rates at age 15, with dropout rates decreasing relative to the Older Cohort (Cueto and Felipe, 2017; Singh et al., 2017; Woldehanna et al., 2017b; Espinoza et al., 2017c). During this period, India saw the largest relative increase in school enrolment, with 91% of the Younger Cohort enrolled in school at age 15 (compared to just 78% of the Older Cohort at the same age, seven years earlier). In Peru and Vietnam, learning outcomes have also increased in tandem with enrolment, as the Younger Cohort performed relatively better at age 15 than the Older Cohort in vocabulary, reading and mathematics tests.

Espinoza-Revello and Porter (2018) found that in all countries, except Vietnam (where it remained stable), time devoted to working by 15-year-olds had decreased significantly in the seven-year gap between cohort measurement for both boys and girls and in rural and urban areas, and especially for girls and rural areas. Time spent on education was also greater for the Younger Cohort. Wellbeing of the Younger Cohort has also consistently been higher, as measured by Cantril's Ladder. In the 2020 survey, when asked about their work patterns prior to the pandemic, significantly fewer Younger Cohort members were working in Ethiopia and India than the Older Cohort at the same age (no significant difference in Peru or Vietnam).

In 2020, we also find that the higher enrolment rates have continued to translate into higher grade completion, as the highest education grade[7] completed at age 19 was still higher for the Younger Cohort than the Older Cohort (see table 2). In 2020, we also find that the higher enrolment rates have continued to translate into higher grade completion, as the highest education grade completed at age 19 was still higher for the Younger Cohort than the Older Cohort, even controlling by differential trends and pre-existing differences between both cohorts (see table 4).

Table 4: Highest education grade difference-in-difference [pre-pandemic]

	Ethiopia	India	Peru	Vietnam
Younger Cohort * 2020	0.698***	2.321***	0.490***	0.387***
	(0.10)	(0.08)	(0.08)	(0.07)
Younger Cohort	0.284**	-0.789***	0.347***	-0.521***
	(0.11)	(0.10)	(0.13)	(0.08)
Age Trend	2.471***	2.402***	2.640***	2.470***
	(0.05)	(0.05)	(0.07)	(0.04)
Younger Cohort * Age Trend	0.062	0.588***	0.090	0.505***
	(0.07)	(0.06)	(0.08)	(0.05)
Constant	2.578***	3.646***	3.165***	3.606***
	(0.12)	(0.10)	(0.14)	(0.09)
Cluster Fixed Effects	Yes	Yes	Yes	Yes
Observations	8,060	8,437	7,540	8,226
Number of individuals	2,862	2,915	2,640	2,964

Note: Robust standard error in parenthesis. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. Age Trend equals captures ages 12, 15 and 19.

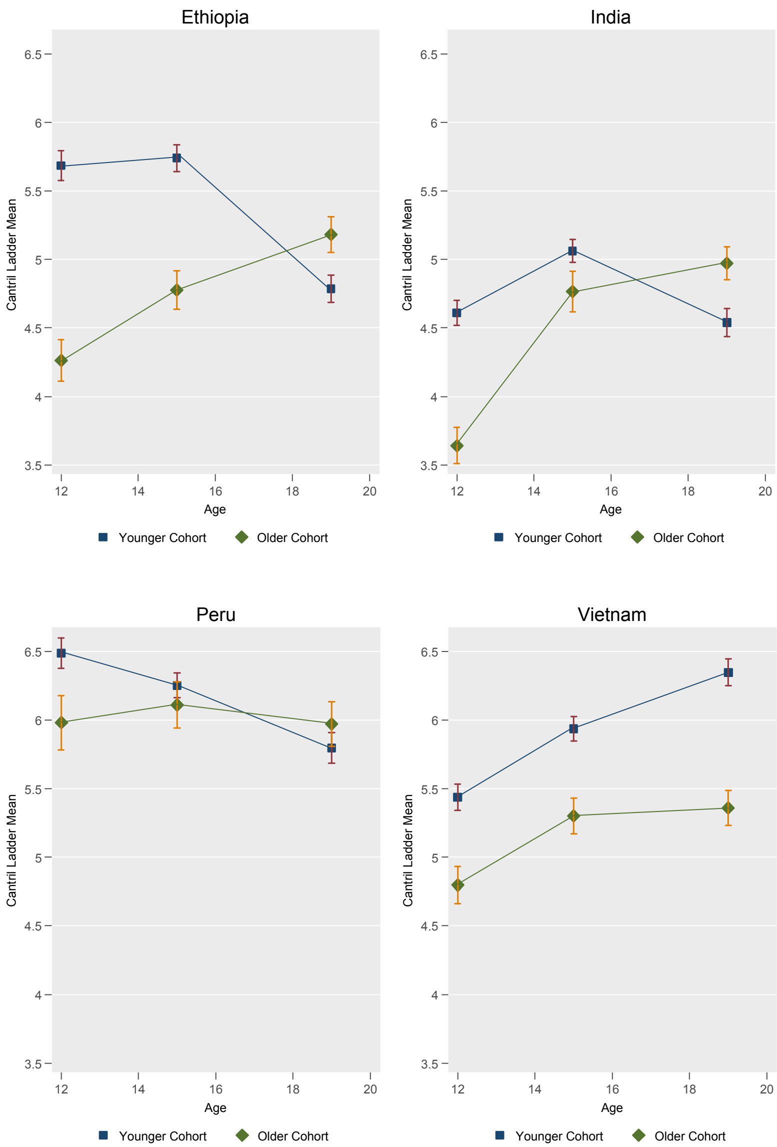
5.2 Wellbeing, wealth, job loss and education during the pandemic

Figure 5 depicts a striking fall in relative wellbeing of the Younger Cohort when compared to the Older Cohort at the same age, particularly for Ethiopia and India. In Peru, wellbeing of the Younger Cohort was also higher and the relative position of the two cohorts has reversed, though confidence intervals overlap. Before 2020, the Younger Cohort had higher wellbeing at the same ages of 12 and 15 in all

[7] Highest education grade is defined such that, beyond high school grades (which are coded as is), undergraduate university degree is coded as 14 years of education and master's/doctorate degree is assigned 15. Post-secondary vocational/technical/pedagogical education is assigned a value of 13. In Peru, Centros Técnico Productivo (CETPRO) is coded the same as grade 12. This definition is adopted for comparability across all four countries.

countries. The exception is Vietnam, where the gap between Younger and Older Cohort has continued to increase.

Figure 5: Subjective well-being at ages 12, 15 and 19



Note: Vertical bars represent 99 per cent confidence intervals around mean values.

Covid Economics 67, 4 February 2021: 172-198

We can test whether the reversal in fortunes shown in the graph is statistically significant using a difference-in-difference framework as described in section 3.2 and the results are shown in table 5.

Table 5: Subjective well-being difference-in-difference

	Ethiopia	India	Peru	Vietnam
Younger Cohort * 2020	-1.012***	-0.968***	-0.219**	-0.093
	(0.09)	(0.08)	(0.09)	(0.09)
Younger Cohort	1.802***	1.038***	0.703***	0.353***
	(0.13)	(0.11)	(0.15)	(0.11)
Age Trend	0. 457***	0.671***	-0.003	0.286***
	(0.04)	(0.04)	(0.05)	(0.04)
Younger Cohort * Age Trend	-0.403**	-0.219***	-0.234***	0.212***
	(0.07)	(0.04)	(0.07)	(0.06)
Constant	3.492***	3.616***	6.412***	4.509***
	(0.12)	(0.11)	(0.14)	(0.10)
Cluster Fixed Effects	Yes	Yes	Yes	Yes
Observations	8,190	8,552	7,215	8,380
Number of individuals	2,862	2,915	2,640	2,964

*Note: Robust standard error in parenthesis. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. Age Trend equals captures ages 12, 15 and 19.*

Even when controlling for differential pre-existing trends, we see a large fall in relative wellbeing in the Younger Cohort versus the Older Cohort at the same age for all countries except Vietnam. Thus, it is not a case of 'business as usual'. The relatively higher wellbeing of the Younger Cohort was already diminishing over time in Ethiopia, India and Peru (Younger Cohort * Age Trend coefficients), but the magnitude of the drop in 2020 is considerably higher especially in Ethiopia and India. The descriptive results presented in section 4 already point to a number of areas of concern that would explain a drop in relative wellbeing for this cohort, including the high reports of economic shocks, worsening food security, illness and increased health expenses (particularly in Peru), fears of infection, and interruptions in education.

In table 6 we compare shocks to household livelihoods in terms of job losses and losses in the source of income (for example collapse of the family enterprise) in the household across cohorts using the difference-in-difference methodology, since a comparable question was asked in 2009, 2013 and 2016. The main difference is that in earlier rounds a longer recall period was used – whether any household member lost their job since the previous visit, whereas in the 2020 phone survey we asked about job loss since the pandemic began. We might expect that the longer recall period of the former would bias our results downwards. However, the difference-in-difference results show that in all countries the Younger Cohort are more likely to report a job/income loss in the household, with an increase ranging from 28 percentage points in Vietnam to 61 percentage points in Peru, which may even be a lower bound of the effect.

Covid Economics 67, 4 February 2021: 172-198

Table 6: Household Livelihood Loss difference-in-difference

Job/Livelihood loss				
	Ethiopia	**India**	**Peru**	**Vietnam**
Younger Cohort * 2020	0.314***	0.600***	0.610***	0.281***
	(0.02)	(0.01)	(0.02)	(0.01)
Younger Cohort	-0.001	0.011	0.043**	0.086***
	(0.02)	(0.01)	(0.02)	(0.01)
Age Trend	-0.005	0.005*	0.022***	0.015***
	(0.01)	(0.00)	(0.01)	(0.00)
Younger Cohort * Age Trend	-0.027***	-0.000	0.008	-0.054***
	(0.01)	(0.01)	(0.01)	(0.01)
Constant	0.146***	0.012	-0.005	-0.018
	(0.02)	(0.01)	(0.02)	(0.01)
Cluster Fixed Effects	Yes	Yes	Yes	Yes
Observations	8,141	8,305	7,982	8,323
Number of individuals	2,862	2,915	2,640	2,964

*Note: Robust standard error in parenthesis. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. Age Trend equals captures ages 12, 15 and 19.*

Next, we assess the change in educational enrolment of the cohort members. Descriptive results showed that many of the 19-year-olds were unable to continue engaging with their education when educational establishments were closed down in all four countries. Table 7 below shows that, in all countries, the Younger Cohort experience a significant fall in relative enrolment loss compared to the Older Cohort at age 19. The results are robust to the inclusion of exact age as well as age of starting primary school. The magnitude of both the relative reduction in enrolment and the relative rise in job losses is largest in Peru and smallest in Vietnam, mirroring the extent of the pandemic in the two countries.

Table 7: Educational enrolment difference-in-difference

Enrolment				
	Ethiopia	**India**	**Peru**	**Vietnam**
Younger Cohort * 2020	-0.209***	-0.136***	-0.530***	-0.123***
	(0.02)	(0.02)	(0.02)	(0.02)
Younger Cohort	-1.155***	-0.054**	-0.195***	-0.080***
	(0.02)	(0.02)	(0.02)	(0.02)
Age Trend	-1.157***	-0.191***	-0.196***	-0.241***
	(0.01)	(0.01)	(0.01)	(0.01)
Younger Cohort * Age Trend	0.131***	0.105***	0.169***	0.079***
	(0.01)	(0.01)	(0.01)	(0.01)
Constant	1.204***	1.139***	1.226***	1.281***
	(0.02)	(0.02)	(0.02)	(0.02)
Cluster Fixed Effects	Yes	Yes	Yes	Yes
Observations	8,135	8,588	7,312	8,073
Number of individuals	2,862	2,915	2,640	2,964

Note: Robust standard error in parenthesis. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. Age Trend equals captures ages 12, 15 and 19.

Covid Economics 67, 4 February 2021: 172-198

In terms of the respondent's own job position, the effects are somewhat mixed. Prior to the pandemic, a third of the India Younger Cohort were working, rising to 40, 58 and 60 percent in Ethiopia, Peru and Vietnam respectively. In India there is a large increase in the proportion working, to 47 percent, but in Peru and Vietnam the proportion falls, by five and twelve percentage points respectively. In Ethiopia there were no overall employment differences. We do not have comparable data on employment for the Older Cohort before 2013, so are unable to undertake a difference-in-difference analysis.

In the phone survey, we asked young people about their perception of the current wealth ranking of their household, but also asked them to give an assessment of their wealth ranking just before the pandemic began. We exploit this pre-pandemic 2020 wealth ranking to run two separate difference-in-differences, one using the pre-pandemic wealth and one using the mid-pandemic wealth. Comparing the two regressions allows us to approximate the impact of the pandemic on the relative change in wealth, with the caveat that the pre-pandemic wealth is a recall question asked during the pandemic, and we may expect some bias.

Table 8: Subjective wealth difference-in-difference before and during the pandemic

	Ethiopia		**India**		**Peru**		**Vietnam**	
	Before	*During*	*Before*	*During*	*Before*	*During*	*Before*	*During*
Younger Cohort * 2020	0.179***	0.025	0.121***	-0.079*	0.383***	0.183***	0.304***	0.254***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Younger Cohort	0.252***	0.251***	0.082	0.082	0.171***	0.171***	-0.472***	-0.472***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)
Age Trend	0.076***	0.075***	0.046**	0.046**	0.150***	0.150***	-0.120***	-0.120***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Younger Cohort * Age Trend	-0.122***	-0.121***	-0.041	-0.041	-0.112***	-0.112***	0.157***	0.157***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Constant	3.117***	3.116***	3.623***	3.641***	3.270***	3.248***	4.001***	4.018***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)
Cluster Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,218	8,218	8,609	8,609	7,924	7,924	8,433	8,433
Number of individuals	2,862	2,862	2,915	2,915	2,640	2,640	2,964	2,964

Note: Robust standard error in parenthesis. * denotes significant at 10%, ** significant at 5% and *** significant at 1%. Age Trend equals captures ages 12, 15 and 19.

Comparing the Younger Cohort*2020 coefficients before and during the pandemic, we can see that the Younger Cohort considered themselves to be worse off during the pandemic than before the pandemic, in all countries except Vietnam.[8] In Ethiopia, before the pandemic, the Younger Cohort were better off relative to the Older Cohort than they were at age 15; however, this progress had been eradicated by the effects of the pandemic. In India, the result is even more extreme, with the Younger Cohort's pre-pandemic progress being reversed such that, relative to the Older Cohort, they are now worse off at age 19 than they were at age 15. In Peru and Vietnam, the Younger Cohort were still relatively better off at age 19 during the pandemic than they were at age 15; however, in Peru the progress had been drastically

[8] In Vietnam, although the point estimate declines, the difference between before the pandemic and during the pandemic is not statistically significant.

Covid Economics 67, 4 February 2021: 172-198

reduced (by 51 per cent) comparing pre- and during the pandemic. In Vietnam, the country least affected by COVID-19, the difference between before and during pandemic is not statistically significant.

In section 5.1 we showed that the Younger Cohort had attained higher levels of education than the Older cohort by the age of 19. We can also interpret the Younger Cohort*Age Trend coefficients in the wellbeing, enrolment and household livelihood loss results above to determine whether the Younger Cohort were improving relative to the Older Cohort at age 15, relative to age 12 (i.e. whether the pre-2020 trend was favouring the Younger Cohort). In the enrolment regressions, the Younger Cohort* Age Trend coefficient is positive (and statistically significant) in all countries, suggesting that the Younger Cohort were becoming relatively better off as they age. This progress has now been reduced in all four countries. In the household livelihood loss regressions, the coefficients on Younger Cohort*Age Trend are negative in Ethiopia and Vietnam, suggesting that the Younger Cohort were becoming relatively less likely to experience a job loss in the household. This has now been reversed, with the Younger Cohort being relatively more likely to experience a livelihood loss in the household at age 19. For the subjective wealth results, there is a negative relative trend for the Younger Cohort in Ethiopia and Peru, suggesting that the (positive) wealth gap was narrowing with the Older Cohort.

5.3 Potential long-term consequences

The results above show a worsening of the life-chances of a cohort of young people affected by a global pandemic at a crucial time in their life. These results are, by definition, short-term, and future rounds of the Young Lives survey will be able to examine how permanent the effects of the pandemic have been. We consider two potential pathways suggesting that consequences may be long-lasting: the correlation between subjective wellbeing and mental health, and the effects of school dropout on later life-outcomes.

A crisis leading to a sharp drop in wellbeing may also have mental health consequences, and a body of evidence documents a vicious cycle between poverty and mental health (Haushofer and Fehr, 2014). Ridley et al. (2020) also document this bi-causal relationship and review the evidence that mental health issues have long term consequences especially in terms of future employment. Recent evidence from the UK has shown that young people and especially young women suffered deteriorations in mental health during Covid-19 lockdowns (Banks and Xu, 2020).

