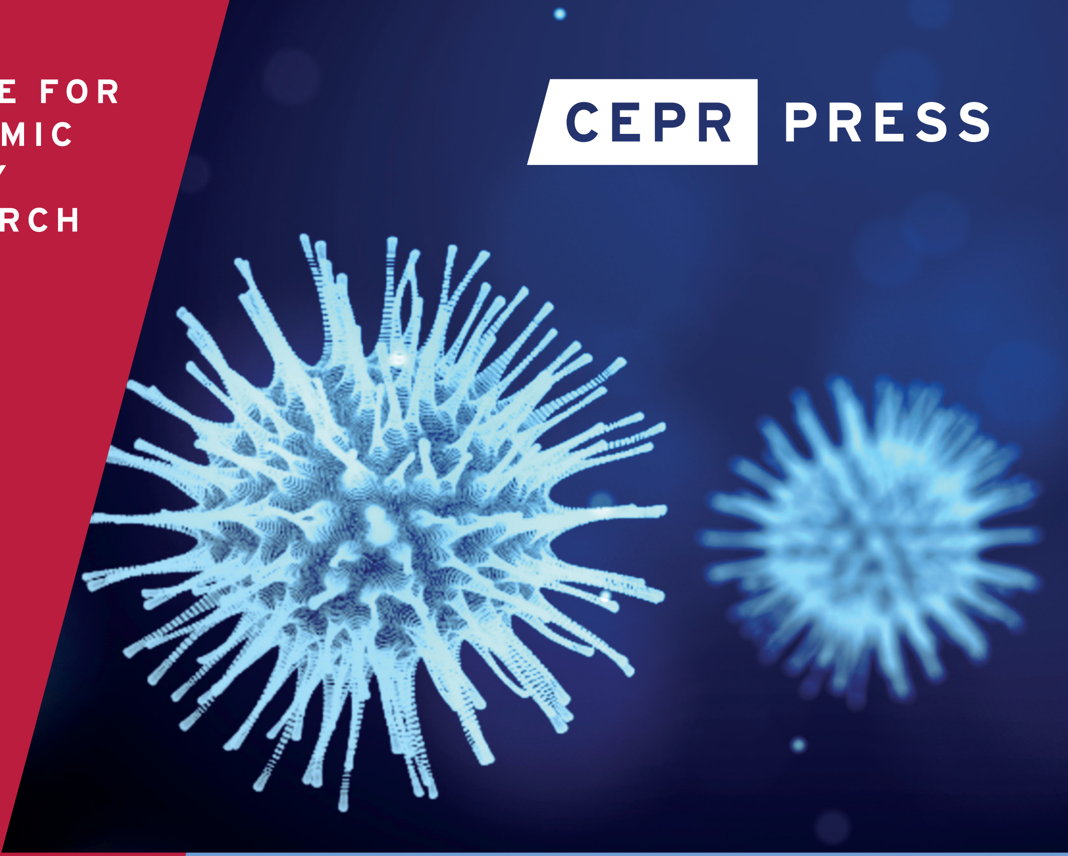
CENTRE FOR
ECONOMIC
POLICY
RESEARCH

CEPR PRESS



COVID ECONOMICS

VETTED AND REAL-TIME PAPERS

ISSUE 74
30 MARCH 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.

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 74, 30 March 2021

Contents

CEPR PRESS

Covid Economics **Issue 74, 30 March 2021**

The welfare cost of vaccine misallocation, delays and nationalism[1]

Christian Gollier[2]

Date submitted: 27 March 2021; Date accepted: 27 March 2021

I calibrate an eco-epidemiological age-structured SIR model of the B.1.1.7 covid variant on the eve of the vaccination campaign in France, under a stop-and-go lockdown policy. Three-quarters of the welfare benefit of the vaccine can be achieved with a speed of 100,000 full vaccination per day. A 1-week delay in the vaccination campaign raises the death toll by approximately 2,500, and it reduces wealth by 8 billion euros. Because of the large heterogeneity of the rates of hospitalization and mortality across age classes, it is critically important for the number of lives saved and for the economy to vaccinate older people first. Any departure from this policy has a welfare cost. Prioritizing the allocation of vaccines to the most vulnerable people save 70k seniors, but it also increases the death toll of younger people by 14k. Vaccine nationalism is modeled by assuming two identical Frances, one with a vaccine production capacity and the other without it. If the production country vaccinates its entire population before exporting to the other, the global death toll would be increased by 20\%. I also measure the welfare impact of the strong French anti-vax movement, and of the prohibition of an immunity passport.

Covid Economics 74, 30 March 2021: 1-24

1 I thank Jiakun Zheng and participants to my keynote lecture at the 14th Financial Risks International Conference in Paris for helpful comments. The research leading to these results has received the support from the ANR grants Covid-Metrics and ANR-17-EURE-0010 (Investissements d'Avenir program).

2 Toulouse School of Economics, University of Toulouse-Capitole.

CEPR PRESS

1 Introduction

At the end of 2020, two key events impacted the dynamics of the covid-19 pandemic in opposite directions. First, the B.1.1.7 ("British") variant emerged. It is more transmissible and more lethal than the original virus. The health measures implemented in France for example, that were strong enough to imply a R0 smaller than 1 for the original virus, were insufficient to maintain the variant's R0 below 1. In the anticipation of a vaccine, and without an effective test-trace-and-isolate strategy, or a cure to the covid-19, the French government implemented a stop-and-go policy to "flatten the curve", implying a terrible death toll among vulnerable people, and a sizable destruction of economic wealth in the medium term. But the good news at the end of 2020 was that several highly effective vaccines started their mass production and inoculation phases. These vaccines do not only erase the most severe consequences of the virus for the infected patients, in particular hospitalization and death. They also eliminate the risk of transmission of the virus from vaccinated but infected patients.

However, the production capacity for these vaccines is too small to allow most countries to win the race between mass vaccination and the dissemination of the new variant. This raises the critical question of the allocation of the flow of available vaccines over time. This issue is complex because of its ethical, health, social and economic implications. The WHO (2020a) has worked out a values framework based on 12 objectives and 6 principles (human wellbeing, equal respect, global equity, national equity, reciprocity, legitimacy). From this framework, WHO (2020b) "justifies an initial focus on direct reduction of morbidity and mortality and maintenance of most critical essential services, while considering reciprocity towards groups that have been placed at disproportionate risks to mitigate consequences of this pandemic (for example, front-line health workers)." Duch et al. (2020) surveyed 13 countries to measure the population's willingness to prioritize the supply of vaccines to different categories of citizens. In most countries, people favor giving priority to key workers and to those at high risk, but the public also favors giving priority to various categories of citizens such as poorer people.

In Table 1, I describe the most recent statistics on the infection-to-ICU and infection-to-fatality rates in France. The later (IFR) takes into account of a 64% increase in the mortality rate of the B.1.1.7 variant observed in the U.K. (Challen et al., 2021). According to Lapidus et al. (2020), the IFR increases exponentially with age, doubling every 5.2 years. This suggests that the vaccination strategy that maximizes the number of lives saved is to prioritize older people, together with people with co-morbidities. Most EU members are currently following a "stop-and-go" policy to "flatten the curve" of the ICU utilization. Because older people are also susceptible to need intensive care in case of infection, giving priority to older people is also useful for the economy, by relaxing the necessary lockdown.[1] In this paper, I measure the welfare benefit for France of this optimal vaccination campaign by combining its wealth and health impacts.

To perform this task, I improve the age-structured SIR model that I used in Gollier (2020c) to compare the welfare impacts of different age-sensitive lockdown policies. I removed from this model its PCR testing element, because no government has used the possibility of mass testing to unlock citizens with a negative test. I replaced this testing element by a vaccination module.

[1] China is currently giving vaccination priority to the 18-60 category of ages. This may be due to the fact that China has a very low rate of prevalence of the virus. The economic effect of this priority rule is thus non-existent.

Covid Economics 74, 30 March 2021: 1-24

Age Class	Prob[ICU if infected]	Prob[deceased if infected]
0-18	0.01%	0.001%
19-64	0.48%	0.30%
65+	1.75%	7.79%

Table 1: Estimation of the infection-ICU and the infection-fatality rates by age class in France. Source: Saltje et al. (2020) for the ICU rate and Lapidus et al. (2021) for the IFR. This IFR is multiplied by 1.64, given the observation by Challen et al. (2021) of the 64% increased lethality of the variant.

The pandemic has both health and wealth impacts. As is usual in health and environmental economics, I use a Value of Statistical Life (VSL) to value lives saved in the welfare function.[2] To perform the welfare evaluation of various health policies, I use the official VSL of 3 million euros prevailing in France (Quinet, 2013). I show that the marginal welfare benefit of the vaccine is quickly decreasing with the speed of the vaccination. Compared to the no-vaccine solution, three-quarters of the welfare cost of the pandemic in 2021 would be eliminated in France with the current speed of 100k vaccinations per day. And postponing the vaccination campaign in France by one week would kill 2,500 additional people along the pandemic, and it would reduce wealth by 8 billion euros. This result could be useful for example when performing the benefit-risk evaluation of the (4 days) suspension of the vaccination campaign when some safety concerns emerged for the AstraZeneca vaccine in mid-March.

Suppose now that, for whatever reason, France does not prioritize the supply of vaccines to its most vulnerable citizens. A possible reason is the existence in France of a strong anti-vax movement. In Section 7, I measure the welfare impact of the presence of 30% anti-vaxxers. In my model, their presence does not affect the intensity of the lockdown, so that it does not worsened the economic crisis. But it increases the death toll by 60k, most of them anti-vaxxers. They also exercise a negative externality on senior pro-vaxxers, 5k of them will die due to additional senior infections during the first three months of the campaign, before their immunization.

Vaccine nationalism is another source of misallocation of the vaccine. In late March, countries like the U.S., the U.K. and Israel have been able to vaccinate a majority of their population, whereas the most vulnerable people in other countries remain exposed to the virus. According to Mullard (2020) given information available at the end of 2020, the U.S. has reserved more than 1.2 billion doses, and Canada has delivery contracts covering more than 9 doses per persons. Hafner et al. (2020) estimate the economic cost of the predicted disruptions in pandemic-sensitive sectors generated by this nationalism. In this paper, I analyze a thought experiment of vaccine nationalism by assuming a world composed of two identical Frances, one with a vaccine production capacity and the other without it. I compare the first-best allocation where vulnerable people of both countries are vaccinated first, to the nationalistic allocation in which the producing country keeps the production for itself until the completion of its vaccination campaign. I show that such an extreme form of

[2]For more information, see for example Drèze (1962), Schelling (1968), Jones-Lee (1974), Shepard and Zeckhauser (1984), Murphy and Topel (2006), Viscusi (2009), and US-EPA (2010).

Covid Economics 74, 30 March 2021: 1-24

vaccine nationalism raises the aggregate death toll by 20%. I also show that the producing country gains so much from banning vaccine exports that any sizable international vaccination cooperation, such as the COVAX project supervised by WHO, looks like a definitive illusion, in spite of its public support (Clarke et al., 2021).

A few papers have examined age-structured SIR models. Most of them examine strategies of mass confinement and/or testing, but none of them have considered a severely constrained vaccination campaign. Acemoglu, Chernozhukov, Werning and Whinston (2020), Favero, Ichino and Rustichini (2020), Fischer (2020) and Wilder et al. (2020) all support a strong sheltering of the vulnerable persons. All these models share the same fundamental structure of the age-structured SIR framework that I use in this paper. Contrary to Gollier (2020b), I suppose here that all parameters of the pandemic are known with certainty.

2 The age-structured SVIR model

The SIR model was introduced by Kermack and McKendrick (1927). As of today, this model remains the backbone of epidemiological literature. It has long been extended to allow for differences across groups. These extensions are referred to as "multi-group", and when focusing on age, "age-structured" or "age-stratified". In the spirit of Acemoglu et al. (2020), Favero et al. (2020) and Gollier (2020c), I examine such an extension of a discrete-time version of the SIR model, by adding an economic module and by allowing for a vaccination stage. The whole population, whose size is normalized to unity, is partitioned in 3 age classes $j \in \{y, m, o\} = \{0-18, 19-64, 65+\}$. The share of class j in the whole population is denoted N_j. Each person is either Susceptible, Vaccinated, Infected, Recovered or Death, i.e., the health status of a person belongs to $\{S, V, I, R, D\}$. This implies that $S_{j,t}+V_{j,t}+I_{j,t}+R_{j,t}+D_{j,t} = N_j$ at all dates $t \geq 0$, where $I_{j,t}$ for example measures the number of infected persons in class j at date t. The number of infected persons at date t is denoted $I_t = \sum_j I_{j,t}$, with a symmetric notation for S_t, V_t, R_t and D_t. I consider a daily frequency.

The flow chart of the SVIR model is described in Figure 1. Day 0 corresponds to the date at which the vaccination campaign begins, with exogenous initial conditions $(S_0, V_0, I_0, R_0, D_0)$. From day 0 on, a flow $\{x_t\}$ of daily vaccinations can be performed.[3] This daily vaccination capacity must be allocated to the different age classes according to a specific allocation strategy. Let $s_t = \{s_{yt}, s_{mt}, s_{ot}\}$ represent this dynamic allocation, with $\sum_j s_{jt} = x_t$ for all t. The total number of people in age class j who have been vaccinated prior to or on day t is

$$v_{jt} = \sum_{\tau=0}^{t} s_{j\tau}. \tag{1}$$

The cumulative number of vaccinated people in the population on day t is $v_t = v_{yt}+v_{mt}+v_{st}$.

Newly vaccinated people are transferred into the V pool. Because antigens take time to be produced, people in that pool remain susceptible. A fraction μ of the V pool is transferred into the R pool every day, i.e. they become immunized. Thus, the mean transit time in the V pool is $1/\mu$ days. I assume that vaccination is 100% efficient after the V-transition, and that infected people who recovered from the virus are permanently immunized. They are

[3] For simplicity, I assume that only one dose per person is sufficient to be vaccinated. Because all vaccines currently distributed in France require two doses, the speed of vaccination in my model should be estimated by dividing by 2 the daily number of doses inoculated.

Covid Economics 74, 30 March 2021: 1-24

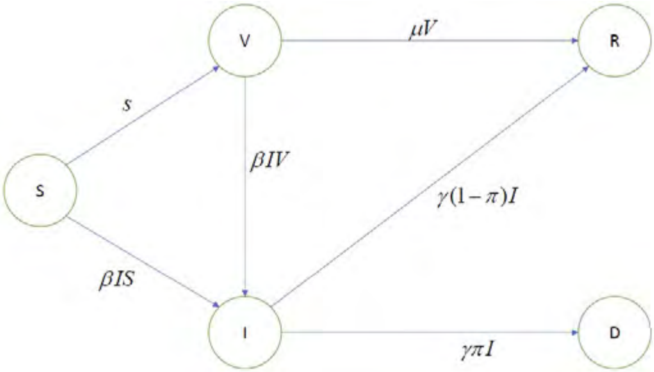


Figure 1: Flow chart of the SVIR model

also all detected as such at no cost. Thus, the R status can be be attained either through a successful vaccination or from recovering from the disease.