The 2020 survey measured mental health in Young Lives participants for the first time, using two validated instruments, the Generalized Anxiety Disorder-7 (GAD-7) questionnaire and Patient Health Questionnaire-8 (PHQ-8) for depression. The GAD-7 can range from 0 to 21, while the PHQ-8 can range from 0 to 24. For both scales, a score above 4 represents at least mild anxiety/depression respectively (Spitzer et al., 2006; Kroenke et al., 2009). There are no comparable data for the Older Cohort, nor previous data for the Younger Cohort. In table 9 we show the prevalence of mild anxiety and depression measured in 2020, and a t-test of the change in subjective wellbeing between 2016 and 2020 comparing individuals reporting symptoms consistent with (at least mild) depression and anxiety, with those who did not. These are associations and not causal, though we consider them to be suggestive. Given that there is little support available for mental health issues in any of the four countries, the danger is that symptoms become worse if untreated, and poor mental health affects later life employment or other life outcomes.

Covid Economics 67, 4 February 2021: 172-198

Table 9: Relationship between change in Cantril ladder and mental health

	Ethiopia				India			
	Mild depression	No depression	Mild anxiety	No anxiety	Mild depression	No depression	Mild anxiety	No anxiety
Prevalence (%)	14.79	85.21	14.99	85.01	9.21	90.79	9.74	90.26
Mean ladder change	-1.10	-0.99	-1.10	-0.99	-0.81	-0.49**	-0.81	-0.49**

	Peru				Vietnam			
	Mild depression	No depression	Mild anxiety	No anxiety	Mild depression	No depression	Mild anxiety	No anxiety
Prevalence (%)	32.22	67.78	40.10	59.90	10.53	89.47	10.00	90.00
Mean ladder change	-0.69	-0.43**	-0.71	-0.38***	-0.25	0.45***	-0.27	0.44***

Note: Mild depression (anxiety) refers to having a PHQ-8 (GAD-7) score over 4, indicating at least mild depression (anxiety). Mean ladder change refers to the mean Cantril ladder in Call 2 (2020) minus the mean ladder in Round 5 (2016). A negative change indicates that the ladder score has declined between 2016 and 2020. Stars relate to t-tests of equality between mild depression (anxiety) and no depression (anxiety) means. * denotes significant at 10%, ** significant at 5% and *** significant at 1%.

The table shows that Peru has very high rates of both depression and anxiety symptoms, and Vietnam much lower rates, which is reflective of the pandemic experiences of the two countries. In all countries except Ethiopia, those who were currently displaying symptoms consistent with at least mild depression (anxiety) had experienced a significantly greater fall in their subjective wellbeing. In all countries, the absolute value of the "ladder" reported subjective wellbeing in 2020 was also significantly lower for those with mental health issues.

Second, we can examine the consequences of school dropout by looking at the trajectories of Older Cohort participants who had dropped out of school by age 19. Among the Older Cohort, children from disadvantaged backgrounds were disproportionately more likely to drop out of school than their peers (Cueto et al., 2016). This trend appears to have been exacerbated by the pandemic as children are being forced to drop out of school due to fee payment difficulties, and poorer students are less likely to engage in online learning. This has important consequences for the life trajectories of the adolescents; previous Young Lives research on the Older Cohort indicates that young girls who dropped out of school were more likely to get married and have a child during adolescence than those who were still studying (Favara et al., 2018). These individuals also have lower aspirations to complete university than their peers. This suggests that the potential increase in school dropout rates due to COVID-19 may have long-lasting consequences that affect the earnings potential and socio-economic status of the Young Lives participants.

6. Conclusion

We examined the effects of the COVID-19 pandemic and related economic crisis on the lives of adolescents in four LMICs by comparing them to a cohort born seven years earlier and surveyed at similar ages using the same survey instruments. The effects are evident across several dimensions of wellbeing, including the adversity experienced by their family (illness and expenses, having no food to eat, family

Covid Economics 67, 4 February 2021: 172-198

member losing job). The young people's lives have been affected in particular with regard to their own time use, with girls particularly harder hit by the increase in responsibilities.

The pandemic has engendered losses in learning and likely cognitive development for today's young generation, with potentially significant long-term implications. Survey work planned for 2021 will allow us to examine how long-term the effects of the pandemic have been, though we suggest at least two reasons for pessimism without external intervention. In particular, the findings suggest a need to support those who are unable to engage or drop out from education early, and mental health support especially in Peru.

References:

Asian Development Bank. 2020. Asian Development Outlook 2020, What Drives Innovation In Asia? Special Topic: The Impact of the Coronavirus Outbreak—An Update. Mandaluyong City, Philippines.

Banati, P., Jones, N. and Youssef, S. Intersecting Vulnerabilities: The Impacts of COVID-19 on the Psycho-emotional Lives of Young People in Low- and Middle-Income Countries. The European Journal of Development Research. DOI: https://doi.org/10.1057/s41287-020-00325-5

Banks J. and Xu, X. 2020. The mental health effects of the first two months of lockdown and social distancing during the Covid-19 pandemic in the UK. *Covid Economics*, 28: 91-118.

Bilinski, A. and Hatfield, L. A. 2019. Nothing to see here? Non-inferiority approaches to parallel trends and other model assumptions. Available: https://arxiv.org/pdf/1805.03273.pdf

Cantril H. 1965. The pattern of human concerns: New Brunswick, N. J.: Rutgers University Press.

Central Reserve Bank of Peru. 2020. Nota Semanal N° 42. Available: https://www.bcrp.gob.pe/docs/Publicaciones/Nota-Semanal/2020/ns-42-2020.pdf

Chikoti, L., Caruso, D. G., Vundru, W. D., Ilukor, J., Kanyanda, S. S. E., Kanyuka, M., Kilic, T., Mleme, T., Moylan, H. G., Mvula-Lazovic, S., Mwale, I., Mwalwanda, T. and Yoshida, N. 2020. *Monitoring COVID-19 Impacts on Households in Malawi: Findings from the Third Round of the High-Frequency Phone Survey (English).* Washington, D.C.: World Bank Group. http://documents.worldbank.org/curated/en/245741604553607232/Findings-from-the-Third-Round-of-the-High-Frequency-Phone-Survey

Clark, A. E. "Four decades of the economics of happiness: Where next?" Review of Income and Wealth 64.2 (2018): 245-269.

Cueto, S. and Felipe, C. 2017. Education and Learning: Preliminary Findings from the 2016 Young Lives Survey (Round 5): Peru. Round 5 Survey Fact Sheet, Oxford: Young Lives.

Cueto, S., Singh, R., Woldehanna, T. and Duc, L. T. 2016. Education Trajectories in Ethiopia, India, Peru and Vietnam: From Early Childhood to Early Adulthood. Policy Brief 30, Oxford: Young Lives.

Covid Economics 67, 4 February 2021: 172-198

ENS Economic Bureau. 2020. GDP shrinks 7.5% in Q2; manufacturing picks up, services sector worst hit. Available: https://indianexpress.com/article/business/economy/indian-economy-gdp-manufacturing-service-sector-7071242/

Escobal J, Flores E. An Assessment of the Young Lives Sampling Approach in Peru. Oxford: Young Lives, 2008.

Espinoza, P., Benny, L., Duc, L. T., Hang, N. T. T. 2017a. Poverty and Intergenerational Change: Preliminary Findings from the 2016 Young Lives Survey (Round 5): Viet Nam. Round 5 Survey Fact Sheet, Oxford: Young Lives.

Espinoza, P., Benny, L., Duc, L. T., Hang, N. T. T. 2017b. Growth and Nutrition: Preliminary Findings from the 2016 Young Lives Survey (Round 5): Viet Nam. Round 5 Survey Fact Sheet, Oxford: Young Lives.

Espinoza, P., Benny, L., Duc, L. T., Hang, N. T. T. 2017c. Education and Learning: Preliminary Findings from the 2016 Young Lives Survey (Round 5): Viet Nam. Round 5 Survey Fact Sheet, Oxford: Young Lives.

Espinoza-Revollo, P. and Porter, C. 2018. Evolving Time Use of Children Growing Up in Ethiopia, India, Peru and Vietnam, 2006-2016. Young Lives, Working Paper 180.

Favara, M., Ellanki, R., Molina, M. A., Porter, C. and Scott, D. 2020. 'Listening to Young Lives at Work in India: Second Call: Young Lives COVID-19 Phone Survey Headlines Report', https://www.younglives.org.uk/sites/www.younglives.org.uk/files/YOL-India-Headlines-PhoneSurvey2-Nov20.pdf

Favara, M., Chang, G. and Sánchez, A. 2018. No longer children: What do Young Lives children do when they grow up? Transitions to post-secondary education and the labour market, Research Report, Oxford: Young Lives.

Galab, S., Reddy, P., Singh, R. and Mukherjee, P. 2017a. Poverty and Intergenerational Change: Preliminary Findings from the 2016 Young Lives Survey (Round 5): United Andhra Pradesh. Round 5 Survey Fact Sheet, Oxford: Young Lives.

Galab, S., Reddy, P., Singh, R. and Mukherjee, P. 2017b. Growth and Nutrition: Preliminary Findings from the 2016 Young Lives Survey (Round 5): United Andhra Pradesh. Round 5 Survey Fact Sheet, Oxford: Young Lives.

Haushofer, J. and Fehr, E. (2014). On the psychology of poverty. Science, 344(6186), 862-867.

Howell, R. T., and Howell, C. J. (2008). The relation of economic status to subjective well-being in developing countries: A meta-analysis. Psychological Bulletin, 134(4), 536–560. https://doi.org/10.1037/0033-2909.134.4.536

International Labour Organisation. 2020a. Youth and COVID-19: Impact on Jobs, Education, Rights and Mental Well-being. Geneva, September.

International Labour Organisation. 2020b. ILO Monitor: COVID-19 and the world of work. Fourth edition Updated estimates and analysis.

Covid Economics 67, 4 February 2021: 172-198

International Labour Organization. 2020c. ILOSTAT database [database]. Available from https://ilostat.ilo.org/data/

International Labour Organization and Asian Development Bank. 2020. Tackling the COVID-19 youth employment crisis in Asia and the Pacific. Bangkok (Thailand), and Manila (Philippines).

International Monetary Fund. 2020. World Economic Outlook: A Long and Difficult Ascent. Washington, DC, October 2020.

International Monetary Fund. 2017. World GDP per Capita Ranking 2017. http://ethiopia.opendataforafrica.org/sijweyg/world-gdp-per-capita-ranking2017-data-and-charts-forecast

Kahneman, D. and A. Deaton, 2010. "High Income Improves Evaluation of Life but not Emotional Well-Being," Proceedings of the National Academy of Science, 107, 16489–493, 2010.

Kroenke, K., Strine, T.W., Spitzer, R.L., Williams, J.B., Berry, J.T. and Mokdad, A.H. The PHQ-8 as a measure of current depression in the general population. J Affect Disord 2009; **114**(1-3): 163-73.

Kumra N. An Assessment of the Young Lives Sampling Approach in Andhra Pradesh, India. Oxford: Young Lives, 2008.

Major, L. E., Eyles, A. and Machin, S. 2020. Generation COVID: Emerging work and education inequalities. A CEP Covid-19 analysis, Paper No.011.

Nguyen, N.P. 2008. An Assessment of the Young Lives Sampling Approach in Vietnam. Oxford: Young Lives.

Onishi, T. 2020. Vietnam Q3 GDP improves to 2.6% growth on rising exports. Available: https://asia.nikkei.com/Economy/Vietnam-Q3-GDP-improves-to-2.6-growth-on-rising-exports

Outes-León, I. and Sánchez, A. 2008. An Assessment of the Young Lives Sampling Approach in Ethiopia. Oxford: Young Lives.

Penny, M. 2018. Growth and Nutrition: Preliminary Findings from the 2016 Young Lives Survey (Round 5): Peru. Round 5 Survey Fact Sheet, Oxford: Young Lives.

Population Foundation of India. 2020. Impact of COVID-19 on young people: Rapid assessment in three states, May 2020 (Bihar, Rajasthan and Uttar Pradesh).

Porter, C., Woldehanna, T., Freund, R., Favara, M. and Scott, D. 2020. 'Listening to Young Lives at Work in Ethiopia: Second Call: Young Lives COVID-19 Phone Survey Headlines Report', https://www.younglives.org.uk/sites/www.younglives.org.uk/files/YOL-Ethiopia-Headlines-PhoneSurvey2-Nov20.pdf

Ridley, M., Rao, G., Schilbach, F. and Patel, V. Poverty, depression, and anxiety: Causal evidence and mechanisms. Science 2020; **370**(6522).

Covid Economics 67, 4 February 2021: 172-198

Roser, M., Ritchie, H., Ortiz-Ospina, E. and Hasell, J. 2020. Coronavirus Pandemic (COVID-19). Published online at OurWorldInData.org. Retrieved from: https://ourworldindata.org/coronavirus

Sánchez, A., Cueto, S., Penny, M., López, J. and Lago, N. 2020. 'Listening to Young Lives at Work in Peru: Second Call: Young Lives COVID-19 Phone Survey Headlines Report', https://www.younglives.org.uk/sites/www.younglives.org.uk/files/YOL-Peru-Headlines-PhoneSurvey2-Nov20-2%2023rd%20.pdf

Sánchez, A. and Pazos, N. 2017. Poverty and Intergenerational Change: Preliminary Findings from the 2016 Young Lives Survey (Round 5): Peru. Round 5 Survey Fact Sheet, Oxford: Young Lives.

Scott, D., Le Thuc, D., Hittmeyer, A., Favara, M. and Porter, C. 2020. 'Listening to Young Lives at Work in Vietnam: Second Call: Young Lives COVID-19 Phone Survey Headlines Report', https://www.younglives.org.uk/sites/www.younglives.org.uk/files/YOL-Vietnam-Headlines-PhoneSurvey2-Nov20.pdf

Singh, R., Reddy, P., Galab, S., and Mukherjee, P. 2017. Education and Learning: Preliminary Findings from the 2016 Young Lives Survey (Round 5): United Andhra Pradesh. Round 5 Survey Fact Sheet, Oxford: Young Lives.

Snape, M. D., & Viner, R. M. (2020). COVID-19 in children and young people. Science, 370(6514), 286-288.

Spaull, N., Oyenubi, A., Kerr, A., Maughan-Brown, B., Ardington, C., Christian, C., Sheperd, D., Casale, D., Espi, G., Wills, G., Bridgman, G., Bhorat, H., Turok, I., Bassier, I., Kika-Mistry, J., Kotze, J., Budlender, J., Visagie, J., Ingle, K., Rossouw, L., Patel, L., Benhura, M., Leibbrandt, M., Mohohlwane, N., Magejo, P., English, R., Daniels, R. C., Hill, R., Zizzamia, R., Jain, R., Burger, R., Taylor, S., van der Berg, S., Köhler, T., Brophy, T., Kollamparambil, U. and Ranchhod, V. NIDS-CRAM Wave 2 Synthesis Findings. Available: https://cramsurvey.org/wp-content/uploads/2020/10/1.-Spaull-et-al.-NIDS-CRAM-Wave-2-Synthesis-Report.pdf

Spitzer, R.L., Kroenke, K., Williams, J.B. and Lowe, B. A brief measure for assessing generalized anxiety disorder: the GAD-7. Arch Intern Med 2006; **166**(10): 1092-7.

Thomas, H., Angrist, N., Cameron-Blake, E., Hallas, L., Kira, B., Majumdar, S., Petherick, A., Phillips, T., Tatlow, H. and Webster, S. 2020. Oxford COVID-19 Government Response Tracker, Blavatnik School of Government.

United Nations. 2020. Policy Brief: The Impact of COVID-19 on children.

Wieser, C., Ambel, A. A., Bundervoet, T. and Haile, A. *Monitoring COVID-19 Impacts on Households in Ethiopia: Results from a High-Frequency Phone Survey of Households, Round 4.* Washington, D.C.: World Bank Group. https://openknowledge.worldbank.org/bitstream/handle/10986/34581/Monitoring-COVID-19-Impacts-on-Households-in-Ethiopia-Results-from-a-High-Frequency-Phone-Survey-of-Households-Round-4.pdf?sequence=1&isAllowed=y

Woldehanna, T., Araya, M. and Pankhurst, A. 2018. Poverty and Intergenerational Change: Preliminary Findings from the 2016 Young Lives Survey (Round 5): Ethiopia. Round 5 Survey Fact Sheet, Oxford: Young Lives.

Woldehanna, T., Araya, M. and Pankhurst, A. 2017a. Growth and Nutrition: Preliminary Findings from the 2016 Young Lives Survey (Round 5): Ethiopia. Round 5 Survey Fact Sheet, Oxford: Young Lives.

Woldehanna, T., Araya, M. and Pankhurst, A. 2017b. Education and Learning: Preliminary Findings from the 2016 Young Lives Survey (Round 5): Ethiopia. Round 5 Survey Fact Sheet, Oxford: Young Lives.

Covid Economics 67, 4 February 2021: 172-198

Macroepidemics and unconventional monetary policy: Coupling macroeconomics and epidemiology in a financial DSGE-SIR framework[1]

Verónica Acurio Vásconez,[2] Olivier Damette[3] and David W. Shanafelt[4]

Date submitted: 28 January 2021; Date accepted: 1 February 2021

Covid Economics 67, 4 February 2021: 199-253

Despite the fact that the current covid-19 pandemic was neither the first nor the last disease to threaten a pandemic, only recently have studies incorporated epidemiology into macroeconomic theory. In our paper, we use a dynamic stochastic general equilibrium (DSGE) model with a financial sector to study the economic impacts of epidemics and the potential for unconventional monetary policy to remedy those effects. By coupling a macroeconomic model to a traditional epidemiological model, we are able to evaluate the pathways by which an epidemic affects a national economy. We find that no unconventional monetary policy can completely remove the negative effects of an epidemic crisis, save perhaps an exogenous increase in the shares of claims coming from the Central Bank ("epi loans"). To the best of our knowledge, our paper is the first to incorporate disease dynamics into a DSGE-SIR model with a financial sector and examine the effects of unconventional monetary policy.

1 All remaining errors are ours.

2 Associate Professor, Université de Lorraine, Université de Strasbourg, Centre National de la Recherche Scientifique (CNRS), Bureau d'Économie Théorique et Appliquée.
3 Professor, Université de Lorraine, Université de Strasbourg, CNRS, BETA.
4 Research Scientist, Université de Lorraine, Université de Strasbourg, AgroParisTech, CNRS, INRAE, BETA.

1 Introduction

The economic effects of the COVID-19 pandemic are unprecedented, far-reaching, and extend to virtually every member of the global market. Global growth was projected at minus 4.9 percent in 2020, and at 6 percent to 7.6 percent depending on the emergence of a second wave (IMF (2020)). COVID-19 was not the first emerging zoonotic or epizoonic disease to threaten a pandemic (Boissay and Rungcharoenkitkul (2020), LePan (2020)), nor will it be the last (Daszak et al. (2001), Jones et al. (2008), Wu et al. (2017)).

Prior to the COVID-19 pandemic, few studies incorporated epidemiology into macroeconomic theory, though this was not the case in microeconomics (see Horan and Wolf (2005), Horan and Fenichel (2007), Fenichel et al. (2011), Lenhart and Workman (2007), Morin et al. (2014), and Morin et al. (2015) for examples). Recent studies have examined the potential economic impacts of pandemics on a macroeconomic scale using Susceptible-Infected-Recovered (SIR) epidemiological models in the line with the macro model developed by Eichenbaum et al. (2020b). However, the role of financial intermediaries in coupled epidemic-economic frameworks has yet to be studied. In addition, previous papers have not focused on the effect of economic remedies - in the form of monetary policies - to reduce the economic burden of epidemics.

In this paper, we use a dynamic stochastic general equilibrium (DSGE) model as in Smets and Wouters (2007), but with a financial sector as in Gertler and Karadi (2011) (GK hereafter), to study the economic effects of an epidemic and the ability of monetary policy to remedy the crisis. Thus, our model is a financial DSGE-SIR model. To the best of our knowledge, we are the first to incorporate SIR dynamics into a DSGE model with a financial sector. Using the GK framework enables us to account for the financial sector of the economy and to assess the efficiency of unconventional monetary policy to combat the economic burdens of an epidemic. It enables us to

Covid Economics 67, 4 February 2021: 199-253

Covid Economics 67, 4 February 2021: 199-253

investigate different recovery paths of the economy following shocks to the system, including an epidemic crisis. For instance, the GK model was used to extensively examine the effects of unconventional monetary policy on macroeconomic outputs following the subprime crisis (Gertler and Karadi (2011), Dedola et al. (2013), Gelain and Ilbas (2017)). Gertler and Karadi (2011) showed that when there is a financial crisis (understood as a negative shock in the quality of capital), the stronger the reaction by the Central Bank, and the smaller the total losses in GDP. In comparison to a simpler model without financial frictions *à la Smet-Wouters*, our financial DSGE-SIR model enables us to study macro-financial feedback loops.

We evaluate the effects of unconventional monetary policy, in particular a form of quantitative easing (QE) or "*epi loans*" policy. We model "*epi loans*" as a Central Bank liquidity injection into the real sector in the form of claims that do not pass-through private banks, similar to those that followed the sub-prime crisis in Europe. This measure can be understood as a light form of "helicopter money" (Friedman (1969)), in the sense that the injected liquidity goes directly to the real sector without direct involvement of fiscal authorities or private banks. However, contrary to"helicopter money", our "*epi loans*" policy must be repaid, thus changing the Central Bank balance sheet by increasing its assets. Further, while "helicopter money" may be highly inflationist, there is no proof that QE policies are, at least not in developed countries (Qianying et al. (2016), Albertazzi et al. (2018), Baumeister and Benati (2013)). In this regard, the Central Bank behaves as last resort lender for the economy.

Our model incorporates six different agents: households, financial intermediates, non-financial goods producers, capital producers, retailers and a government. It also considers the existence of a Central Bank that conducts conventional and unconventional monetary policy. From a methodological point of view, this study goes further than Smets and Wouters (2007) and Gertler and Karadi (2011) by coupling the la-

Covid Economics 67, 4 February 2021: 199-253

bor sector to an epidemiological SIR model rather than assuming that each household chooses the quantity of hours it wants to work in each period. We suppose that labor supply is given by the quantity of people in good health, and is exogenously driven by the SIR model. In addition, we suppose that the government may dispense unemployment benefits to those who can no longer work due to illness.

In general, we find significant GDP losses due to an epidemic shock, with the effect on the labor market echoing throughout the economy. We observe declines in household consumption, non-financial intermediary capital, and capital producer investment following the trajectories of labor and production, and financial intermediaries experiencing declines in the quantity and composition of expected discounted terminal wealth. The Central Bank increases its share of total credits that it finances to compensate for losses in investment and production. What is particularly interesting is that it is feasible to have a severe epidemic that does not result in a large economic loss, provided that the recovery rate is sufficiently high to allow workers to quickly return to the labor force. The nature of the epidemic thus has a strong impact on the macroeconomic response.

In terms of monetary policy, we find that no unconventional monetary policy can completely remove the negative economic effects of the crisis, besides perhaps an exogenous increase in the share of claims coming from the Central Bank. Our "*epi loans*" policy is a form of QE policy related to Friedman (1969) "helicopter money", in that the Central Bank takes savings from households and issues it as claims to be used to buy physical capital rather than re-financing private banks. The injected liquidity goes directly to the real sector.

Our framework is not directly targeted towards COVID-19, but instead models a representative epidemic. That being said, it can be tailored to any combination of epidemiological models or economic parameters, making it possible to calibrate the model to a specific disease or country. While we believe that our model is relevant

CEPR PRESS

to the current pandemic, we hope that its contribution extends to epidemics more generally.

The paper is structured as follows. Section 2 presents related literature. The model is presented in Section 3, whereas Section 4 describes the elements of the calibration and model simulation. Section 5 analyzes the response of the economy to the epidemic shock and investigates the effect of monetary policy. Finally, Section 6 concludes.

2 Related Literature

Since the beginning of the COVID-19 pandemic, there has been an explosion of literature investigating the macroeconomics of pandemics. In this section, we briefly survey the literature, presenting the main methodological choices and key results, and explain in more detail how we depart from those studies. We categorize the literature into two thematics: the economic impacts of a pandemic and the effects of policy response.

2.1 Economic impacts of a pandemic

A first line of literature outlines the channels through which the pandemic shock affects the economy. Carlsson-Szlezak et al. (2020a), Carlsson-Szlezak et al. (2020b), and Brodeur et al. (2020), identified three broad patterns that have emerged from the current pandemic. The first is a direct impact generated by a reduced consumption of goods and services (a demand shock), which is exacerbated by social distancing and pessimistic expectations in the short-run. The second is an indirect impact based on financial market shocks and their effects on the real side of the economy. Household wealth will likely fall (wealth effects) as precautionary savings increase (due to uncertainty), leading to declines in new consumption spending. The third set

Covid Economics 67, 4 February 2021: 199-253

of effects consist of supply-side disruptions. Declines in production due to containment and mitigation policies negatively impact supply chains, labor demand, and global employment and, as a consequence, unemployment and GDP losses strongly increase. In addition, a negative supply shock can trigger a demand shortage that leads to a contraction in output and employment larger than the supply shock itself (Guerrieri et al. (2020)). The existence of "wait-and-see" attitudes adopted by economic agents (described by Baldwin and DiMauro (2020)) are likely to reinforce the previous effects by generating additional uncertainty. All in all, different types of recovery geometry - "V-shaped", "U-shaped", "WU-shaped", or "L-shaped"- are possible depending on the persistence of shocks and government interventions.

The basis for these findings are predominantly theoretical in nature, and can be seen as hypotheses to be tested and re-evaluated. Therefore, economists have empirically assessed the economic impacts of the pandemic, as well as delved deeper into their theoretical foundations. We divide them into three sub-groups based on their methodology.

Our first sub-group quantitatively assesses the potential response of the economy to a pandemic crisis, mostly from a macroeconometric perspective. Ludvigson et al. (2020) assessed the macroeconomic impact of COVID-19 in the United States from historical data using a vector auto-regression VAR model. They quantified the potential response of the economy by comparing the current pandemic shock to a series of large disaster shocks in US time series data. Using the costly disaster index, they found that a 60 standard deviations shock from the mean can generate a 12.75 percent drop in industrial production. Chudik et al. (2020) developed a threshold-augmented dynamic multi-country model (TGVAR) to estimate the global as well as country-specific macroeconomic effects of the identified COVID-19 shock. They showed that the most-developed economies will likely experience deeper, longer-lasting effects. For example, they found evidence of long-term, carry-over effects for

Covid Economics 67, 4 February 2021: 199-253

Covid Economics 67, 4 February 2021: 199-253

countries like the United States and the United Kingdom, but not for developing Asian countries. Milani (2021) used a standard GVAR to investigate the importance of interconnections between countries. He found that the unemployment responses varied widely across countries after a health shock. Bonadio et al. (2020) developed a quantitative framework to simulate a negative global labor shock and examine the role of global supply chains in explaining the intensity of the real GDP downturn due to the COVID-19 shock. They found that "re-nationalization" of global supply chains would not make countries more resilient to pandemic-induced contractions in labor supply. Baqaee and Farhi (2020) stressed the role of non-linearities associated with complementarities in consumption and production in response to the COVID-19 shock using a multi-sector, neoclassical model.

Another set of studies relies on static or dynamic computable general equilibrium models, focusing on international spillovers and sectoral effects. A family of Computable General Equilibrium (CGE) were developed to study the macroeconomic impacts of pandemics on a global scale and trade. In particular, the popular CGE G-Cubed (Mckibbin and Fernando (2020)) and ENVISAGE (Maliszewska et al. (2020)) models have been extended to account for COVID-19. Both extensions focused on the importance of spillover effects in a globalized economy when assessing the GDP and macroeconomic losses. Mihailov (2020) implemented potential economics responses within a standard Galí-Smets-Wouters DSGE model (Galí et al. (2011)) calibrated to US, France, Germany, Italy and Spain. In all cases, the negative effects are quite damaging and last between one and two years on average. However, these papers treat epidemics as completely exogenous shocks without the integration of epidemic dynamics. Our work extends this literature by explicitly incorporating an epidemiological model into a macroeconomic framework, taking into account the dynamics of the economic patterns, incorporating a financial sector, and exploring the role of financial intermediaries and the use of unconventional monetary policies. The intro-

CEPR PRESS

duction of financial market disruptions, as in GK, allow us to analyze the effects of unconventional monetary policies.

Our work is more akin to the works of Bodenstein et al. (2020), Eichenbaum et al. (2020a,b,c), Angelini et al. (2020) or Krueger et al. (2020). These studies develop more-or-less simple macroeconomic neoclassical models, in which agents consume goods and work, combined with disease models that are standard in the epidemiology literature. However, they treat the labor market in a markedly different way than us. To be more specific, in those models agents choose the number of hours to work, with household consumption and labor changing the number of susceptible and infected individuals. The more a person consumes or works, the more s/he is in contact with others and the probability of infection is higher. Supply hours decrease not because people of getting sick, but because infected individuals are less productive (lower revenue) (Eichenbaum et al. (2020b)) and individuals know that if they work, they have a higher risk of infection. We do not follow this assumption, choosing to assume that sick individuals cannot or are not allowed to work. We believe that this assumption is reasonable, does not impact our results, and avoids introducing addition assumptions (such as homogenous mixing) into the model. Further, to the best of our knowledge, our paper is the first to directly consider the financial sector in this framework.

From a methodological point of view, our model is closest to Bodenstein et al. (2020), whom enlarge a ECB-BASE model with the dynamics of a SIR model with two distinct population groups. They embed a canonical epidemiology model (SIR) in a Real Business Cycle (RBC) type model. In contrast, we mix a financial DSGE *à la* GK and a SIR model and as a consequence, our model enables us to study the interplay between the real economy and the financial sector.

Covid Economics 67, 4 February 2021: 199-253

Covid Economics 67, 4 February 2021: 199-253

2.2 Economic Policies

A key challenge for policy makers is to identify suitable policies to mitigate the adverse economic effects of epidemics. Kaplan et al. (2020) demonstrated that the role of the government is not just to balance lives and livelihood (health versus economic output), but also over who should bear the burden of the economic crisis. This should be taken into account when investigating the optimality of lockdown and fiscal policies. Krueger et al. (2020) extended the Eichenbaum et al. (2020a,b,c) studies to analyze the "Swedish case". They found that a no government intervention with flexible resource allocation can lead to a substantial mitigation of economic and human costs of the COVID-19 crisis. Other papers have stressed the need for government intervention, particularly economic policies. Elenev et al. (2020) focused on the interrelationships between corporate and financial sectors and real macro-economy output. They found evidence that a no-intervention policy generates a negative feedback loop between corporate default and weakness in the financial intermediary sector and creates a macroeconomic disaster. They studied the role of corporate credit policies to mitigate this situation, and suggested the implementation of conventional or unconventional monetary policies, which we explicitly consider here. Faria-e Castro (2020) analyzed different types of discretionary fiscal policies to smooth household incomes in a simple DSGE model. Conditional and unconditional transfers to households were effective mitigation policies, with expansion of unemployment insurance as the best targeted measure.

In a theoretical model with multiple equilibria, Céspedes et al. (2020) demonstrated that traditional expansionary fiscal policy had no beneficial effects, while conventional monetary policy had a limited effect when the discount rate was low. Unconventional policies, including helicopter drops of liquid assets, equity injections and loan guarantees, were able to keep the economy at a higher equilibrium in terms of productivity and unemployment. In a similar fashion, Sharma et al. (2020) de-

CEPR PRESS

veloped a so-called "Mark-0 Agent-Based Model" based on the model by Gualdi et al. (2015). They simulated several policies including giving easy credit to firms and "helicopter money", i.e. injecting new money into households savings. Here, we analyze similar policy questions but, in contrast to Sharma et al. (2020), we build a DSGE-SIR framework with microeconomic foundations. Kiley (2020) added exogenous shocks to a GK framework to mimic the COVID-19 recession. He found that the use of extraordinary policy actions, such as a QE program of government bonds, may support recovery. We also depart from the GK model, but contrary to Kiley (2020) we explicitly incorporate epidemic dynamics. Our main value added is that our model enables us to take into account interactions between an epidemic and the economy, as well as the financial and real economic sectors, and to study the potential for monetary policy (specifically unconventional monetary policy) to mitigate the effects of an epidemic.

Covid Economics 67, 4 February 2021: 199-253

3 The Model

In this paper, we construct a so-called financial DSGE model like the one developed in Gertler and Karadi (2011). However, in contrast to the usual financial DSGE models, we enlarge our model with a SIR block (see Atkeson (2020)).

Our DSGE model is a neo-keynesian micro-founded aggregate representation of a national economy, in which we assume that there is an infinite number of economic agents divided into households, financial intermediates, non-financial goods producers, capital producers, and retailers, which individually chooses quantities of goods, production factors, bonds and eventually prices in order to maximize their own well-being (e.g. preferences for households and profits for bankers, capital producers, non-financial firms, and retailers). The model also includes a government and a Central Bank that conducts conventional and unconventional monetary policy.

We couple the DSGE model to a classic epidemiological model of an epidemic

Covid Economics 67, 4 February 2021: 199-253

(F.Brauer and Castillo-Chavez (1994, 2012), Hethcote (2000)) and suppose that labor supply is directly tied to the proportion of healthy individuals. For the sake of simplicity, we do not impose stochastic shocks to the economy, and take the trajectory of labor supply, which is affected by the disease, as a deterministic, exogenous shock to the economy. In this way we isolate the effects of the epidemic on the model economy.