People with the S status and the V status face the same risk to become infected. They can be infected by meeting an infected person. Following the key assumption of all SIR models, this number of new infections is assumed to be proportional to the product of the densities of infected and susceptible persons in the population, weighted by the intensity of their social interaction. Under the SIR framework, and with no further justification, this is quantified as follows:

$$I_{i,t+1} - I_{i,t} = \left(\sum_{j=1}^{J} \beta_{ijt} I_{j,t}\right)(S_{i,t} + V_{i,t}) - \gamma_i I_{i,t}. \tag{2}$$

I will soon describe how β_{ijt}, which measures the intensity of the risk of contagion of a susceptible person in class i by an infected person in class j at date t, is related to the social interactions between these two groups and by the confinement policy. Once infected, a person in age class i quits this health state at rate γ_i, as described by the last term in equation (2). The net outflow of susceptible persons between days t and $t+1$ combines people who are infected and people who get vaccinated:

$$S_{i,t+1} - S_{i,t} = -\left(\sum_{j=1}^{J} \beta_{ijt} I_{j,t}\right) S_{i,t} - s_{it}. \tag{3}$$

Similarly, the net outflow from the V pool is given by the following equation:

$$V_{i,t+1} - V_{i,t} = s_{it} - \left(\sum_{j=1}^{J} \beta_{ijt} I_{j,t}\right) V_{i,t} - \mu V_{i,t}. \tag{4}$$

Covid Economics 74, 30 March 2021: 1-24

There are two exit doors to the infection status, as one can either recover from the virus or die:

$$R_{i,t+1} - R_{i,t} = (1-\pi_i)\gamma_i I_{i,t} + \mu V_{i,t} \tag{5}$$

$$D_{i,t+1} - D_{i,t} = \pi_i \gamma_i I_{i,t}. \tag{6}$$

The mortality rate among the infected persons of class i at date t is denoted π_i. In this paper, I compare health policies that all share the same property of never overwhelming hospitals. This allows me to assume that the mortality rate is constant along the pandemic cycle. Equations (2), (3), (4), (5) and (6) fully describe the age-structured SVIR model examined in this paper. The dynamics of the pandemic depends in particular upon the β coefficients, which are sensitive to the intensity of the social interaction within and across different age groups. They also depend upon the policy of social distancing. Symptomatic infected people are quarantined, whereas the remainder of the population – which includes the asymptomatic infected people – faces some restrictions in terms of social distancing. I assume that a fraction κ of infected people is asymptomatic and cannot be identified during their contagion period.

The policy of social distancing on day t is described by vector $\{b_{jt}\}$ where $b_{jt} \in [0,1]$ is the intensity of the lockdown imposed to age class j. Symptomatic infected people have a low contagion index β_q because they are quarantined. Asymptomatic infected people cannot be detected and are just partially confined. They have a contagion index $\underline{\beta} b_{jt} + \overline{\beta}(1-b_{jt})$. Thus, infected people in age class j have a mean contagion of $\beta_q(1-\kappa) + (\underline{\beta} b_{jt} + \overline{\beta}(1-b_{jt}))\kappa$. Susceptible people in age class i are confined in intensity b_{it}. Given the frequency α_{ij} of interactions between age-classes i and j, the rate of transmission of the virus between infected people of age class j and susceptible people of age class i is given by:

$$\beta_{ijt} = \alpha_{ij}\Big(\beta_q(1-\kappa) + (\underline{\beta} b_{jt} + \overline{\beta}(1-b_{jt}))\kappa\Big)(1-b_{it}) \tag{7}$$

An important feature of equation (7) is that the intensity of the contagion between age classes i and j is a quadratic form of the confinement intensities b_i and b_j. In the case of a uniform confinement rule, the intensity of contagion is quadratic in the intensity b of confinement. This is due to the fact that the lockdown reduces the interaction from both sides, infected and susceptible.

How can we compare different policies in relation to their welfare impacts? Two dimensions should be taken into account. First, life is valuable, so death has a welfare cost. Let me associate a cost ℓ_j to the death of a person in age class j.[4] The pandemic has also an economic cost associated to the deaths, quarantines, confinements and vaccination during the pandemic. I assume that quarantined people are unable to work. A fraction ξ_j of confined people in class j can telework. The value loss of a person in class j who cannot work is denoted w_j. For workers, w_m can be interpreted as their labor income. For young people,

[4]Some recovered people suffer from long-lived side effects after their infection. Because this phenomenon remains difficult to measure in frequency, intensity and duration, I have not included this adverse effect of the pandemic in my welfare analysis. Other missing welfare effects of the pandemic include the psychological cost of the measures of social distancing, or the increasing risk of new variants when the rate of prevalence increases.

Covid Economics 74, 30 March 2021: 1-24

Covid Economics 74, 30 March 2021: 1-24

w_y includes the lost human capital due to the reduced quality of their education during lockdown. For the retired people, it's the value of their contributions to the common good. We must also take account of the economic cost of mass vaccination. In total, assuming a unit cost of vaccination equaling p, the economic loss of the pandemic in class j is measured as follow:

$$W_j = pv_{jT} + w_j \sum_{t=0}^{T} \Big((1-\xi_j) b_{jt} (S_{j,t} + \kappa I_{j,t} + (1-\omega) R_{j,t}) + (1-\kappa) I_{j,t} + D_{j,t} \Big), \qquad (8)$$

where T is the time horizon of the social planner. I assume that a proportion ω of people with the R status receives an "immunity passport" which allows them to be relieved from the lockdown constraints. Finally, the total loss is thus equal to

$$L = \sum_{j=1}^{J} \Big(\ell_j D_{j,T} + W_j \Big). \qquad (9)$$

A key dimension of the health policy during a pandemic is the risk of overwhelming the health care system facing limited capacities in health workers, beds, ICUs or respirators. I summarize this capacity problem by a capacity limit on covid ICUs in hospitals. The social distancing policy $\{b_t\}$ is aimed at making sure that the national ICU capacity $\overline{ICU}$ is never overwhelmed. I assume that at the end of the infection period, a fraction h_i of infected people needs an ICU.

$$newICU_{i,t} = h_i \gamma_i I_{i,t},$$

where h_i is the fraction of infected people in class i developing an acute version of the virus and requiring intensive care. Because the mean duration in intensive care is T_{ICU}, the total number of people of age class i in intensive care on day t is given by

$$ICU_{i,t} = \sum_{\tau=1}^{T_{ICU}} newICU_{i,t-\tau}.$$

I constrain health policies to make sure that the ICU capacity is never overwhelmed: $\sum_j ICU_{j,t} \leq \overline{ICU}$. Finally, I assume that the virus can be obliterated by an aggressive testing-and-tracing strategy if the global infection rate in the whole population goes below some threshold I_{min}.

In this paper, I measure the impact of the vaccination strategy on social welfare under the standard uniform "stop-and-go" lockdown policies that have been implemented in Europe after the first wave of the pandemic. These policies have the advantage of preserving some ICUs, but they ignore the fact that the short term economic advantage of the weak lockdown could be dominated by the medium term cost of the much longer duration of the lockdown, waiting for herd immunity or a mass vaccination campaign. They also ignore the benefits of sheltering more intensely the most vulnerable fraction of the population (Gollier, 2020c). So, I assume $b_{jt} = b_t$. The limited social acceptability of these measures justifies the more realistic approach considered in this paper. The stop-and-go policy is characterized by three possible intensities of confinement, $b^l < b^m < b^h$, and three ICU thresholds: $0 \leq r_l < r_m < r_h \leq \overline{ICU}$. I assume that the medium intensity b^m of lockdown is implemented on day 0. This intensity is maintained as long as ICU_t remains in between r_l and r_h. If ICU_t goes below r_l, the intensity is reduced to b^l, and remains at that level as long as ICU_t is below r_m. If ICU_t goes above r_h, the lockdown intensity is increased to b^h, and remains at that level as long as ICU_t is above r_m. Finally, we must recognize that the usefulness of the lockdown is reduced when the proportion of vaccinated people increases. I therefore assume that the effective lockdown intensity is linearly decreasing with the fraction of vaccinated people: $b_t = b^i(1 - v_t)$.