In this section, we first describe the epidemiological model and how it relates to households and labor supply. We then describe how households behave, the structure of financial, non-financial and capital producers, and retailers. Finally, we explain how the government intervenes in the economy and monetary policies conducted by the Central Bank. Variables, definitions, and parameters are summarized in Figures 1 and 2 and Tables 1 to 3. For details on the full derivation of the model, see the Appendix.

3.1 Epidemiological Model

In order to model the spread of an epidemic, we use a Susceptible-Infected-Recovered (SIR) model as in F.Brauer and Castillo-Chavez (1994, 2012), Hethcote (2000), and Lenhart and Workman (2007). The SIR model is a type of compartmental epidemiological model in which the total population, N_t, is divided into three classes or types of individuals: susceptible individuals, S_t, who can incur the disease but are not yet infected; infected individuals, $\widetilde{I}_t$, who have the disease and can spread it to susceptible individuals; and recovered individuals, $\widetilde{R}_t$, who have contracted the disease but have recovered and are immune to future infections (Figure 2). For simplicity, we assume a constant population size, abstracting from natural births and deaths[1], and

[1]The validity of this assumption depends on the timescale of the analysis and the nature of the disease in question. Take for example, a single, localized epidemic and a population such that the disease could reasonably circulate throughout the entire population. For diseases like the cold, flu, or measles, an epidemic may last weeks or months and accounting for births and deaths would not be appropriate; for diseases lasting years or a lifetime (AIDS/HIV, hepatitis C, or tuberculosis), including births and deaths is more reasonable (Hethcote (2000)).

Covid Economics 67, 4 February 2021: 199-253

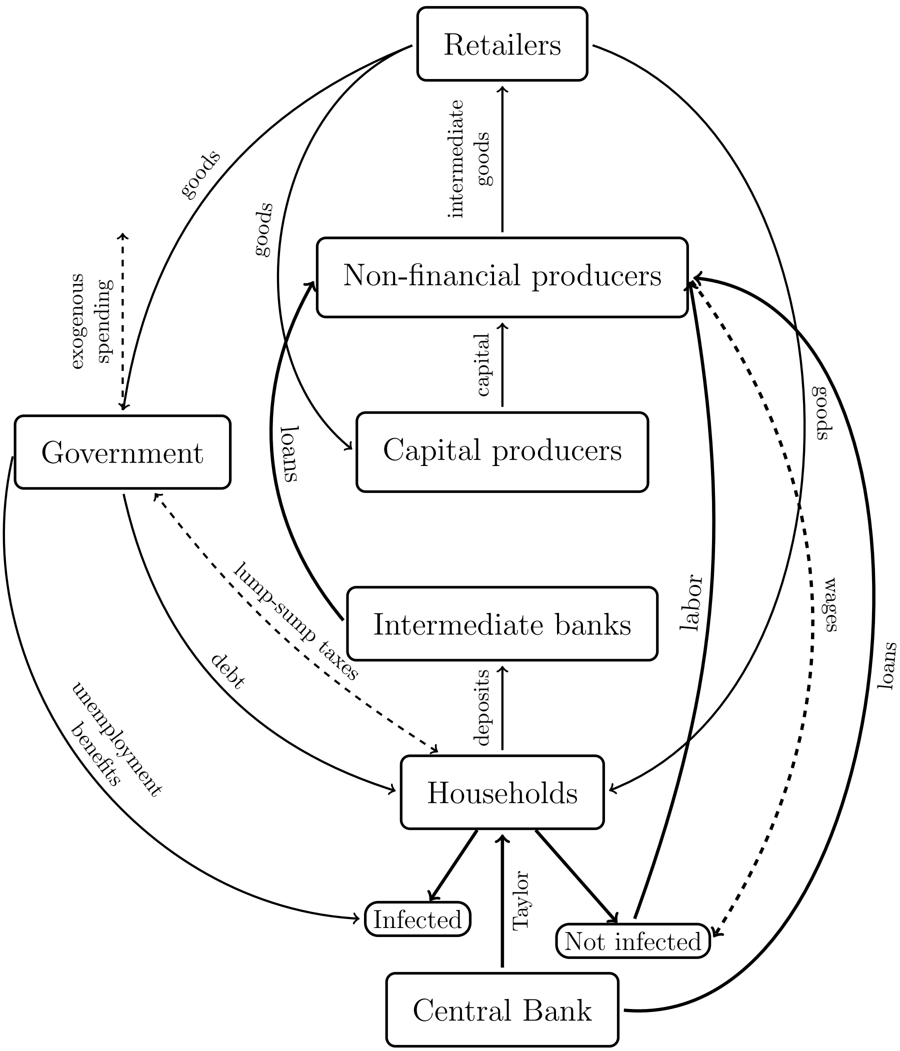


Figure 1: Economic Model Schema

normalize N_t to 1. Then S_t, $\widetilde{I}_t$ and $\widetilde{R}_t$ can be interpreted as shares or proportions of individuals of each class in the general population.

We can write the dynamics of the epidemic over time as:

$$S_{t+1} - S_t = -\alpha_v S_t \widetilde{I}_t \tag{1}$$

$$\widetilde{I}_{t+1} - \widetilde{I}_t = \alpha_v S_t \widetilde{I}_t - \gamma_v I_t \tag{2}$$

$$\widetilde{R}_{t+1} - \widetilde{R}_t = \gamma_v \widetilde{I}_t \tag{3}$$

where $1 = S_t + \widetilde{I}_t + \widetilde{R}_t$. The difference equations in (1)-(3) are equivalent to a system of ordinary differential equations solved via a Euler approximation. Susceptible and infected individuals make contact and transmit the disease with a constant probability α_v, and infected individuals recover at a rate γ_v. We assume that after recovery, individuals are immune from future infection.

Figure 2: SIR Schema

The model assumes a closed population (no immigration or emigration) with a constant population size (no births or deaths) and a well-mixed population. That is, each individual in the population has an equal probability of interacting with every other individual. Extensions of the basic SIR model relax these assumptions to take into account multiple populations of individuals (Bichara et al. (2015)), endemic disease (Hethcote (2000)), heterogeneous mixing (Morin et al. (2014), Morin et al. (2015)), age structure (Hethcote (2000)), and other classes of individuals such as exposed or asymptomatic, vaccinated or hospitalized (Chowell et al. (2003),Hethcote (2000), Lenhart and Workman (2007)). However, relaxing our basic assumptions greatly complicates the analysis and is left for future work.

Covid Economics 67, 4 February 2021: 199-253

CEPR PRESS

Covid Economics 67, 4 February 2021: 199-253

The epidemic affects the economy via the labor supply. Following Bodenstein et al. (2020), we assume that in absence of disease, labor supply L_t is equal to the total working force, $L_t = N_t$. However, as the epidemic spreads in the general population, we assume that infected individuals stay home and do not work, then the labor force is reduce by the quantity of infected people I_t. Thus, in each period, labor supply is given as $L_t = N_t$ - $\widetilde{I}_t$.

3.2 Households

We assume a continuum of perfectly competitive households in the economy indexed by $j \in [0, 1]$. Susceptible, infected, and recovered individuals are assumed to be evenly distributed among households. Each household consumes domestic goods, and, if healthy, supplies identical labor services to the non-financial production sector. Households pay/receive lump sum taxes, collect profits from all firms, have the option to lend funds to competitive financial intermediates or buy government bonds and, when infected, receive unemployment benefits.

At each time period t, a typical household j chooses consumption C_t to maximize the following lifetime expected utility function:

$$\mathbb{E}_t \left[\sum_{k=0}^{\infty} \beta^k U \left(C_{t+k}(j) \right) \right] \tag{4}$$

where $U(C_t(j))$ is the net utility of household consumption of non-financial goods and $\beta \in (0, 1)$ is the discount factor.

We allow for internal habit formation in consumption as in Christiano et al. (2005). Thus, the instantaneous utility at time t is given by:

$$U(C_t(j)) = (log(C_t(j) - hC_{t-1}(j))) \tag{5}$$

where $h \in [0, 1)$ represents the internal habit formation parameter. The latter gov-

Covid Economics 67, 4 February 2021: 199-253

erns how household preferences for past consumption affects utility over time. A high value of h means that past consumption is important, so as to maintain the current level of utility, the household must consume at least the same quantity as the last time period. A low value of h implies that households only care about present consumption. Note that we do not introduce a trade-off between consumption and labor since labor supply is determined by the epidemic. With this formulation, we implicitly assume that all those who can work are willing to do it.

Within each household there may be a portion of infected people, whom do not work but receive unemployment compensation b_t. The remaining individuals - susceptible and/or recovered - may be divided in two groups: workers and bankers. Workers do so for non-financial intermediate firms and receive a real salary W_t in exchange for the total amount of labor provided L_t. Bankers manage financial intermediaries and gain earnings. We assume that each member of the household gives their respective revenues to the household and that there is perfect consumption insurance. That is, consumption is equally distributed within households regardless if everyone in them is able to work.

Each household consumes final goods produced by retailers at price P_t and invests/deposits an amount B_t in government bonds and intermediary deposits. We assume that investing in government bonds and depositing into intermediate banks are equivalent and perfectly substitutable, as both are risk-less and pay the same rate. Each are one-period real bonds, which pay a gross real rate of return R_t such that $R_{t+1} := \frac{1+i_t}{\Pi_{t+1}}$, where i_t is the nominal interest rate fixed by the Central Bank and $\Pi_{t+1} := \frac{P_{t+1}}{P_t}$ represents price inflation.

Share holders of retailers, capital firms, financial and non-financial firms receive real profits. We assume that each household owns an equal share of all firms and receives an aliquot share $D_t(j)$ of aggregate profits D_t, i.e. the sum of dividends of all retailers $D_{r,t}$, intermediate private banks $D_{b,t}$, intermediate non-financial firms $D_{m,t}$, and capital producers $D_{k,t}$. Thus $\int_0^1 D_t(j) = D_t := \int_0^1 (D_{r,t}(i) + D_{b,t}(i) + D_{m,t}(i) + D_{k,t}(i))di$ where i indexes an individual firm in each sector. Households pay/receive T_t lump-sum transfers.

For the sake of tractability, all households are identical and choose consumption and investment in the same manner. Then dropping the j subscript, we may write the real budget constraint for each household as:

$$C_t + B_{t+1} \leq b_t (1 - L_t) + W_t L_t + R_t B_t + T_t + D_t \tag{6}$$

Each household solves (4) under the budget constraint (6). The solution of this maximization problem gives us the following Euler equation that describes the evolution of consumption along an optimal path[2]:

$$1 = \beta \mathbb{E}_t \left[\frac{\lambda_{c,t+1}}{\lambda_{c,t}} R_{t+1} \right] \tag{7}$$

where $\lambda_{c,t}$ represents the marginal lifetime discounted utility function at t. Equation (7) says that, at the optimum, each consumer is indifferent to consuming one more unit today and saving that unit (by buying bonds) to consume in the future.

Assuming internal habit formation yields:

$$\lambda_{c,t} = \frac{1}{C_t - hC_{t-1}} - \beta h \mathbb{E}_t \left[\frac{1}{C_{t+1} - hC_t} \right] \tag{8}$$

Thus we define the stochastic real discount factor for the entire economy from period t to $t + i$ as:

$$\Lambda_{t,t+i} := \beta^i \frac{\lambda_{c,t+i}}{\lambda_{c,t}} \tag{9}$$

[2]Cf. Appendix for derivation.

Covid Economics 67, 4 February 2021: 199-253

Covid Economics 67, 4 February 2021: 199-253

3.3 Financial Intermediates

For the time being we present the financial intermediate's problem assuming that the Central Bank does not apply unconventional monetary policy, i.e. it does not directly lend to non financial firms. We will relax this hypothesis in the next section.

We assume an infinite continuum of financial intermediates indexed by j. Each intermediate recovers a quantity $B_{t+1}(j)$ of deposits from households, which pays a gross interest rate R_{t+1}, and issues a quantity $Z_t(j)$ of financial claims to non-financial producers at a real price of Q_t per claim[3]. Denote $\Omega_t(j)$ as the net worth of banker j in period t such that:

$$\Omega_t(j) = Q_t Z_t(j) - B_{t+1}(j) \tag{10}$$

Given that assets acquired by bankers earn a rate of return $R_{k,t+1}$ on claims, then bankers' wealth at period $t+1$ is:

$$\Omega_{t+1}(j) = R_{k,t+1} Q_t Z_t(j) - R_{t+1} B_{t+1}(j) \tag{11}$$

And using equation (10) yields:

$$\Omega_{t+1}(j) = (R_{k,t+1} - R_{t+1}) Q_t Z_t(j) + R_{t+1} \Omega_t(j) \tag{12}$$

Note the difference in subscripts between the banker rate of return ($R_{k,t+1}$) and the gross interest rate (R_{t+1}).

[3]In reality, the Central Bank also sells claims. Therefore, we should differentiate private claims $Z_{p,t}$ from government claims $Z_{g,t}$. However, for the sake of presentation, we abstract from this distinction in this section.

CEPR PRESS

We assume that bankers cannot default on their loans. Then a banker j operates if and only if the following condition holds:

$$\mathbb{E}_t \Lambda_{t,t+1+i} \left(R_{k,t+1+i} - R_{t+1+i} \right) \geq 0, \quad i \geq 0 \tag{13}$$

where $\Lambda_{t,t+1+i}$ is defined as in (9). In other words, if a banker must borrow more than its income, then it will not remain a banker.

In each period t, a fraction f of household members are bankers; the remaining proportion are workers. We assume that a fraction θ of bankers in the current period remain bankers in the next time period. That is, $(1-\theta)f$ bankers become workers and a similar number of workers become bankers[4].

Accordingly, each banker has the following expected discounted terminal wealth:

$$\begin{aligned} V_t(j) &= \sum_{i=0}^{\infty} (1-\theta)\theta^i \Lambda_{t,t+1+i} \Omega_{t+1+i}(j) \\ &= \sum_{i=0}^{\infty} (1-\theta)\theta^i \Lambda_{t,t+1+i} \left((R_{k,t+1+i} - R_{t+1+i}) Q_{t+i} Z_{t+i}(j) + R_{t+1+i} \Omega_{t+i}(j) \right) \end{aligned} \tag{14}$$

Under condition (13), bankers may want to increase their assets indefinitely by borrowing more and more funds from households. Furthermore, a banker can decide to divert funds, i.e. transfer a fraction or even the totality of assets to its own household for personal gain. Creditors are aware of this possibility as they know that there may be a fraction λ of funds that will never be recovered. However, they can impose a borrowing constraint to ensure that bankers do not divert all funds. Therefore, households are willing to supply funds to a bank only if the banker's expected discounted terminal wealth $V_t(j)$ is at least as large as the banker's gain

[4]As explained in Gertler and Karadi (2011), this assertion implies that the average "survival time" for a banker at any period is $\frac{1}{1-\theta}$. This insures that bankers cannot fund all investments from their own capital and that the relative proportion of each type of household remains constant over time.

Covid Economics 67, 4 February 2021: 199-253

CEPR PRESS

Covid Economics 67, 4 February 2021: 199-253

form diverting funds $\lambda Q_t Z_t(j)^5$:

$$V_t(j) \geq \lambda Q_t Z_t(j) \tag{15}$$

where in each period t, banker j chooses $Z_t(j)$ in order to maximize (14) subject to constraint (15).

The leverage ratio is the value of total loans of a banker to non-financial producers divided by the net worth of that banker. It is a measure of the proportion of worth that a banker lends. Define $\phi_t(j)$ as the leverage ratio of banker j as:

$$\phi_t(j) := \frac{Q_t Z_t(j)}{\Omega_t(j)} \tag{16}$$

Note that the leverage ratio can be greater than one (e.g. bankers can lend more than they have), depending on interest rates.

As in Gertler and Karadi (2011), suppose that the solution of this problem has the following form:

$$V_t(j) = \nu_t Q_t Z_t(j) + \eta_t \Omega_t(j) \tag{17}$$

where ν represents the expected discounted marginal value that the banker gains by expanding claims, and η represents the expected marginal value of an extra unit of wealth. Equation (17) forms the initial guess of the solution, which is required in order to solve the problem. See the Appendix for details.

If constraint (15) is binding, then we arrive at an interior solution with:

$$\nu_t = \mathbb{E}_t \Lambda_{t,t+1} \Gamma_{t+1} \left(R_{k,t+1} - R_{t+1}\right), \quad \eta_t = \mathbb{E}_t \Lambda_{t,t+1} \Gamma_{t+1} R_{t+1} \tag{18}$$

$$\Gamma_{t+1} = 1 - \theta + \theta \left(\nu_{t+1} \phi_{t+1}(j) + \eta_{t+1}\right), \quad \phi_t(j) = \frac{\eta_t}{\lambda - \nu_t} \tag{19}$$

[5] See Gertler and Karadi (2011) for an extensive explanation of this condition.

Covid Economics 67, 4 February 2021: 199-253

If constraint (15) does not bind, then our solution is a corner with:

$$\nu_t = 0, \quad \eta_t = 1, \quad \Gamma_t = 1, \quad \phi_t(j) \text{ is undetermined} \tag{20}$$

As long as $0 < \nu_t < \lambda$, the incentive constraint holds and the banker will increase its assets. In contrast, when $\nu_t > \lambda$, the incentive constraint is not binding and the expected discounted value of the banker always exceeds gains from diverting funds.

Aggregating the wealth of all existing bankers, we have[6]:

$$\Omega_{t+1} = \left(\left(R_{k,t+1} - R_{t+1}\right)\phi_t + R_{t+1}\right)\Omega_t \tag{21}$$

Recall that, at each date t, not all bankers remain bankers to the next time period, and a portion of households become new bankers. We assume that bankers who exit give their earnings to their own household and the household gives the new banker startup funds, equal to a fraction $\frac{\epsilon}{1-\theta}$ of the value of assets that existing bankers had earned in their last operating period.

Accordingly, the total net worth of all bankers is the sum of the existing bankers and new bankers such that:

$$\Omega_t = \Omega_{e,t} + \Omega_{n,t} \tag{22}$$

Given that the probability of a banker at time t remaining a banker at time $t+1$ is equal to θ, then we may re-write (22) as:

$$\Omega_t = \theta\left(\left(R_{k,t} - R_t\right)\phi_{t-1} + R_t\right)\Omega_{t-1} + \epsilon Q_t Z_{t-1} \tag{23}$$

[6]Since all bankers are created equal and they choose the same quantity of claims, then their choice of $Z_t(j)$ will not depend upon j, neither deposits $B_t(j)$. Then ϕ_t is independent of j.

3.4 Central Bank and Public Loans

Until now, we have assumed that only private banks receive deposits from households (B_t) and lend funds to intermediate producers (Z_t). Here, we relax this assumption to consider a Central Bank which conducts unconventional monetary policy, managing the epidemic by issuing of bonds and lending money to non-financial firms.

As explained in Gertler and Kiyotaki (2010), there are many ways in which the Central Bank may behave. Since our objective is to study how the public authority may fight an epidemic crisis using public loans, we assume that the Central Bank issues government bonds $B_{g,t}$ to consumers at gross interest rate R_t and - using that income with respect to its budget constraint - issues financial claims $Z_{g,t}$ to intermediate non-financial producers at price Q_t, for which the government earns a stochastic rate of return $R_{k,t+1}$.

Let $Q_tZ_{p,t}$ be the value of assets coming from private banks, $Q_tZ_{g,t}$ the value of assets coming from the Central Bank, and Q_tZ_t the total value of intermediate assets (i.e. the sum of assets from private and Central banks). Note that in the eyes of borrowers and lenders in our model, private deposits/claims and government bonds/claims are equivalent in the sense that they have the same price and interest rates.

The Central Bank has both an advantage and a disadvantage with respect to private lenders. We assume that government assets come with an efficiency cost of τ per claim[7], but that, assuming the government can always honor its debts, there are no limitations in the number of bonds it can supply[8]. Therefore, it is not subject to an incentive constraint. As a consequence the Central Bank may also

[7] As explained in Gertler and Karadi (2011) and Gertler and Kiyotaki (2010), the government faces additional costs of evaluating and monitoring borrowers that privates banks do not have. This is because private banks possess specific knowledge of the market not readily available to the Central Bank.

[8] By abstracting from solvency problems, we are assuming that the government can always print money to pay its debts. In reality, solvency problems can emerge and be aggravated by sovereign debt and credit-rating agencies. We leave this for future work.

Covid Economics 67, 4 February 2021: 199-253

CEPR PRESS

Covid Economics 67, 4 February 2021: 199-253

issue government debt to financial intermediates without constraint. Private banks fund government bonds by issuing households deposits at the same rate as they lend them from the Central Bank. Thus, only private assets financed with private banks face the incentive constraint.

Suppose that in each period the Central Bank lends a fraction ψ_t of total credit. Then, using equation (16), we write the total value of intermediate assets as:

$$Q_t Z_t = \phi_t \Omega_t + \psi_t Q_t Z_t = \Phi_t \Omega_t \tag{24}$$

where $\Phi_t := \frac{\phi_t}{1-\psi_t}$ is the leverage ratio for total intermediate funds (public and private). The choice of ψ_t will be explained in Section 3.8.

3.5 Intermediate Non-Financial Firms

Let there exist a continuum of perfectly competitive, homogenous intermediate goods producers that produce a differentiated non-financial good that is sold at real price $P_{m,t}$[9]. Each of them uses two inputs: labor L and capital K.

Following Gertler and Karadi (2011) we assume that at the end of period t, each intermediate producer acquires a quantity K_{t+1} of capital from the capital producers to be used in production in time $t+1$. After production in period $t+1$, the firm may sell capital back to the capital producer and/or refurbish depreciated capital. We assume that the cost of replacement is unity and that there are no adjustment costs. Thus, intermediate goods firms face a static problem, solving their profit maximization problem one period at a time rather than maximizing expected profit over the lifetime of the firm.

Goods producers finance physical capital by borrowing from financial intermediates[10]. Note that borrowers are not constrained by the quantity of claims Z_t they

[9]Following Gertler and Karadi (2011) we do not introduce price stickiness through intermediate goods producers, but rather do so by assuming that retailers are monopolistic.
[10]Private and public financial intermediaries are perfect substitutes in the eyes of the borrower.

Covid Economics 67, 4 February 2021: 199-253

want to purchase. However, as intermediate private banks are constrained by the quantity of funds they may obtain from households, there is an indirect effect of the interest rate $R_{k,t}$ on goods producer dynamics.

Each goods producer then purchases a quantity Z_t of capital claims, in which each claim equals one unit of capital $Z_t = K_{t+1}$ and that the price per unit capital is Q_t. It follows that $Q_t K_{t+1} = Q_t Z_t$.

Recall that goods producers are homogeneous and all behave in the same fashion. Then we can write the quantity of intermediate non-financial goods $Y_{m,t}$ produced by the representative physical goods producer at time t as a Cobb-Douglas production function involving capital and labor such that[11]:

$$Y_{m,t} := K_t^{\alpha} L_t^{1-\alpha} \tag{25}$$

where the subscript m differentiates intermediate goods ($Y_{m,t}$) from final goods (Y_t), and α is the elasticity of production with respect to capital. As we assume no stochastic shocks, we abstract here from quality capital shocks as in Merton (1973) and a total factor productivity shock as in classic DSGE models (Smets and Wouters (2007)).

Each goods producer chooses quantities of labor and capital in order to maximize its profit. The solution to this problem yields the following first order conditions:

$$W_t = (1-\alpha) P_{m,t} \frac{Y_{m,t}}{L_t} \tag{26}$$

$$R_{k,t} = \frac{\alpha P_{m,t} \frac{Y_{m,t}}{K_t} + (1-\delta) Q_t}{Q_{t-1}} \tag{27}$$

where δ is the capital depreciation rate. As we are in a perfect competitive frame-

[11]Since we assume that retailers are monopolistic, one unit of intermediate good $Y_{m,t}$ does not necessary equal one unit of final good Y_t. As shown in the Appendix, these quantities are related by the equation $Y_{m,t} = v_{p,t} Y_t$ at equilibrium, where $v_{p,t}$ is the price dispersion of the aggregated final good.

work, equations (26) and (27) establish that intermediate good producers choose the quantity of labor to equate real wages and the marginal product of labor, and quanty of capital such that the real price of capital equals the net return after depreciation.

3.6 Capital Producers

There exists a continuum of perfectly competitive, homogeneous capital production firms. At the end of each period t, capital producers may produce new capital by buying final goods from retailers $I_{n,t}$ (i.e. investing), purchase non-depreciated capital from intermediate good producers at price Q_t, repair depreciated capital at cost unity, and/or sell capital to intermediate goods producers at price Q_t. In doing so, total aggregate capital accumulates in the following fashion:

$$K_{t+1} := (1-\delta)\, K_t + I_{n,t} \tag{28}$$

where δ is the capital depreciation rate and $I_{n,t}$ is net/new capital investment.

Furthermore, we assume that there is no adjustment or investment cost associated with repairing capital. However, producing new capital does face an adjustment cost associated with changing the level of investment. Thus, capital producer profit can be written as[12]:

$$D_{k,t} = \left((Q_t - 1) I_{n,t} - f\left(\frac{I_{n,t}}{I_{n,t-1}}\right) I_{n,t} \right) \tag{29}$$

A representative capital producer chooses the quantity of net capital investment $I_{n,t}$ to maximize its discounted profits:

$$\mathbb{E}_t \sum_{i=0}^{\infty} \Lambda_{t,t+i} \left((Q_{t+i} - 1) I_{n,t+i} - f\left(\frac{I_{n,t+i}}{I_{n,t-1+i}}\right) I_{n,t+i} \right) \tag{30}$$

[12]See the Appendix for a detailed derivation.

Covid Economics 67, 4 February 2021: 199-253

CEPR PRESS

Covid Economics 67, 4 February 2021: 199-253

where the adjustment cost function ($f(\cdot)$) depends on net capital investment at times t and $t-1$. Specifically, it is defined as:

$$f\left(\frac{I_{n,t}}{I_{n,t-1}}\right) = \frac{\kappa}{2}\left(\frac{I_{n,t}}{I_{n,t-1}} - 1\right)^2, \kappa > 0 \tag{31}$$

Remark that the adjustment cost is zero at the steady state, and that this cost is increasing with temporal changes in investment.

The first order condition for profit maximization yields:

$$Q_t = 1 + f\left(\frac{I_{n,t}}{I_{n,t-1}}\right) + f'\left(\frac{I_{n,t}}{I_{n,t-1}}\right)\frac{I_{n,t}}{I_{n,t-1}} - \mathbb{E}_t\Lambda_{t,t+1}f'\left(\frac{I_{n,t+1}}{I_{n,t}}\right)\left(\frac{I_{n,t+1}}{I_{n,t}}\right)^2 \tag{32}$$

This equation is the marginal Tobin's "Q" which, given asset prices, defines the optimal investment demand function. Remark that with no adjustment costs, $Q_t = 1$.

3.7 Retailers

Let there be a continuum of monopolistic *normal retailers* indexed by $h \in [0, 1]$, and a continuum of perfectly competitive *super retailers* that purchase and assemble final goods produced by *normal retailers* in order to produce an aggregate final good that will be sold at price P_t. We assume that *super retailers* are homogeneous and all behave in the same fashion (*normal retailers* are not treated as homogeneous).

The *super retailer* is characterized by the following CES production function:

$$Y_t := \left(\int_0^1 Y_t(h)^{\frac{\epsilon_p - 1}{\epsilon_p}} dh\right)^{\frac{\epsilon_p}{\epsilon_p - 1}} \tag{33}$$

where $Y_t(h)$ is final good produced by *normal retailer* h, and ϵ_p is the elasticity of substitution of choosing between *normal retailer* goods.

Given the prices of normal retailer goods $P_t(h)_{h\in[0,1]}$ and the final aggregated good price P_t, the *super retailer* chooses the quantities of *normal retailers* goods

$(Y_t(h))_{h\in[0,1]}$ in order to maximize its profit. The solution yields the following demand function for good h:

$$Y_t(h) = \left(\frac{P_t(h)}{P_t}\right)^{-\epsilon_p} Y_t \quad \forall h \tag{34}$$

Notice that the production function of the *super retailer* includes constant returns to scale and that firms are perfectly competitive, meaning that firms experience zero profits at equilibrium. We therefore obtain the following equation for the price of the final aggregate good:

$$P_t = \left(\int_0^1 P_t(h)^{1-\epsilon_p} dh\right)^{\frac{1}{1-\epsilon_p}}. \tag{35}$$

Each *normal retailer* h uses intermediate goods, produced by the intermediate goods firms, to "pack" the intermediate goods and sell them to the *super retailers* at price $P_t(h)$. We assume that it takes one unit of intermediate good to produce one unit of normal final output. Thus, the marginal cost for each *normal retailer* is the intermediate price $P_{m,t}$, which is the same for all *normal retailers*.

We introduce nominal price rigidity as in Calvo (1983). In each period t, a fraction $(1-\theta_p)$ of *normal retailers* can re-optimize their nominal price $(P_t(h) = P_t^*(h))$, while the remaining fraction can only partially adjust their prices according to past inflation. If firm h cannot change its price for i periods, then its normalized price after i periods is:

$$\prod_{s=1}^{i} \Pi_{t+s-1}^{\chi} \frac{P_t(h)}{P_{t+i}} \tag{36}$$

where $\chi \in (0,1)$ reflects the price response to inflation and $\Pi_t := \frac{P_t}{P_{t-1}}$ represents the level of inflation from period $t-1$ to t.

Covid Economics 67, 4 February 2021: 199-253

CEPR PRESS

Covid Economics 67, 4 February 2021: 199-253

Profits for *normal retailer* h at date t is then given by:

$$\left(\prod_{s=1}^{i}\Pi_{t+s-1}^{\chi}\frac{P_t(h)}{P_t}-P_{m,t}\right)Y_t(h) \tag{37}$$

Given the option, each *normal retailer* firm will choose to readjust its price. The choice of $P_t^*(h)$ does not depend on the specific household h because all firms that are able to choose their prices will do so in the same fashion. Furthermore, firms only consider future states in which re-optimization is not possible thus each firm h chooses $P_t(h)$ to maximize expected discounted profits:

$$\mathbb{E}_t\sum_{k=0}^{\infty}\theta_p^i\Lambda_{t,t+i}\left(\prod_{s=1}^{i}\Pi_{t+s-1}^{\chi}\frac{P_t(h)}{P_{t+i}}-P_{m,t+i}\right)Y_{t+i}(h) \tag{38}$$

subject to equation (34).

The first order condition of this problem yields:

$$\mathbb{E}_t\sum_{i=0}^{+\infty}\theta_p^i\Lambda_{t,t+i}Y_{t+i}(h)\left(\frac{P_t^*}{P_{t+1}}\prod_{s=1}^{i}\Pi_{t+s-1}^{\chi}-\mathcal{M}P_{m,t+i}\right)=0 \tag{39}$$

where $\mathcal{M}=\frac{\epsilon_p}{\epsilon_p-1}$ is the desired price markup, absent from inflation. This equation gives the optimal price setting condition.

Finally, using the fact that a fraction $(1-\theta_p)$ of *normal retailers* can optimize prices while the rest index prices to past inflation, equation (35) can be written as:

$$P_t^{1-\epsilon}=\theta_p\left(\Pi_{t-1}^{\chi}P_{t-1}\right)^{1-\epsilon}+(1-\theta_p)\left(P_t^*\right)^{1-\epsilon} \tag{40}$$

3.8 Government, Monetary Policy and the Market Clearing Condition

The government distributes unemployment benefits b_t, issues public debt $B_{g,t}$ to households for which it pays a gross interest rate R_t, sells claims $Z_{g,t}$ to non-financial firms at price Q_t and gross interest rate of return of $R_{k,t}$, recovers/pays lump-sum taxes, and spends its own expenditures G_t.

As discussed previously, there is a portion of the population that is infected and is not part of the labor force. We assume that they receive at least partial unemployment benefits from the government. We define those benefits b_t as:

$$b_t = \zeta W_t, \quad \zeta \in [0, 1) \tag{41}$$

where ζ is the rate of unemployment compensation and W_t real wages. Thus, unemployment benefits are proportional to wages earned from working.

As explained in Subsection 3.4, in each period, the government via the Central Bank, lends a fraction ψ_t of total credit to financial intermediates. However, government assets come with an inefficiency cost of $\tau \in [0, 1]$ per claim. (Recall that private banks are more efficient in that they have better access to market information.) Then government expenditure on financial intermediates is given by $\tau\psi_t Q_t K_{t+1}$.

We assume as well that government consumption of final goods is always constant, $G_t := \omega_g Y_t$, where ω_g is the steady state share of GDP that the government uses for its own expenditures. Assuming that transfers automatically adjust at each date, the government faces the following budget constraint:

$$G_t + \tau\psi_t Q_t K_{t+1} + b_t(1 - L_t) + \psi_t Q_t Z_t = T_t + (R_{k,t} - R_t)\, B_{g,t} + B_{g,t+1} \tag{42}$$

Equation (42) equates all expenditures (final good consumption, expenditures to non-financial intermediaries, and unemployment benefits) to revenue (lump sum taxes, interest from debt).