Because older people faces a much larger risk of needing intensive care and of mortality in case of infection, the efficient vaccination strategy is to allocate the vaccine in priority to this age class.[5] The benchmark calibration of the model is based on the assumption that the vaccination campaign allocates the vaccine according to this first-best rule. I then examine the welfare cost of alternative allocation strategies.

3 Calibration of the SVIR model

I calibrate the model on French data. I normalize the French population of n =67 million people to unity. The size of the population in the different age classes is $N = (0.227, 0.568, 0.205)$. At date $t = 0$, I assume that 1% of the population is infected, uniformly across the 3 age classes. At that time, there is a number $R_{.,0} = (0.24, 0.17, 0.12).N$ of recovered people in the population.[6] I also assume that 1% of the population is in the I status at that date. All others are in the S pool on day 0.[7]

I calibrate the virulence of the B.1.1.7 variant as follows. According to Volz et al. (2020), it is 40% to 70% more transmissible than the original virus. I therefore increase the $(\underline{\beta}, \overline{\beta})$ by 50% compared to my original calibration in Gollier (2020c). It yields $\underline{\beta} = 0.15$ and $\overline{\beta} = 0.9$, whereas I continue to assume that quarantined (symptomatic) individuals do not transmit the virus. According to Challen et al. (2021), the B.1.1.7 variant is also 64% more lethal than the original virus. Thus, I multiplied by a factor 1.64 the historical infection-fatalities ratio estimated for France by Lapidus et al. (2021). This yields a infection-fatality ratio π equaling 7.79% and 0.3% for respectively the 65+ and the 19-64. Compared to the calibration for the original virus, these are very bad news.

The daily outflow rate $\gamma_i = \gamma = 1/18$ from the infection pool is assumed to be the same across age classes. This corresponds to the observation that infected people remain sick for 2 or 3 weeks on average. The daily outflow rate $\mu = 1/20$ from the recently vaccinated V pool to immunity R pool corresponds to a mean time of 20 days to develop antigens. The rate of asymptomatic cases is particularly difficult to calibrate. The Center for Evidence-Based Medicine has estimated this rate somewhere between 5% and 80%.[8] He, Lau, Wu et al. (2020) found a 95% confidence interval of [25%, 69%] for the proportion of asymptomatic cases. The US Center for Disease Control and Prevention (CDC) has edicted 5 scenarios of the pandemic with two plausible levels of the rate of asymptomatic, 0.2 and 0.5, with a

[5]More generally, the vaccine should be allocated on the basis of a vulnerability index that would include the existence of co-morbidities. This is how the categorization of the population should be interpreted in this model. This research suffers from the lack of information about the number of people with relevant co-morbidities, their social interaction and their labour participation. In this paper, I also ignore the critical importance of vaccinating people serving vulnerable people in hospitals and nursing homes.

[6]In its report of March 11, 2021, the Conseil Scientifique chaired by J.-F. Delfraissy stated that 17% of the French population tested positive to the SARS-CoV-2 antigen in early 2021, with twice as much immunized people among younger people than among people aged 50 or more.

[7]This also means that the death toll is reset to 0 on day 0.

[8]https://www.cebm.net/covid-19/covid-19-what-proportion-are-asymptomatic/

Covid Economics 74, 30 March 2021: 1-24

Covid Economics 74, 30 March 2021: 1-24

central assumption at 0.35.[9] I assumed a $\kappa = 35\%$ rate of asymptomatic people. The social contact matrix across age classes has been estimated in France by Béraud, Kazmercziak, Beutels, Levy-Bruhl, Lenne, Mielcarek et al. (2015). Social interactions go down with age, within and across age classes. I approximate their results by the following contact matrix:

$$\alpha_{..} = \begin{pmatrix} 2 & 0.5 & 0.25 \\ 0.5 & 1 & 0.25 \\ 0.25 & 0.25 & 0.5 \end{pmatrix} \tag{10}$$

The social distancing policy is characterized by the lockdown intensities $b^l = 0$, $b^m = 40\%$ and $b^h = 80\%$, and by the ICU thresholds (r_l, r_m, r_h) of respectively 30%, 60% and 90% of the ICU capacity $\overline{ICU}$. The minimum rate of infection below which the virus can be obliterated in the population is assumed to be $I_{min} = 30,000/n$.

Wealth losses are measured in fractions of annual GDP (around 2,400 billion euros). I assume that a full lockdown would reduce the flow of wealth production by $\xi = 50\%$, coming from a mixture of people who cannot telework and of the inefficient nature of teleworking technologies compared to work in presence. This is in line with the estimation of a 8.3% of GDP loss in France in 2020, assuming a 20% average intensity of lockdown during that year.[10] I assume an economic loss of a full confinement by a middle-aged person equaling $1/N_m$. This means that a 100% confinement of the middle-aged people without any telework capability during one year would generate a 100% GDP loss. In this calibration, telework halves that loss. I also assume that confining a young or a senior person yields no economic loss. This is in line with the worrying fact that GDP does not take account of most contributions of these two age classes to the wealth of the nation.

In the benchmark calibration of the model, I prohibit immunity passports, so that $\omega = 0$. Recovered and vaccinated people are assumed to be confined with the same intensity as susceptible people.

What is the cost of the vaccination campaign? The purchasing prices of the vaccines have mostly remained secret as I write this paper. The Belgian health authorities told the media that the EU purchased the AstraZeneca vaccine at a unit price of 2.15 euros.[11] Pharmacists are allowed to inoculate the vaccine in France since mid-March 2021. They are paid 10 euros per inoculation. Because two doses are necessary, I estimate the total cost of the vaccination to around 30 euros per person. This implies a total cost around 2 billion euros, or approximately $p = 0.1\%$ of annual GDP.

In France in 2021 , we have 6733 beds in ICU. The probability of requiring an ICU bed in case of infection has been estimated by Saltje et al. (2020). It equals 0.01%, 0.48% and 1.75% for the 3 age classes.[12] It remains to calibrate the value of lives. I discuss this critical issue in Gollier (2020a), remarking in particular that the absence of any democratic debate on this issue over the last five decades during which Western governments used a "value of statistical life" for policy evaluation is problematic. In this paper, I value a life lost at 100

[9] https://www.cdc.gov/coronavirus/2019-ncov/hcp/planning-scenarios.html

[10] https://www.insee.fr/fr/statistiques/5018361

[11] Hafner et al. (2020) claim that the United States deal for the Pfizer/BioNTech agreement was set at the much larger price of 19.50 USD per dose.

[12] The ICU probability is smaller than the mortality rate for the seniors, probably because many of them die in nursing home without benefiting from an intensive care unit.

Covid Economics 74, 30 March 2021: 1-24

	Value	Description
γ	1/18	Daily recovery rate
μ	1/20	Daily immunization rate among newly vaccinated
β_q	0	Daily contagion rate of quarantined persons
$\underline{\beta}$	0.15	Daily contagion rate of confined persons
$\overline{\beta}$	0.9	Daily contagion rate of working persons
κ	35	Proportion of asymptomatic positives (in %)
ω	0	Proportion of immunized people with an immunity passport
ξ	0.5	Proportion of telework
$\underline{I_{min}}$	30000	Extinction threshold of the pandemic
$\overline{ICU}$	6733	ICU capacity
(b^l, b^m, b^h)	(0,40,80)	Intensities of lockdown (in%)
$(r_l, r_m, r_h)/\overline{ICU}$	(30,60,90)	Policy limits in ICU capacity (in%)
N	(22.7, 56.8, 20.5)	Age-distribution of population (in %)
π	(0.002, 0.30, 7.79)	Infection-fatality proportion (in %)
h	(0.01, 0.48, 1.75)	Prob. of ICU if infected (in %)
R_0/N	(24,17,12)	Fraction of initially immunized people (in %)
$\alpha_{1.}$	(2, 0.5, 0.25)	Intensity of transmission from young
$\alpha_{2.}$	(0.5, 1, 0.25)	Intensity of transmission from adult
$\alpha_{3.}$	(0.25, 0.25, 0.5)	Intensity of transmission from senior
T_{ICU}	15	Days in ICU
w	(0, 176, 0)	Economic loss of confinement (in % of GDP/cap)
ℓ	(100,100,100)	Value of life lost (in years of GDP/cap)
p	0.1	Cost of vaccine for the entire population (in % of GDP)

Table 2: Benchmark calibration of the SVIR model.

annual GDP/cap, independent of age. This is aligned with the official VSL of 3 million euros in France (Quinet, 2013).

This benchmark calibration is summarized in Table 2. In my reference scenario, I will assume that France is able to maintain its current speed of vaccination at 200k doses per day (see Figure 2), i.e. 100k full vaccinations per day. This is compatible with a start of the vaccination campaign in late January 2021. In reality, the French campaign started earlier, but at a much lower speed.

4 Welfare impacts of the vaccination campaign

In this section, I examine the dynamics of the pandemic as a function of the speed of the vaccination campaign. In Figure 3, I describe this dynamics when a constant flow of 100k vaccinations per day is performed. This corresponds to the objective of vaccination of France for the spring of 2021. The two graphs on the left describe the health policy, in terms of the intensity of lockdown (top) and of vaccination (bottom). The seniors not yet naturally immunized are fully vaccinated within the first 110 days of the campaign. It takes 200 more days to vaccinate the middle-aged people that have not yet been infected at that time. The vaccination campaign is finished before the end of the year. A mild gradually decreasing lockdown is imposed for 260 days, with a short period of strong lockdown after the first two months of the campaign to limit the exponential growth of ICU utilization that occurs at that time. This shows that the speed of vaccination is too slow to compensate for the large transmission rate of the new variant. When reversing to the milder intensity of lockdown, a new wave of the virus hits the country, but it concerns only the younger generations with a low rate of hospitalization. This implies that this second wave does not require imposing a new intense lockdown, in spite of the fact that the number of daily new cases is larger than during the first wave. Herd immunity is attained within 300 days from the vaccination campaign and from the fraction of the population that recovered from the infection.

Table 3 describes the welfare costs of the pandemic from day 0 of the vaccination campaign. For this speed of 0.1×10^6 vaccinations per day, one should expect 92k lives lost. The vaccination of the seniors is not fast enough to save 50k of them from the deadly new variant. The purely economic GDP loss in 2021 is estimated around 14%, coming mostly from the extended duration of the lockdown. The cost of the vaccination campaign counts for 0.07% of annual GDP. Finally, valuing lives at 100 years of annual GDP/cap raises the welfare cost of the pandemic from day 0 to 28% of annual GDP.

It is a useful theoretical exercise to compare this outcome to what would have happened in the absence of a vaccine. Under this scenario described in the first line of Table 3, the stop-and-go policy is a dead-end, with no other outcome than herd immunity in the long run. A long succession of ups and downs in the lockdown policy will be necessary to preserve hospital, and herd immunity would be attained only after 3 years, with a cumulative economic loss of 35% of annual GDP. Under these catastrophic circumstances, the new variant would kill 470k people, 85% of them being older than 65 years. This dismal outcome reminds us how bad was the news of the emergence of this B.1.1.7 variant on the eve of 2021 in France. The good news is that the 100k/day vaccination campaign reduces the number of deaths among seniors by 87% and among adults by 42%. The economic loss of the pandemic is reduced from 35% to 14% of annual GDP. The welfare loss is reduced by a factor 4 when aggregating economic and human costs of the pandemic.

vaccine speed	lives lost 19-64	lives lost 65+	lives lost total	loss wealth	loss total
10^6/day				%GDP	%GDP
0.00	72705	396464	469351	34.71	104.80
0.05	55387	78780	134337	18.45	38.50
0.10	41641	50026	91817	13.82	27.53
0.15	32857	41609	74605	11.13	22.26
0.20	26159	37166	63450	9.31	18.78
0.25	22642	32883	55638	8.04	16.34
0.50	16245	29151	45470	5.06	11.84

Table 3: Impacts of the pandemic as a function of the speed of the vaccination campaign, starting from day-0 of the campaign.

A key insight from Table 3 is the steeply decreasing nature of the marginal benefit of

Covid Economics 74, 30 March 2021: 1-24

Covid Economics 74, 30 March 2021: 1-24

accelerating the vaccination campaign. If going from 0 to 100k vaccinations per day reduces the welfare cost of the pandemic by 73%, going from a speed of 100k/day to 200k/day reduces it by only 30%. Three-quarters of the total cost of the pandemic since day 0 can be eliminated with the benchmark 100k speed. The dynamics of the pandemic under 200k vaccinations per day is described in Figure 4. The increased speed of vaccination is again primarily beneficial to the seniors in their race between vaccination and infection. But it also allows for a reduction of the intensity and of the duration of the lockdown, which is beneficial to the economy.

In Figure 5, I represent the welfare benefit of the vaccination campaign as a function of its speed. This welfare benefit is measured in euros per capita rather than by the reduction in total loss expressed in a fraction of annual GDP. For a speed of 100k/day, it equals (0.1048-0.2753) multiplied by 2400×10^9 and divided by 67×10^6. It equals 27,679 euros per capita. For a unit cost of vaccination at 30 euros, this vaccination campaign has a social return of approximately 100,000%.

The decreasing marginal benefit of the speed of vaccination should not hide the fact that countries implementing a faster vaccination campaign will vastly outperform the others both in terms of lives saved and economic performances.

It is useful to measure the welfare cost of forcing immunized people to face the same restrictions as the remainder of the population in spite of the absence of any health and economic benefit of this egalitarian rule. The refusal of the immunity passport is based on an egalitarian principle that is symmetric to the prohibition of requiring a more intense lockdown for more vulnerable people. These prohibitions are not compatible with the minimization of the number of lives lost, or of the economic loss. Offering an immunity passport to immunized people, i.e. replacing $\omega = 0$ in the calibration by $\omega = 1$, reduces the economic cost of the pandemic from 14% to 9.5% in the benchmark case with 100k vaccinations per day.

In this paper, I combine a vaccination campaign with a stop-and-go policy of lockdown and social distancing. I follow this approach because most western governments currently consider that there is no socially acceptable alternative. But one may question whether this stop-and-go policy is optimal. In this section, I have shown that it is a viable policy in the context of the development of a massive vaccination campaign, which provides a medium term exit to the pandemic. It is legitimate to ask whether a "no-covid" policy would generate a better outcome. To answer this question, let me re-calibrate the same model with $b^l = b^m = b^h = 0.8$, i.e., with the imposition of a 80% lockdown until the rate of prevalence I_{min} is attained to eradicate the virus with a test-trace-and-isolate procedure. Under this no-covid policy, the rate of prevalence I_{min} is attained after 78 days to eradicate the virus. The economic loss is limited to 8% of annual GDP, and fatalities are limited to 13,351. At a speed of vaccination of 100k per day, the vaccination campaign is almost irrelevant for this eradication strategy (although the herd immunity that the vaccination campaign creates is key for the stability of the no-covid outcome). Notice that this result favorable to the no-covid policy heavily relies on the possibility to implement an efficient test-trace-and-isolate strategy at the end of the lockdown, and on the necessity to coordinate such a policy at the EU level. It also raises the question of the social acceptability of a strong lockdown in the spring of 2021.