Unconventional monetary policy ψ_t is set in the following manner:

$$\psi_t = \bar{\psi}_t + \omega \mathbb{E}_t \left[(logR_{k,t+1} - logR_{t+1}) - (logR_k - logR) \right] \tag{43}$$

Covid Economics 67, 4 February 2021: 199-253

Covid Economics 67, 4 February 2021: 199-253

where $\bar{\psi}_t$ is defined as our "*epi loans*", $\omega > 0$ is the Central Bank credit feedback parameter, and $logR_k - logR$ is the steady state risk-premium. The feedback parameter governs the intensity of the reaction of the Central Bank to changes in the spread relative to the steady state risk premium. When the risk-premium is larger than its steady state, the Central Bank expands its credit with the larger the ω, the greater the credit expansion. In our baseline simulations, we treat $\bar{\psi}_t$ as a constant equal to zero. We then relax this assumption, taking $\bar{\psi}_t$ as a deterministic, exogenous shock, to study the ability of our "*epi loans*" to alleviate the negative effects of the epidemic.

Suppose that the Central Bank also conducts conventional monetary policy by setting nominal interest rates, i_t, following a Taylor rule of the form:

$$1 + i_t = (1 + i_{t-1})^{\phi_i} \left(\frac{1}{\beta} \left(\frac{\Pi_t}{\Pi} \right)^{\phi_\pi} \left(\frac{Y_t}{Y_{ss}} \right)^{\phi_y} \right)^{1-\phi_i}, \tag{44}$$

where Π_t is the steady state of inflation and Y_{ss} is the steady state GDP in a scenario without disease. In this formulation the parameter ϕ_y measures the response of the Central Bank to the output gap, which contrary to other DSGE models, we define as the deviation of current GDP with respect to the steady state GDP without an epidemic[13].

Finally, we have the following Fisher relation that links nominal interest rates fixed by the Central Bank to the gross real interest rate fixed by the market:

$$1 + i_t = R_{t+1}\mathbb{E}_t\Pi_{t+1} \tag{45}$$

Market clearing conditions established that production is divided between consumption, net investment, government expenditures in goods, and government finan-

[13]Generally, in classic DSGE models, the output gap is defined as the deviation of current GDP with respect to its steady state. In our model, depending on the type of disease, it is possible to have different steady states values for Y. We believe that the real output gap should be measured as the deviation with respect to a fixed value of Y.

Covid Economics 67, 4 February 2021: 199-253

cial intervention.

$$Y_t = C_t + I_{n,t} + f\left(\frac{I_{n,t}}{I_{n,t-1}}\right) I_{n,t} + G + \tau\psi_t Q_t K_{t+1} \tag{46}$$

Equation (46) closes the model.

4 Parameter Calibration and Simulation Analysis

Details on model aggregation and calculation of the the steady state values are given in the Appendix. Each time period corresponds to a quarter. Baseline parameter values are summarized on Table 3. Calibration of our baseline parameters follows Smets and Wouters (2007) and Gertler and Karadi (2011) for the U.S. economy. Specifically, the discount factor β is set to ensure a 4% annual interest rate, with the elasticity of substitution among final goods taken to yield a steady-state price markup of 31%. The output of elasticity of capital α is calibrated assuming a "labor share" of approximately 2/3 and the bankers' survival rate is fixed at 0.975, which assumes that bankers remain bankers on average for 10 years. We fix the share of unemployment compensation ζ to 0.5. As in Gertler and Karadi (2011), the private banks' parameters λ and ϵ are fixed to meet the following targets: a risk-premium steady state of 100 basis points and a steady state leverage ratio of 4. Initial conditions and baseline epidemiological parameters were chosen to illustrate a full epidemic cycle, and are *not* meant to represent a specific disease.

Simulation of the model proceeds in two steps. First, we calculate the trajectories of the number of susceptible, infected, and recovered individuals given initial conditions and epidemic parameters. The dynamics of the epidemic were solved using a first-order Euler approximation for a time horizon of 150 periods, corresponding to the time scale of the economic model. We then used the trajectory of infected individuals as a deterministic, permanent shock to the real economy. In this way,

Table 1: State and control variables

Variable	Symbol	Type
Epidemic block		
Susceptible	S	State
Infected	$\tilde{I}$	State
Recovered	$\tilde{R}$	State
Households		
Labor	L	Control/State
Consumption	C	Control
Deposit = Government bonds	B	Control
Financial Intermediates		
Quantity of financial claims issued by private banks	Z_p	Control
Non-financial intermediates and capital producers		
Intermediate non-financial goods	Y_m	Control
Capital	K	Control/State
Labor	L	Control/State
Net capital investment	$I_{n,t}$	Control
Retailers and Capital Producers		
Normal retailed good price	$P(h)$	Control

Covid Economics 67, 4 February 2021: 199-253

Table 2: Model definitions and outcomes

Variable	Symbol
Households	
Total population	N
Real discount factor from date t to $t+1$	$\Lambda_{t,t+1}$
Good price = Aggregate retailer's price	P
Total real profits	D
Lump-sum taxes	T
Marginal lifetime discounted utility function	λ_c
Real wage	W
Financial Intermediates	
Total quantity of financial claims	Z
Bankers' net worth	Ω
Expected discounted terminal wealth	V
Leverage ratio of private banks	ϕ
Auxiliary variable	Γ
Risk-less gross real rate of return	R
Claims gross real rate of return = Capital rate of return	R_k
Financial claims price	Q
Total leverage ratio (public and private)	Φ
Marginal value of banker's gain w.r.t claim income	ν
Marginal value of banker's gain w.r.t wealth	η
Existing banker's net worth	Ω_e
New banker's net worth	Ω_n
Private deposits	B_p
Private bank profit	$D_{b,t}$
Non-financial intermediates and capital producers	
Intermediate non-financial good price	P_m
Intermediate non-financial profit	$D_{m,t}$
Capital producer profit	$D_{k,t}$
Adjustment cost function of investment	$f(\cdot)$
Retailers and Capital Producers	
Aggregate super retailed good	Y
Normal retailed good	$Y(h)$
Normal retailed good price	$P(h)$
Optimal normal retailed good price	P^*
Normal retailer profit	$D_{r,t}$
Price dispersion	$v_{p,t}$
Central Bank and Government	
Level of goods price inflation	Π
Fraction of total credits financed by the Central Bank	ψ
Quantity of financial claims issued by the Government	Z_g
Unemployment compensation	b
Government consumption	G
Nominal interest rate	i
GDP without disease	$\bar{Y}$
Inflation without disease	$\bar{\Pi}$
Government bonds	B_g
Exogenous fraction of publicly intermediate assets	$\bar{\psi}$

Covid Economics 67, 4 February 2021: 199-253

CEPR PRESS

agents possess perfect foresight regarding the future states of the epidemic when computing their optimal solutions. We solve the economic block from a set of initial conditions to the steady-state of both economic and epidemic blocks[14].

In order to test the effectiveness of unconventional monetary policy to mitigate the epidemic crisis, we first establish a baseline model scenario with an epidemic and study the economic consequences of changes in the epidemic structure. We then implement unconventional monetary policy by testing the sensitivity of the model to the steady state leverage ratio for private banks, the intensity of the reaction of the Central Bank to changes in the spread, and our "*epi loans*" policy. All model simulations were conducted in Dynare 4.6.1. All source code and simulation data can be found on the Open Science Framework (osf.io/j7m65).

5 Results and Discussion

This section is divided in four parts. First, we present our baseline results of the model and the different pathways by which the epidemic affects the economy. Second, we describe the economic response to changes in epidemiological parameters (transmission and recovery rates). Third, we discuss the effects of unemployment compensation on the economy. Finally, we evaluate the potential of monetary policies to remedy the economic burden of the epidemic. For each of our results, we compare the trajectories of our economic variables to those in the absence of disease (or the "no-disease" case). When changing model parameters, we re-calculate the trajectories of the no-disease case to correspond to the new set of parameters.

[14]We solve the linearized version of the perfect foresight model with the Newton method, which uses sparse matrices to simultaneously solve all equations in every period.

Covid Economics 67, 4 February 2021: 199-253

Table 3: Parameter Calibration

Parameter	Symbol	Calibrated Value/Baseline
Epidemic block		
Initial condition of susceptible	S_0	0.9
Initial condition of infected	$\widetilde{I}_0$	0.1
Initial condition of recovered	$\widetilde{R}_0$	0
Transmission rate	α_v	0.4
Recovery rate	γ_v	0.1
Households		
Discount factor	β	0.99
Internal habit formation	h	0.71
Financial Intermediates		
Bankers' survival rate	θ	0.972
Fraction of claims income that can be diverted	λ	Function of risk premium at steady state, leverage ratio at steady state and θ
Proportional transfer to the new bankers	ϵ	Function of risk premium at steady state, leverage ratio at steady state, θ and $\bar{\psi}$
Risk premium at steady state	$R_k - R$	0.01/4
Leverage ratio at steady state	ϕ	4
Non-financial intermediates and capital producers		
Capital depreciation	δ	0.025
Price indexation to inflation	χ	0.24
Calvo price parameter	θ_p	0.66
Capital share	α	0.33
Retailers and Capital Producers		
Adjustment cost constant	κ	5.74
Elasticity of substitution between normal retailers	ϵ_p	4.167
Price markup	$\mathcal{M}$	Function of θ_p
Central Bank and Government		
Efficiency cost	τ	0.001
Unemployment rate compensation	ζ	0.5
Feedback parameter	ω	10
Taylor rule response to inflation	ϕ_π	2.04
Taylor rule response to output gap	ϕ_y	0.08
Taylor rule inertia	ϕ_i	0.81
Steady state share of GDP that Government expends	ω_g	0.18

Covid Economics 67, 4 February 2021: 199-253

Covid Economics 67, 4 February 2021: 199-253

5.1 Baseline Results

Our baseline results are summarized in Figures 3 and 4 . For brevity, we focus on a set of core variables of the model.

By assumption, the epidemic decreases the quantity of available labor (only healthy individuals are allowed to work), which at its maximum severity decreases the workforce by 45%. This effect on the labor market echoes throughout the economy, with declines in household consumption, non-financial intermediary capital, and capital producer investment following the trajectory of labor. The first is a consequence of lost wages and equality in the market clearing condition. The latter two follow declines in production due to a lower workforce.

Regarding financial intermediaries, the epidemic primarily affects their expected discounted terminal wealth (V). Both components of wealth - net worth (Ω) and claim selling (QZ) - are affected. This is because a decrease in capital translates to a decrease in claims demand ($K_{t+1} = Z_t$), which has a negative impact on claim prices (Q) compared to the no-disease case. We observe significant declines in GDP, reaching a maximum loss of 20% compared to the no-disease case.

What is particularly interesting is that as the crisis starts, the Central Bank increases its share of total credits that it finances (ψ) to compensate for losses in investment and production that follow declines in labor. This is because, while decreases in investment in capital and production of goods provoke decreases in interest rates (risk-less and capital rate of return), the observed spread in the interest rates is still higher than the steady-state.

Similarly, we observe an increase in inflation during the epidemic. In this model, the standard relationships between supply and demand and prices holds. If price increases (decreases), then the supply (demand) side dominates as the DSGE framework shifts back to equilibrium. In a perfectly competitive market, as overall production decreases with the epidemic, we would expect to see a larger than observed increase

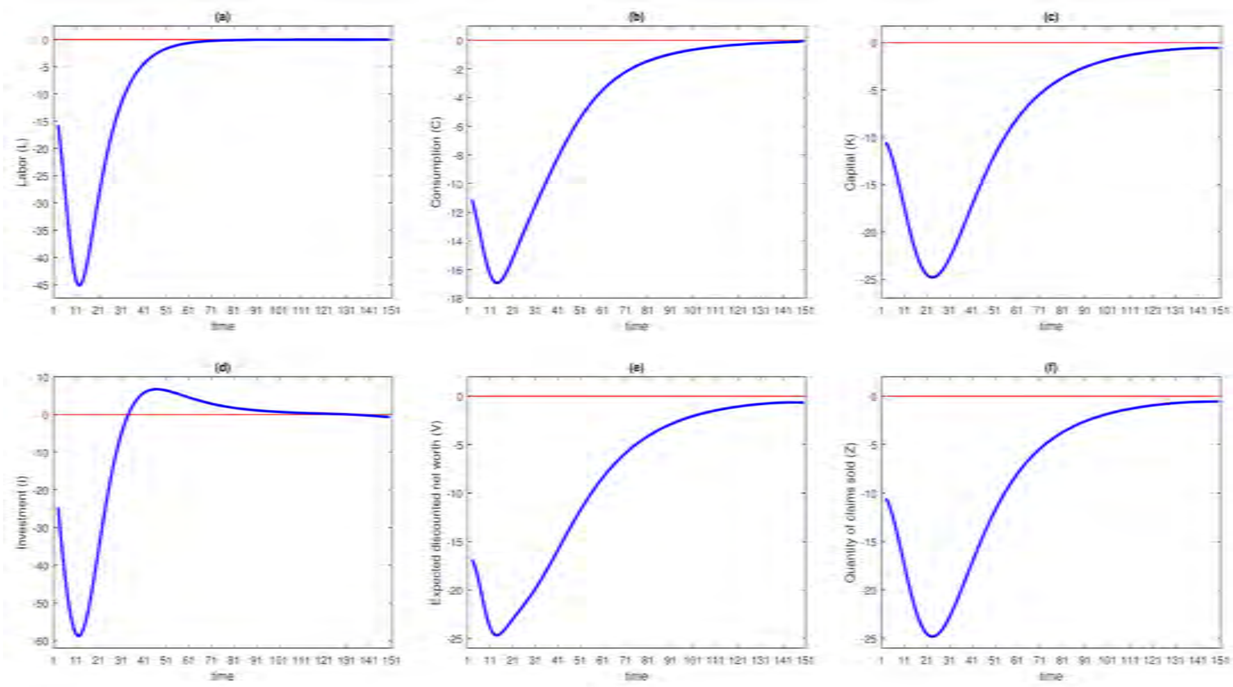


Figure 3: Baseline results for labor (a), consumption (b), capital (c), investment (d), expected discounted net worth (e), and the quantity of claims sold (f). Reported values are the percent deviation from the no-disease case. The red line corresponds to a zero percent change.

Covid Economics 67, 4 February 2021: 199-253

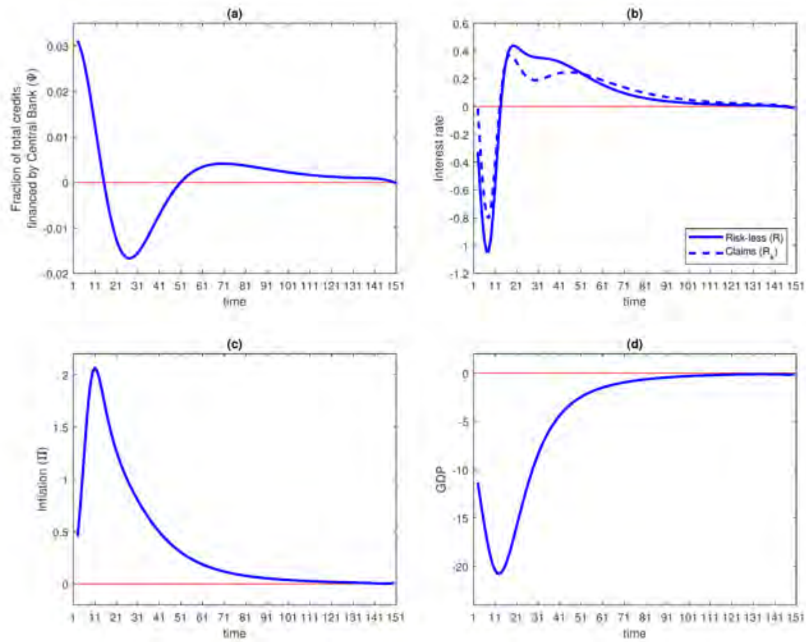


Figure 4: Baseline results for the fraction of total credits financed by the Central Bank (a), interest rates (b), inflation (c), and GDP (d). Reported values are the percent deviation from the no-disease case. For comparison, the red line corresponds to a zero percent change.

in prices (at least in the early stages of the epidemic). However, the increase in inflation is less than that of a perfectly competitive framework because of sticky prices.

5.2 Economic Response to Changes in Epidemic Structure

Holding all economic parameters constant, we vary the epidemiological parameters to understand how structural changes in the epidemic profile affect the economy. We find marked changes in cumulative GDP, with the recovery rate being the primary driver (Figure 5a). Indeed, at moderate to high recovery rates the model is relatively insensitive to the infection rate.

In our framework, the main burden of disease on the economy is in the labor supply: only healthy people are allowed to work. Therefore, an epidemic that persists for a long time in the population (low recovery rate) and, consequently, keeps people from working, will be the most costly. Even if we have a highly contagious epidemic (high infection rate), as long as it can pass through the population quickly (moderate or high recovery rate), then the overall burden in terms of GDP will be less.