Covid Economics 74, 30 March 2021: 1-24

5 The welfare cost of delaying the start of the campaign

A simple way to measure the urgency of the vaccine is obtained from performing the thought experiment of a one-week translation of the vaccination campaign. This experiment is related to the suspension by France and Germany (together with other EU members on a different time frame) of the AstraZeneca vaccine from the afternoon of Monday March 15 to the morning of Friday March 19. This interruption in the distribution of that vaccine (which represented half of the daily doses distributed in France in mid-March) was related to a suspicion of a lethal side effect after a number of people developed blood clots and thrombosis soon after receiving a dose.

Technically, as of 16 March 2021, around 20 million people in the UK and the EU had received the vaccine, and the European Medicines Agency (EMA) had reviewed 25 cases of blood clots in this cohort, 9 of which resulted in death. A causal link with the vaccine is not proven. Overall the number of thromboembolic events reported after vaccination was lower than that expected in the general population.[13]

It is useful to compare this potential adverse effect of the vaccine with the additional lives lost and economic cost associated to delaying the campaign by one week. As shown in Table 4 and in Figure 6, this delay to launch the campaign increases the death toll by 2,481 and it reduces GDP by 0.34%, or more than 8 billion euros. These estimations suggest that France suffered heavily from the half-week suspension of the AstraZeneca vaccination campaign, without any identified benefit. Moreover, the suspension reduced the public confidence in the vaccination.[14]

delay	lives lost			loss	
	19-64	65+	total	wealth	total
0 day	41641	50026	91817	13.82	27.53
7 days	41980	52168	94298	14.16	28.23

Table 4: Impacts of delaying the vaccination campaign by one week.

6 The welfare cost of randomizing the allocation of the vaccine

In this section, I compare the outcome of the health policy when vaccines are prioritized on the basis of vulnerability (proxied in this model by age), to the outcome when no such priority is implemented. More precisely, I assume here that vaccines are randomly distributed until the whole population get inoculated. This is related to various tendencies to allocate the vaccine to specific groups of people on the basis of other principles than vulnerability. WHO (2020b) justified many of these alternatives principles to allocate priority to the vaccine,

[13] https://www.ema.europa.eu/en/news/covid-19-vaccine-astrazeneca-benefits-still-outweigh-risks-despite-possible-link-rare-blood-clots

[14] If the suspension occurs during the campaign rather than at its start, the number of lives lost is smaller because the most vulnerable are already immunized. For example, if the 1-week suspension takes place after 60 days, the death toll is increased by 1862 compared to the benchmark. The economic loss remains unchanged at 0.34%.

such as a compensation for front-line essential workers (health workers, teachers,,...). Other allocation procedures are also discussed, such as the creation of a free market for the vaccine, or prioritizing the poor. Public decision-makers are indeed right to integrate other morale principles of justice when allocating the scarce vaccine supply. In this section, I inform them about the utility cost of integrating these other dimensions into their decisions, in the extreme case of an allocation procedure orthogonal to vulnerability.

It is noteworthy that my model cannot take account of the observed heterogeneity in the intensity of social interactions within a specific age-class. Specific individuals and professions have more potential than others to transmit the virus to vulnerable people. The best examples are health workers in nursing homes. There is a clear efficiency rationale for offering a high priority to these individuals.

I describe in Figure 7 the dynamics of the pandemic under a random distribution of the vaccine with 100k vaccination per day. Obviously, the randomization improves the welfare of those who were not prioritized in the benchmark, i.e., the two younger classes. They are much less infected, and their mortality rate drops. The opposite outcome prevails for the seniors. Globally, the second wave imposes less stress to ICUs, but a high ICU utilization prevails longer at the end of the pandemic. Because the randomized vaccination procedure reduces the circulation of the virus, the virus can be erased earlier. This reduces the economic loss by 1% of annual GDP, as shown in Table 5. But the global death toll is increased by 56k, with 70k more fatalities among the seniors, whereas 14k middle-aged lives will be saved.

allocation	lives lost			loss	
procedure	19-64	65+	total	wealth	total
first-best	41641	50026	91817	13.82	27.53
random	27277	120463	147807	12.83	34.89

Table 5: Impacts of fully randomizing the allocation of the vaccine.

7 The externalities generated by the anti-vaxxers

The presence of anti-vaxxers provides another illustration of the welfare cost of an inefficient allocation of the vaccines. France is the western country with the larger share of anti-vaxxers.[15] Suppose that 30% of the French population, uniform across age classes, are going to prefer not to be inoculated. What are the consequences of these individual choices on social welfare? In Figure 8, I depicted the dynamics of the pandemic in that context. Table 6 summarize my findings. This phenomenon has several implications. First, many more senior anti-vaxxers will die. But because the virus will circulate more intensely in the senior age class, more senior vaccinated people who are not yet immunized (they have the V status) will also die. Remember that senior people interact much more within their own age class than with other classes, so that the presence of senior anti-vaxxers is a very bad news for other senior people. This illustrates the negative externality that the anti-vaxxers exercise

[15] In a February 2021 survey conducted by Imperial College London, among 15 surveyed countries, France had the highest proportion of respondents who stated that they would not take any covid-19 vaccine (44%).

Covid Economics 74, 30 March 2021: 1-24

on pro-vaxxers. How can we measure this effect? If everyone would be inoculated, we should expect 35k deaths among the senior pro-vaxxers. In reality, with 30% anti-vaxxers in the population, I predict that 40k senior vaxxers will die. Thus, the negative externality of the anti-vaxxers on senior pro-vaxxers is estimated around 5k additional deaths among this pro-vaxxer population.

	lives lost			loss	
	19-64	65+	total	wealth	total
Without anti-vax					
global	41641	50026	91817	13.82	27.53
With 30% anti-vax					
global	41080	114333	155548	13.73	36.91
vaxxers	24442	40160	64691		
anti-vaxxers	16638	74173	90857		

Table 6: Impacts of 30% anti-vaxxers.

A second effect comes from the fact that younger people will be inoculated earlier than in the benchmark scenario. The virus will circulate less in these age classes as soon as they start their vaccination period. Globally, the ICU capacity is more stressed because of the misallocation of the vaccine during that second wave, with many senior people needing intensive care. But the net effect of the presence of anti-vaxxers on middle-aged pro-vaxxers is positive. Indeed, without the anti-vax movement, one should expect 29k lives lost among middle-aged pro-vax at the end of the pandemic. Thanks to the anti-vaxxers, this death toll is limited to 24k for this category of people, a reduction by 5k deaths. This is a positive externality from the anti-vax movement. At the aggregate level across age classes, 419 more pro-vaxxers will die due to the presence of the anti-vaxxers. It is noteworthy that I assume that all people that are vaccinated and that are not infected before producing antigens become fully immunized. This assumption is based on currently available scientific information about the efficacy of the 3 vaccines used in France.[16] In an initial version of this paper, I assumed an efficacity rate of 95%, which implied a much larger global negative externality from anti-vaxxers.