This result has interesting implications for the relationship between disease's basic reproductive number (an epidemiological measure of the severity of a disease) and GDP (an economic measure of the well-being of an economy). The basic reproductive number (R_0) is defined as the average number of secondary infections that occur when a single individual is introduced into a population where everyone is susceptible (F.Brauer and Castillo-Chavez (2012), Hethcote (2000)). In general, if $R_0 > 1$ then the disease will spread through the population, and if $R_0 < 1$, then the disease will die out. The bigger the R_0, then the worse or more severe the disease. For a standard SIR model, it is defined as the ratio of the infection and recovery rates (α_v/γ_v) (Diekmann et al. (1990), Diekmann et al. (2010), Heffernan et al. (2005)).

Covid Economics 67, 4 February 2021: 199-253

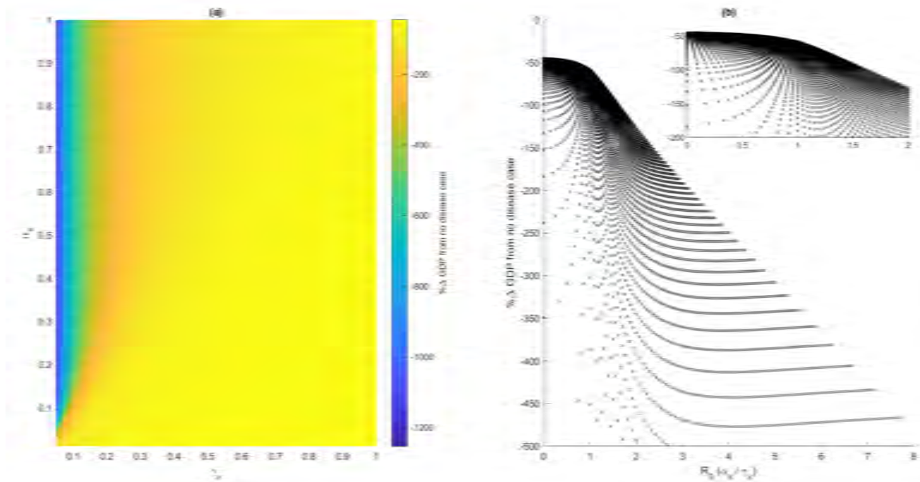


Figure 5: Sensitivity of GDP losses to epidemic parameters. Panel (a) presents the percent change in GDP for different combinations of disease transmission (α_v) and recovery (γ_v) rates. Color corresponds to the magnitude of GDP losses compared to the no-disease case. Dark blue (yellow) indicates greater (less) loss. Panel (b) relates the disease R_0 - generated from the epidemic parameters in panel (a) - to the percent change in GDP from the no-disease case. Though not tailored to a specific disease, for comparison the R_0 for COVID-19 is estimated to be between 1.4-6.5 (Cheng and Shan (2019)), 3.4 for H1N1 avian influenza (Chang et al. (2010)), 1.5-1.9 for Ebola (Khan et al. (2015)), and between 3.5-6 for smallpox (Hethcote (2000)).

Given the effects of the epidemiological parameters and GDP, a higher R_0 does not necessarily translate to greater GDP loss (Figure 5b). It is feasible to have a severe epidemic (in an epidemiological sense of the word) that does not result in a large economic loss, if the recovery rate is sufficiently high to allow workers to quickly return to the labor force. However, it is worth stressing that this result depends on a number of simplifying - albeit, we believe acceptable - assumptions. The model assumes a constant population size with homogeneous mixing, where the primary burden of disease is via the labor force. It does not account for deaths, vaccinations or treatments, nor quarantines or epidemic-related business closures. We leave further investigation to future work.

5.3 Unemployment Compensation

Next, we evaluate the quantity of unemployment benefits distributed to households who are unable to work due to infection. We find that, contrary to real-world expectations, distributing unemployment benefits generates no change in GDP compared to the baseline scenario. In a Keynesian framework, we would expect that compensating workers would help counterbalance the negative effects of the epidemic on GDP. The reason for this is that because households are Ricardian - a not unheard of phenomenon empirically (Evans and Hasan (1994)) - they are forward-looking and, in response to increases in government spending, choose to save today expecting to pay higher taxes later. This leads to no change in consumption. Ricardian consumer behavior is a common assumption in neoclassical models, which warrants future consideration when evaluating unemployment benefits as an economic policy.

Covid Economics 67, 4 February 2021: 199-253

Covid Economics 67, 4 February 2021: 199-253

5.4 Can monetary policy help fight the adverse effects of an epidemic?

In order to answer this research question, we individually vary a set of economic parameters, holding all the other parameters at their baseline values. We concentrate our analysis on financial parameters only, specifically focusing on three policy instruments. Remark that in this model, changing the economic parameters never provokes a change in labor. This is because we take labor as exogenously determined by the epidemic.

We start by first considering the steady-state leverage ratio for private banks (ϕ), defined as the total loans that a private bank can issue compared to its net worth (Figure 6). We find that the higher the leverage ratio, the higher the injection of funds from the Central Bank into the economy (ψ). This effect is observed because with a higher leverage ratio at the steady state, there is a greater probability of banks to sell claims. As this occurs, it causes the spread in the interest rates to increase, leading the Central Bank to further insert money into the economy. We also find a compositional shift in bankers' wealth, with income from selling claims (net worth) increasing (decreasing) with an increase in the steady-state leverage ratio. However, we do not observe a marked change in GDP compared to the baseline scenario.

Second, we test the sensitivity of Central Bank to a change in the spread via the feedback parameter ω (Figure 7). As the Central Bank responds more intensively to changes in the spread, it injects a higher quantity of funds into the economy during the beginning of the epidemic (when the difference in the spread is highest), and then drops off in the later stages. Volatility in the variation of the spread is greater with ω. This affects the quantity and composition of bankers' wealth, with higher wealth stemming from a smaller decrease in net worth. We find no effect on GDP losses. However, we observe that when the Central Bank reacts more intensively to changes in the spread, reductions in consumption are smaller than the baseline. This

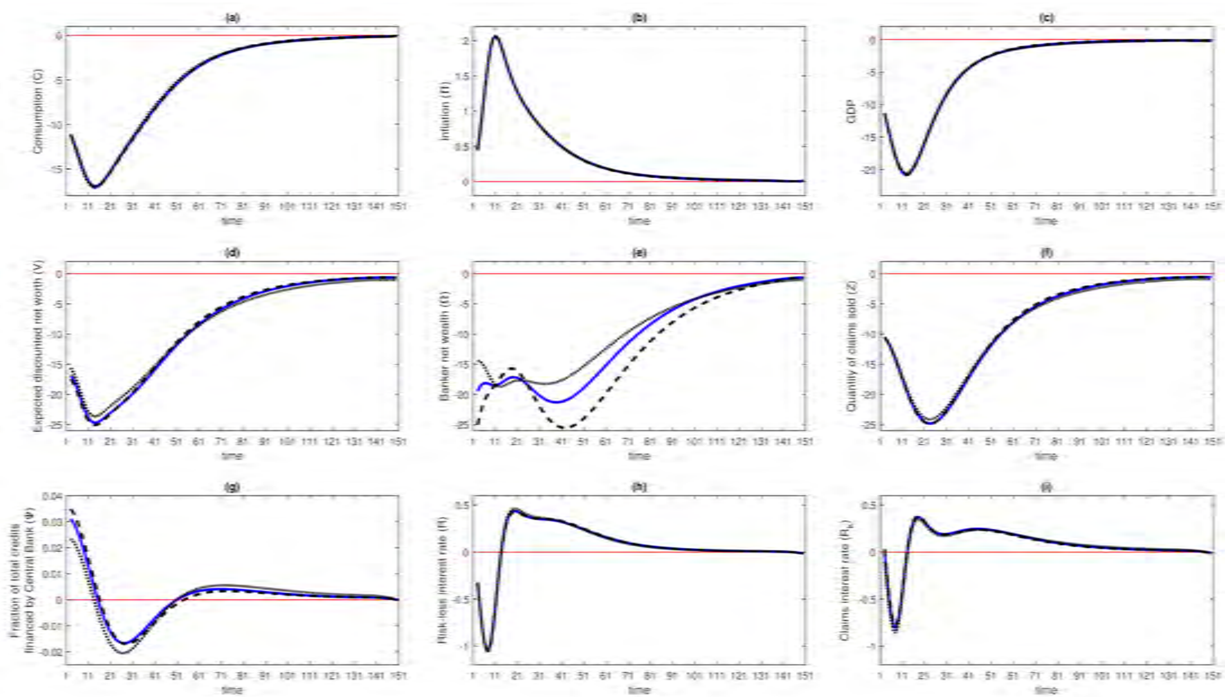


Figure 6: Model sensitivity to the steady state leverage ratio (ϕ). Recall that the results are reported as the percent change from the no-disease case. Line style and color indicates the value of the steady state leverage parameter: ϕ=2 (dotted, black), ϕ=4 (solid, blue; baseline), and ϕ=6 (dashed, black).

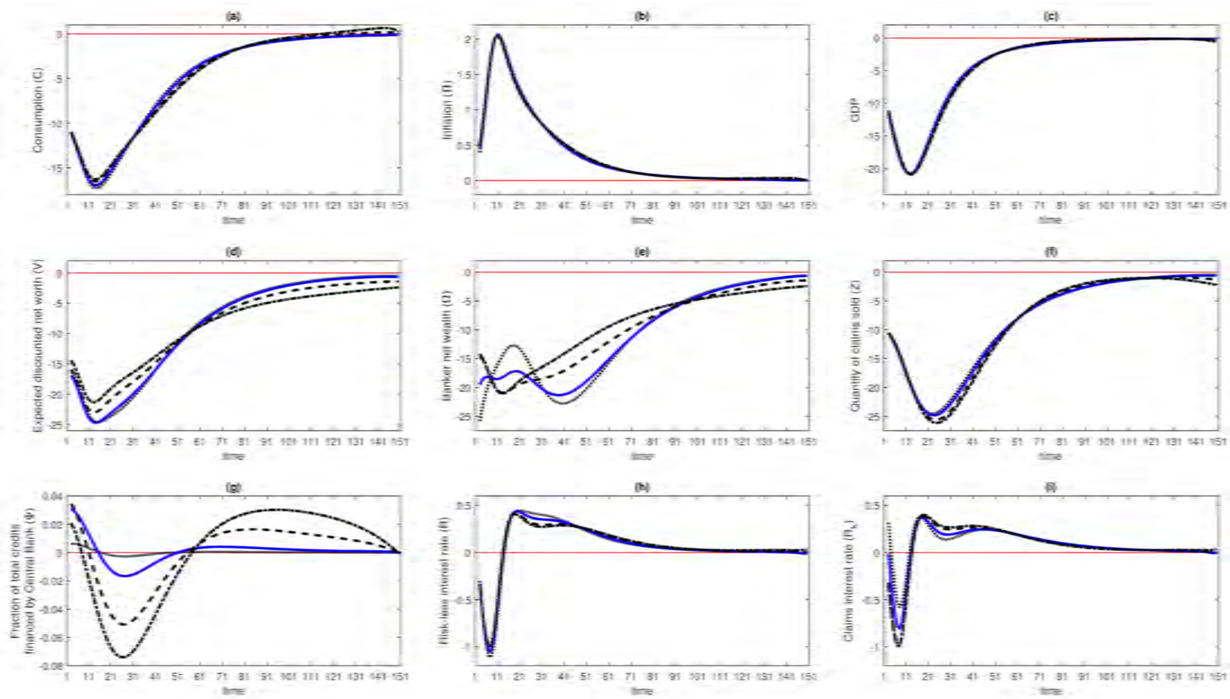


Figure 7: Model sensitivity to the feedback parameter (ω). Note that results are reported as the percent change from the no-disease case. Line style and color indicates the value of the feedback parameter: ω=1 (dotted, black), ω=10 (solid, blue; baseline), ω=100 (dashed, black), and ω=1000 (dot-dashed, black).

Covid Economics 67, 4 February 2021: 199-253

last result may suggest that, when talking about consumption, a stronger reaction to the spread is better for households.

Finally, we evaluate the use of "*epi loans*" to mitigate the effects of the epidemic (Figure 8). This takes the form of an exogenous shock on the steady state fraction of publicly intermediate assets $\bar{\psi}$, which affects the share of total claims the Central Bank finances (ψ). We assume that the Central Bank (with a cost) administers liquidity directly to the real economy in the form of claims that are transformed (one to one) into capital, and it does so from the beginning of the epidemic to its peak (in our case, this is about period 20).

Our definition of "*epi loans*" is an extreme form of a QE policy, but not exactly "helicopter money" as proposed by Friedman (1969). Instead of giving money directly to households with no expectation of being repaid, the Central Bank increases its share of total claims issued, and firms subsequently purchase capital without having to pass through private banks. Thus our "*epi loans*" directly affect demand by incentivizing investment, and should be thought of as expanding Central Bank intermediation rather than expanding the money supply.

With this policy we observe a smaller reduction in GDP compared to the baseline case. This should not come as a surprise given the fact that any increase in ψ will automatically increase GDP in the form of income obtained by the sale of claims. It is important to note, however, that although GDP loss is less than the baseline, the expected discounted terminal wealth of banks is reduced and the share of claims sold by private banks decreases. These are counterbalanced by an increase in the total quantity of claims sold such that the overall reduction of capital is smaller than the baseline. For households, this means that consumption is lower compared to the baseline case. An increase in claims reduces real rental interest rates and makes the acquisition of capital more attractive, incentivizing the investment in physical capital. As a side effect, we observe an expected increase in inflation. By reducing

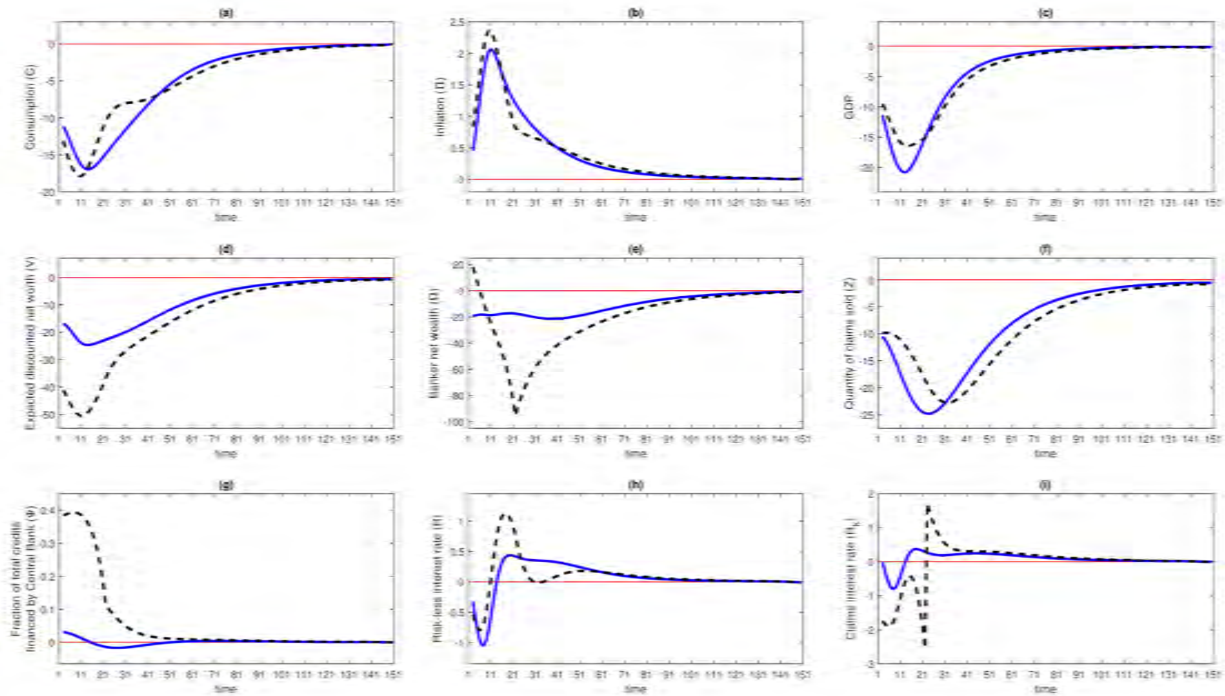


Figure 8: *Epi loans* ($\bar{\psi}$). Results are reported as the percent change from the no-disease case. The solid, blue line indicates the baseline model. The black, dotted line indicates a model implementing "*epi loans*" ($\bar{\psi}$=0.5). Note that the Central Bank administers "*epi loans*" from period 1 until peak of the epidemic (period 20).

CEPR PRESS

demand, we drive up prices. However, it is important to remark that the increase in inflation, at its worst, is only 0.3% higher than that without an "*epi loans*" policy. Our results are in line with those proposed by Sharma et al. (2020), Céspedes et al. (2020), and Kiley (2020).

6 Conclusion

For the first time, we use a financial DSGE-SIR model to study the response of economy to an epidemic shock. We summarize our findings into three primary contributions.