On their side, the anti-vaxxers benefit from the herd immunity built by the vaccination effort of the pro-vaxxers. At the aggregate level, if nobody would get the vaccine, one should expect that 141k anti-vaxxers will die. But the presence of the pro-vaxxers in the population will reduce the death toll faced by the anti-vaxxers to 91k, a 35% reduction. This is the positive externality exercised by pro-vaxxers on anti-vaxxers.

Finally, the global effect of a 30% strong anti-vax movement would increase the death toll by 64k, a 69% increase compared to the benchmark without the movement and an efficient vaccination campaign of 100k vaccinations per day. The presence of anti-vaxxer has a small positive effect on the economy by reducing the duration of the lockdown.

[16]See for example the report dated 11 March 2021 by the French "Conseil Scientifique" for the pandemic.

Covid Economics 74, 30 March 2021: 1-24

8 The welfare cost of vaccine nationalism

Vaccine nationalism is another good example of misallocation of a vaccine, because vulnerable people in importing countries will be vaccinated (if they survive) potentially long after people with much lower risk in vaccine-rich countries. To explore this effect, let me examine the following thought experiment. Suppose that the world is made up of two identical Frances as described in this paper, except that one France, named the producer, controls the unique production site of the vaccine whereas the other must import the vaccine for its vaccination campaign. Finally, suppose that the production site has a production capacity of 200k vaccines per day. I compare two solutions. In the first-best solution under the veil of ignorance, the two countries equally share the resource by vaccinating 100k people each every day. Figure 3 describes the dynamics of the pandemic in the two countries in that context. Suppose alternatively that the producing country is able to secure priority in the allocation of the vaccine so that its whole population must be vaccinated before allowing exportation. For the producing country, the dynamics of the virus is described in Figure 4.

In the nationalistic scenario, the importing country must wait 211 days before starting its vaccination campaign. In that country, this long delay has dramatic consequences in terms of lives lost that is only partially compensated by the more intense and longer lockdown, as described in Figure 9. I summarized the impacts of the different international allocations of the vaccine in Table 7. The importing country must maintain some form of social distancing rules for almost one year, whereas the producing country can fully exit the pandemic within 6 months. This implies that the economic damage in that country is more than twice its equivalent in the producing country. And the death toll at the end of the pandemic is more than 150% larger in the importing country. Given the large discrepancy between the intensities of the health and economic crises incurred by the producing and importing countries, it is illusory to expect any politically acceptable cooperation to allocate the vaccine capacity efficiently at the international level, in spite of the efforts of the World Health Organization (COVAX).

scenario	lives lost			loss	
	19-64	65+	total	wealth	total
First-best					
Mean	41641	50026	91817	13.82	27.53
Nationalistic					
Mean	32560	78708	111398	14.42	31.04
Producer	26159	37166	63450	9.31	18.78
Importer	38969	120250	159347	19.53	43.31

Table 7: Impacts of vaccine nationalism.

Because of the vastly inefficient allocation of the vaccine in this nationalistic scenario, the worldwide death toll is 20% larger than under the first best allocation, yielding 39k additional deaths globally. Because the wealth creation technology used in this model is linear, the average economic loss of the pandemic is increased only marginally, from 13.82% of world annual GDP to 14.42%. Global welfare is reduced by approximately 13%.

9 Conclusion

Because the degree of vulnerability to the B.1.1.7 variant is highly sensitive to individual characteristics such as the age of the infected person, and because the covid vaccines are a scarce resource in 2021, it is critically important to allocate them wisely. If the objective is to minimize the welfare loss, the optimal solution is to give vaccination priority to the most vulnerable people. I first show that, under this optimal rule, the marginal benefit of the vaccine quickly decreases with the cumulated number of vaccinated people in the population. The key issue is to vaccinate the most vulnerable people quickly, so that the pressure on ICUs and hospitals can be relaxed, together with the intensity of the lockdown. For France, the planned speed of vaccination is not sufficient to compensate for the emergence of the highly transmissible variant, so that the intensity of the lockdown must be temporarily increased to "flatten the curve". The race undertaken by our vaccination campaign against the variant cannot be won in the short term given its high virulence and the lack of vaccination capacity. However, the current vaccination capacity at 100k vaccinations per day, if maintained permanently at that level, would reduce the welfare cost of the pandemic by 74%. Doubling the vaccination capacity would only reduce the welfare cost by an additional 8% (to 82% of the initial cost). This result should not hide the dismal death toll of the pandemic.

The objective of this paper was to estimate the welfare cost of the misallocation of the vaccine, with a special focus on the consequences of the vaccine nationalism that is currently raging in the western world. By vaccinating low-risk people in vaccine-rich countries before high-risk people in vaccine-poor countries, we worsen the global welfare consequences of the pandemic. There is no doubt that the vaccine-rich countries will greatly benefit from hoarding their vaccine. But under the veil of ignorance, this allocation is undesirable. In a simple two-country model, I show that the extreme form of vaccine nationalism in which vaccine-rich countries fully prioritize their own population before exporting their vaccine, the global death toll could be increased by 20%.

The allocation of the vaccines entails a large range of societal issues. Counting the number of additional fatalities and the additional GDP loss of the different possible allocations provides only a partial view of the deeper societal questions that emerge in this context. For example, some workers have faithfully accepted to expose themselves to the virus to save other lives, or to exercise essential activities for the economy. Decision-makers may consider a reciprocity or recognition measure that could take the form of giving them priority for the vaccine. My ambition in this paper is limited to the measure of the measurable costs of such a decision, in terms of expected lives lost and economic loss. Finally, my estimations should be taken with caution, given the many uncertainties surrounding many parameters of the standard SIR model calibrated on the new variant.

Covid Economics 74, 30 March 2021: 1-24

Bibliography

Acemoglu, D., V. Chernozhukov, Ivan Werning and Michael Whinston, (2020), A multi-risk SIR model with optimally targeted lockdown, NBER WP 27102.

Béraud G, S. Kazmercziak, P. Beutels, D. Levy-Bruhl, X. Lenne, N. Mielcarek et al., (2015), The French connection: The first large population-based contact survey in France relevant for the spread of infectious diseases, *PLoS ONE* 10,

Challen, R., E. Brooks-Pollock, J.M. Read, L. Dyson L, K. Tsaneva-Atanasova, L. Danon, (2021), Risk of mortality in patients infected with SARS-CoV-2 variant of concern 202012/1: matched cohort study, *The British Medical Journal* 372. BMJ 2021;372:n579

Clarke, P.M., L.S.J. Roope, P. Loewen, J.-F. Bonnefon, A. Melegaro, J. Friedman, M. Violato, A. Barnett, and R. Duch, (2021), Public opinion on global rollout of COVID-19 vaccines, mimeo, Toulouse School of Economics.

Drèze, J., (1962), L'utilité sociale d'une vie humaine, *Revue Francaise de Recherche Opérationnelle*, 23, 93-118.

Favero, C., A. Ichino and A. Rustichini, (2020), Restarting the economy while saving lives under covid-19, WP Bocconi University.

Duch, R., L.S.J. Roope, M. Violato, M.F. Becerra, T. Robinson, J.-F. Bonnefon, J. Friedman, P. Loewen, P. Mamidi, A. Melegaro, M. Blanco, J. Vargas, J. Seither, P. Candio, A.G. Cruz, X. Hua, A. Barnett, P.M. Clarke, (2021), Who should be first in line for the COVID-19 vaccine? Surveys in 13 countries of public's preferences for prioritisation, medRxiv 2021.01.31.21250866

Fischer, C., (2020), External costs and benefits of policies to address COVID-19, mimeo.

Gollier, C., (2020a), If herd immunity is the objective, on whom should it be built?, *Environmental and Resource Economics* 76, 671-683. Prepublished in *Covid Economics* 16, 98-114.