First, due to the epidemic, the economy is likely to experience a deep recession. With our baseline calibration, we observe significant declines in GDP, reaching a maximum loss of 20% compared to the no-disease case. Although not directly comparable to other papers, for illustrative purposes Angelini et al. (2020), Chudik et al. (2020) and Bodenstein et al. (2020) found decreases in GDP post COVID-19 between 1.5% to 2.5%, 15%, and 20% to 30% respectively. However, our framework our can be tailored to any combination of epidemiological models or economic parameters, making it possible to be calibrated to specific diseases and countries.[15]

Second, the profile of the epidemic has a significant effect on the shape of the recession. An epidemic that persists for a long time in the population (low recovery rate) and, consequently, keeps people from working, will be the most costly. Even if we have a highly contagious epidemic (high infection rate), as long as it can pass through the population quickly (moderate or high recovery rate), then the overall

[15] One could, for example, calibrate the epidemiological model to the COVID-19 epidemic. As COVID-19 is generally accepted to have an asymptomatic phase (Bi et al. (2020), He et al. (2020)), one would use a Susceptible-Asymptomatic-Infected-Recovered (SAIR) epidemiological model, which allows for asymptomatically-infectious individuals (F.Brauer and Castillo-Chavez (2012), Hethcote (2000)). Estimations of epidemiological model parameters have been conducted by Fanelli and Piazza (2020), Liangrong et al. (2020), Prem et al. (2020), and Yin et al. (2020), among others. However, it should be noted that there is uncertainty in estimations of these model parameters, as they will vary by country, the quality and timeframe of the data, the choice and timing of management strategies, accessibility to treatment and vaccines, as well as general assumptions inherent to disease models (such as homogeneous mixing or age structure).

Covid Economics 67, 4 February 2021: 199-253

recession will be less. This is because, in our model, as long as people are able to work, there should not be a reduction in production. We can infer that measures to decrease recovery time - such as treatments (which directly increases the recovery rate) and vaccination (which prevents individuals from getting sick) - could prove fruitful in minimizing economic losses of an epidemic. However, while straightforward to model in an epidemiological model (F.Brauer and Castillo-Chavez (2012), Hethcote (2000), Lenhart and Workman (2007)), these measures come with associated costs and the optimum usage is difficult to ascertain in a "macro-epidemic" framework. We leave this for future work.

Finally, we found that, with the exception of increasing the share of claims from the Central Bank, our unconventional monetary policies cannot negate the negative economic effects of the crisis. However, as last resort lender, the Central Bank could use an unconventional monetary policy to exogenously increase its share of total claims issued ("*epi loans*"), which firms will then use to buy capital. This policy has the potential to lessen total losses in GDP, partially mitigating the economic recession, without being extremely inflationary, a side effect which has worried economists since the first use of unconventional monetary policies after the sub-prime crisis (e21 Staff (2010)). This is an encouraging thought as many industrialized countries have announced billions in stimulus to combat the COVID-19 crisis.

References

Albertazzi, U., B. Becker, and M. Boucinha (2018, January). Portfolio rebalancing and the transmission of large-scale asset programmes: evidence from the euro area. Working Paper Series 2125, European Central Bank.

Angelini, E., M. Darracq-Paries, S. Zimic, and M. Damjanovic (2020). Ecb-basir:

Covid Economics 67, 4 February 2021: 199-253

a primer on the macroeconomic implications of the covid-19 pandemic. Working Paper Series 2431, European Central Bank.

Atkeson, A. (2020, March). What will be the economic impact of covid-19 in the us? rough estimates of disease scenarios. Working Paper 26867, National Bureau of Economic Research.

Baldwin, R. and B. DiMauro (2020, July). *Mitigating the COVID Economic Crisis: Act Fast and Do Whatever It Takes A VoxEU.org Book*.

Baqaee, D. and E. Farhi (2020, May). Nonlinear production networks with an application to the covid-19 crisis. Working Paper 27281, National Bureau of Economic Research.

Baumeister, C. and L. Benati (2013, June). Unconventional Monetary Policy and the Great Recession: Estimating the Macroeconomic Effects of a Spread Compression at the Zero Lower Bound. *International Journal of Central Banking 9*(2), 165–212.

Bi, Q., Y. Wu, S. Mei, C. Ye, X. Zou, Z. Zhang, X. Liu, L. Wei, S. Truelove, T. Zhang, W. Gao, C. Cheng, X. Tang, X. Wu, Y. Wu, B. Sun, S. Huang, Y. Sun, J. Zhang, and T. Feng (2020, April). Epidemiology and transmission of covid-19 in 391 cases and 1286 of their close contacts in shenzhen, china: a retrospective cohort study. *The Lancet Infectious Diseases 20*.

Bichara, D., Y. Kang, C. Castillo-Chavez, R. Horan, and C. Perrings (2015). "SIS and SIR epidemic models under virtual dispersal". *Bulletin of Mathematical Biology 77*, 2004–2034.

Bodenstein, M., G. Corsetti, and L. Guerrieri (2020, May). Social Distancing and Supply Disruptions in a Pandemic. Covid Economics 19, CEPR.

Boissay, F. and P. Rungcharoenkitkul (2020, April). Macroeconomic effects of Covid-19: an early review. BIS Bulletins 7, Bank for International Settlements.

Covid Economics 67, 4 February 2021: 199-253

Bonadio, B., Z. Huo, A. A. Levchenko, and N. Pandalai-Nayar (2020, May). Global supply chains in the pandemic. Working Paper 27224, National Bureau of Economic Research.

Brodeur, A., I. Grigoryeva, and L. Kattan (2020). Stay-at-Home Orders, Social Distancing and Trust. GLO Discussion Paper Series 553, Global Labor Organization (GLO).

Calvo, G. (1983). "Staggered Prices in a Utility-Maximizing Framework". *Journal of Monetary Economics 12*(3), 383–398.

Carlsson-Szlezak, P., M. Reeves, and P. Swartz (2020a). Understanding the Economic Shock of Coronavirus. *Harvard Business Review*.

Carlsson-Szlezak, P., M. Reeves, and P. Swartz (2020b). What Coronavirus Could Mean for the Global Economy. *Harvard Business Review*.

Céspedes, L. F., R. Chang, and A. Velasco (2020, May). The macroeconomics of a pandemic: A minimalist model. Working Paper 27228, National Bureau of Economic Research.

Chang, C., C. Cao, Q. Wang, Y. Chen, Z. Cao, H. Zhang, L. Dong, J. Zhao, M. Xu, M. Gao, S. Zhong, Q. He, J. Wang, and X. Li (2010). "The novel H1N1 Influenza A global airline transmission and early warning without travel containments". *Chinese Science Bulletin 55*, 3030–3036.

Cheng, Z. and J. Shan (2019). "Novel coronavirus: Where we are and what we know". *Infection 48*, 155–163.

Chowell, G., P. Fenimore, M. Castillo-Garsow, and C. Castillo-Chavez (2003). "SARS outbreaks in Ontario, Hong Kong, and Singapore: The role of diagnosis and isolation as a control mechanism". *Journal of Theoretical Biology 224*, 1–8.

Covid Economics 67, 4 February 2021: 199-253

Christiano, L. J., M. Eichenbaum, and C. L. Evans (2005). Nominal rigidities and the dynamic effects of a shock to monetary policy. *Journal of Political Economy 113*(1), 1–45.

Chudik, A., K. Mohaddes, M. H. Pesaran, M. Raissi, and A. Rebucci (2020, September). A counterfactual economic analysis of covid-19 using a threshold augmented multi-country model. Working Paper 27855, National Bureau of Economic Research.

Daszak, P., A. Cunningham, and A. Hyatt (2001). "Anthropogenic Environmental Change and the Emergence of Infectious Diseases in Wildlife". *Acta Tropica 78*, 103–116.

Dedola, L., P. Karadi, and G. Lombardo (2013). Global implications of national unconventional policies. *Journal of Monetary Economics 60*(1), 66–85.

Diekmann, O., J. Heesterbeek, and J. Metz (1990). "On the definition and the computation of the basic reproduction ratio R0 in models for infectious diseases in heterogeneous populations". *Journal of Mathematical Biology 28*, 365–382.

Diekmann, O., J. Heesterbeek, and M. Roberts (2010). "The construction of next-generation matrices for compartmental epidemic models". *Journal of the Royal Society Interface 7*, 873–885.

e21 Staff (2010). An Open Letter to Ben Bernanke. *Economics21.org*.

Eichenbaum, M. S., S. Rebelo, and M. Trabandt (2020a, June). Epidemics in the neoclassical and new keynesian models. Working Paper 27430, National Bureau of Economic Research.

Eichenbaum, M. S., S. Rebelo, and M. Trabandt (2020b, March). The macroeconomics of epidemics. Working Paper 26882, National Bureau of Economic Research.

Covid Economics 67, 4 February 2021: 199-253

Eichenbaum, M. S., S. Rebelo, and M. Trabandt (2020c, May). The macroeconomics of testing and quarantining. Working Paper 27104, National Bureau of Economic Research.

Elenev, V., T. Landvoigt, and S. VanNieuwerburgh (2020, May). Can the covid bailouts save the economy? Covid Economics 17, CEPR.

Evans, P. and I. Hasan (1994). Are consumers ricardian? evidence for canada. *The Quarterly Review of Economics and Finance 34*(1), 25 – 40.

Fanelli, D. and F. Piazza (2020). Analysis and forecast of covid-19 spreading in china, italy and france. *Chaos, Solitons and Fractals 134*, 109761.

Faria-e Castro, M. (2020, April). Fiscal Policy during a Pandemic. Covid Economics 2, CEPR.

F.Brauer and C. Castillo-Chavez (1994). *"Ecological Time Series"*, Chapter "Basic Models in Epidemiology", pp. 410–477. New York: Raven Pressr.

F.Brauer and C. Castillo-Chavez (2012). *"Mathematical Models in Population Biology and Epidemiology"*. New York: Springer-Verlag.

Fenichel, E., C. Castillo-Chavez, M. Ceddia, G. Chowell, P. G. P. G. Hickling, G. Holloway, R. Horan, B. Morin, C. Perrings, M. Springborn, L. Velazquez, and C. Villalobosi (2011). "Adaptive human behavior in epidemiological models". *Proceedings of the National Academy of the Sciences 108*, 6306–6311.

Friedman, M. (1969). *"The Optimum Quantity of Money and Other Essays"*, Chapter "The Optimum Quantity of Money", pp. 1–50. Chicago: Adline Publishing Company.

Galí, J., F. Smets, and R. Wouters (2011, May). Unemployment in an estimated new keynesian model. Working Paper 17084, National Bureau of Economic Research.

Covid Economics 67, 4 February 2021: 199-253

Gelain, P. and P. Ilbas (2017). Monetary and macroprudential policies in an estimated model with financial intermediation. *Journal of Economic Dynamics and Control 78*(C), 164–189.

Gertler, M. and P. Karadi (2011). A model of unconventional monetary policy. *Journal of Monetary Economics 58*(1), 17 – 34. Carnegie-Rochester Conference Series on Public Policy: The Future of Central Banking April 16-17, 2010.

Gertler, M. and N. Kiyotaki (2010). Chapter 11 - financial intermediation and credit policy in business cycle analysis. Volume 3 of *Handbook of Monetary Economics*, pp. 547 – 599. Elsevier.

Gualdi, S., M. Tarzia, F. Zamponi, and J.-P. Bouchaud (2015). Tipping points in macroeconomic agent-based models. *Journal of Economic Dynamics and Control 50*, 29 – 61. Crises and Complexity.

Guerrieri, V., G. Lorenzoni, L. Straub, and I. Werning (2020, April). Macroeconomic implications of covid-19: Can negative supply shocks cause demand shortages? Working Paper 26918, National Bureau of Economic Research.

He, D., S. Zhao, Q. Lin, Z. Zhuang, P. Cao, M. H. Wang, and L. Yang (2020). The relative transmissibility of asymptomatic covid-19 infections among close contacts. *International Journal of Infectious Diseases 94*, 145 – 147.

Heffernan, J., R. Smith, and L. Wahl (2005). "Perspectives on the basic reproductive ratio". *Journal of the Royal Society Interface 2*, 281–293.

Hethcote, H. (2000). "The Mathematics of Infectious Diseases". *SIAM Review 42*(4), 599–653.

Horan, R. and E. Fenichel (2007). "Economics and ecology of managing emerging infectious animal diseases". *American Journal of Agricultural Economics 89*, 1232–1238.

Horan, R. and C. Wolf (2005). "The economics of managing infectious wildlife disease". *American Journal of Agricultural Economics 87*, 537–551.

IMF (2020). World Economic Outlook: A Long and Difficult Ascent. World Economic Outlook 1, International Monetary Fund.

Jones, K., N. Patel, M. Levy, A. Storeygard, D. Balk, and P. D. J.L. Gittleman (2008). "Global trends in emerging infectious diseases". *Nature 451*, 990–993.

Kaplan, G., B. Moll, and G. L. Violante (2020, September). The great lockdown and the big stimulus: Tracing the pandemic possibility frontier for the u.s. Working Paper 27794, National Bureau of Economic Research.

Khan, A., M. Naveed, M. Dur-E-Ahmad, and M. Imran (2015). "Estimating the basic reproductive ratio for the Ebola outbreak in Liberia and Sierra Leone". *Infectious Diseases of Poverty 4*, 13.

Kiley, M. T. (2020, Oct). Pandemic Recession Dynamics: The Role of Monetary Policy in Shifting a U-Shaped Recession to a V-Shaped Rebound. Finance and Economics Discussion Series 2020-083, Board of Governors of the Federal Reserve System (U.S.).

Krueger, D., H. Uhlig, and T. Xie (2020, April). Macroeconomic dynamics and reallocation in an epidemic: Evaluating the "swedish solution. Covid Economics 5, CEPR.

Lenhart, S. and J. Workman (2007). *"Optimal Control Applied to Biological Models"*. London: Chapman and Hall.

LePan, N. (2020). A visual history of pandemics.

Liangrong, P., W. Yang, D. Zhang, C. Zhuge, and L. Hong (2020, February). Epidemic analysis of covid-19 in china by dynamical modeling.

Covid Economics 67, 4 February 2021: 199-253

Ludvigson, S. C., S. Ma, and S. Ng (2020, April). Covid-19 and the macroeconomic effects of costly disasters. Working Paper 26987, National Bureau of Economic Research.

Maliszewska, M., A. Mattoo, and D. Mensbrugghe (2020, April). *The Potential Impact of COVID-19 on GDP and Trade: A Preliminary Assessment.*

Mckibbin, W. and R. Fernando (2020, April). The global macroeconomic impacts of covid-19: Seven scenarios. Covid Economics 10, CEPR.

Merton, R. C. (1973). An intertemporal capital asset pricing model. *Econometrica 41*(5), 867–887.

Mihailov, A. (2020, April). Quantifying the Macroeconomic Effects of the COVID-19 Lockdown: Comparative Simulations of the Estimated Galí-Smets-Wouters Model. Economics Discussion Papers em-dp2020-07, Department of Economics, Reading University.

Milani, F. (2021). Covid-19 outbreak, social response, and early economic effects: a global var analysis of cross-country interdependencies. *Journal of Population Economics 34*(1), 223–252.

Morin, B., C. Perrings, A. Kinzig, and S. Levin (2015). "The social benefits of private infectious disease-risk mitigation". *Theoretical Ecology 8*, 467–479.

Morin, B., C. Perrings, S. Levin, and A. Kinzig (2014). "Disease risk mitigation: The equivalence of two selective mixing strategies on aggregate contact patterns and resulting epidemic spread". *Journal of Theoretical Biology 363*, 262–270.

Prem, K., Y. Liu, T. Russell, A. Kucharski, R. Eggo, N. Davies, M. Jit, P. Klepac, S. Flasche, S. Clifford, C. Pearson, J. Munday, S. Abbott, H. Gibbs, A. Rosello, B. Quilty, T. Jombart, F. Sun, C. Diamond, and J. Hellewell (2020, March). The

Covid Economics 67, 4 February 2021: 199-253

effect of control strategies to reduce social mixing on outcomes of the covid-19 epidemic in wuhan, china: a modelling study. *The Lancet Public Health 5*.

Qianying, C., F. Andrew, H. Dong, and Z. Feng (2016). Financial crisis, us unconventional monetary policy and international spillovers. *Journal of International Money and Finance 67*, 62 – 81.

Sharma, D., J.-P. Bouchaud, S. Gualdi, M. Tarzia, and F. Zamponi (2020, July). V-, U-, L-, or W-shaped recovery after COVID: Insights from an Agent Based Model. Covid Economics 40, CEPR.

Smets, F. and R. Wouters (2007). "Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach". *American Economic Review 97*(3), 586–606.

Wu, T., C. P. A. Kinzig, J. Collins, B. Minteer, and P. Daszak (2017). "Economic growth, urbanization, globalization, and the risks of emerging infectious diseases in China: A review". *Ambio 46*, 18–29.

Yin, Z., H. An, and D. W. Shanafelt (2020, Oct). Best-fit epidemiological models for covid-19: New cases in korea.

Covid Economics 67, 4 February 2021: 199-253