Gollier, C., (2020b), Pandemic economics: Optimal dynamic confinement under uncertainty and learning, *Geneva Risk and Insurance Review* 45, 80-93. Prepublished in *Covid Economics* 34, 1-14.

Gollier, C., (2020c), Cost-benefit analysis of age-specific deconfinement strategies, *Journal of Public Economic Theory* 22, 1746-1771. Prepublished in *Covid Economics* 24, 1-31.

Hafner, M., E. Yerushalmi, C. Fays, E. Dufresne, and C. Van Stolk, (2020), COVID-19 and the cost of vaccine nationalism, Santa Monica, CA: RAND Corporation.

He, X., E.H.Y. Lau, P. Wu et al., (2020), Temporal dynamics in viral shedding and transmissibility of COVID-19, *Nature Medicine* 26, 672-675. https://doi.org/10.1038/s41591-020-0869-5.

Jones-Lee M. (1974) The value of changes in the probability of death and injury, *Journal of Political Economy* 82, 835-849.

Kermack, W.O., and A.G. McKendrick, (1927), A contribution to the mathematical theory of epidemics, *Proceedings of the Royal Society* 115, 700-721.

Lapidus, N., J. Paireau, D. Levy-Bruhl, X. de Lamballerie, G. Severi, M. Touvier, M. Zins, S. Cauchemez, F. Carrat, (2021), Do not neglect SARS-CoV-2 hospitalization and fatality risks in the middle-aged adult population, *Infect Dis Now*.

Mullard, A., (2020), How COVID vaccines are being divvied up around the world, *Nature* (30 Nov 2020).

Murphy, K. M. and R. H. Topel, (2006), The value of health and longevity, *Journal of Political Economy* 114, 871-904.

Quinet, E., (2013), L'évaluation socioéconomique des investissements publics, *Commissariat Général à la Stratégie et à la Prospective*, Paris.

Salje,H., C. Tran Kiem, N. Lefrancq, N. Courtejoie, P. Bosetti, et al., (2020), Estimating the burden of SARS-CoV-2 in France. .pasteur-02548181

Schelling, T., (1968), The life you save may be your own, in "Problems in public expenditure analysis" (Chase, S.B., ed.), Washington, D.C., The Brookings Institution, 127-162.

Shepard, D.S., and R.J. Zeckhauser, (1984), Survival versus Consumption, *Management Science* 30, 423-39.

US-EPA, (2010), Valuing mortality risk reductions for environmental policy: A white paper, SAB-EEAC Review Report.

Viscusi, W.K., (2009), The devaluation of life, *Regulation & Governance* 3, 103-127.

Volz, E. et al. (2020), Transmission of SARS-CoV-2 lineage B.1.1.7 in England: Insights from linking epidemiological and genetic data, medRxiv 2020.12.30.20249034.

Wilder, B., M. Charpignon, J. Killian, O. Han-Ching, A. Mate, S. Jabbari, A. Perrault, A. Desai, M. Tambe and M. Majumder, (2020), The role of age distribution and family structure on COVID-19 dynamics: A preliminary modeling assessment for Hubei and Lombardy, mimeo.

Covid Economics 74, 30 March 2021: 1-24

WHO, (2020a), WHO SAGE values framework for the allocation and prioritization of COVID-19, World Health Organization, Geneva.

WHO, (2020b), WHO SAGE roadmap for prioritizing uses of covid-19 vaccines in the context of limited supply, World Health Organization, Geneva.

Covid Economics 74, 30 March 2021: 1-24

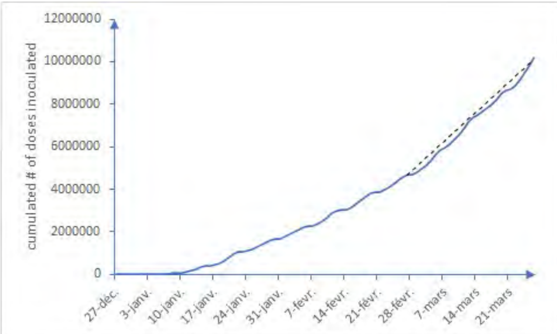


Figure 2: Cumulated number of doses inoculated in France during the first three months of 2021. The dashed curve corresponds to a speed of vaccination of 200k doses per day.

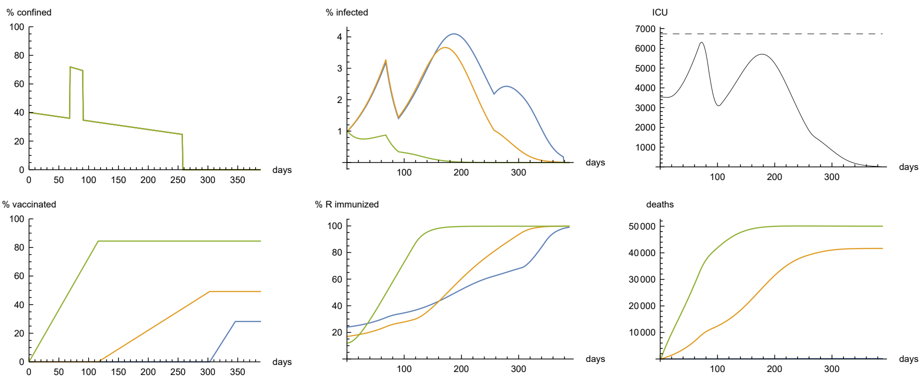


Figure 3: Dynamics of the pandemic under 100k vaccinations per day. The blue, orange and green curves correspond respectively to the young, middle and old age classes.

Covid Economics 74, 30 March 2021: 1-24

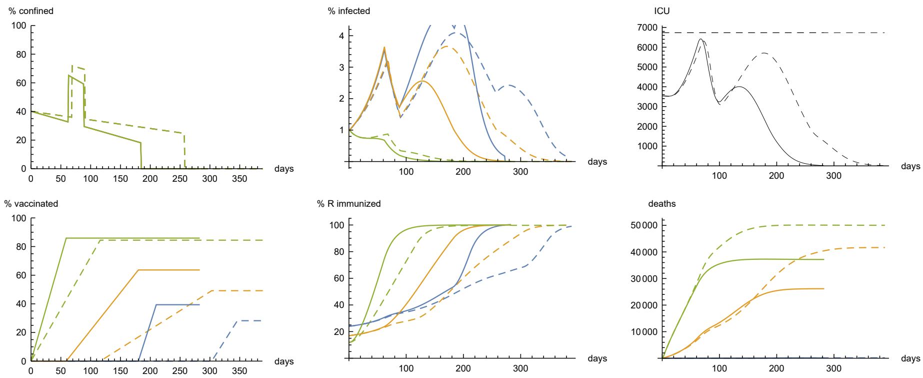


Figure 4: Dynamics of the pandemic under 200k vaccinations per day. Dashed curves correspond to the dynamics under the benchmark vaccination speed of 100k vaccinations per day.

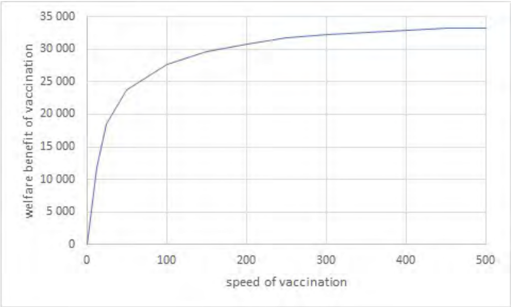


Figure 5: Welfare benefit (in euros per capita) of the vaccination campaign as a function of the speed of vaccination (in thousands of vaccinations per day).

Covid Economics 74, 30 March 2021: 1-24

Covid Economics 74, 30 March 2021: 1-24

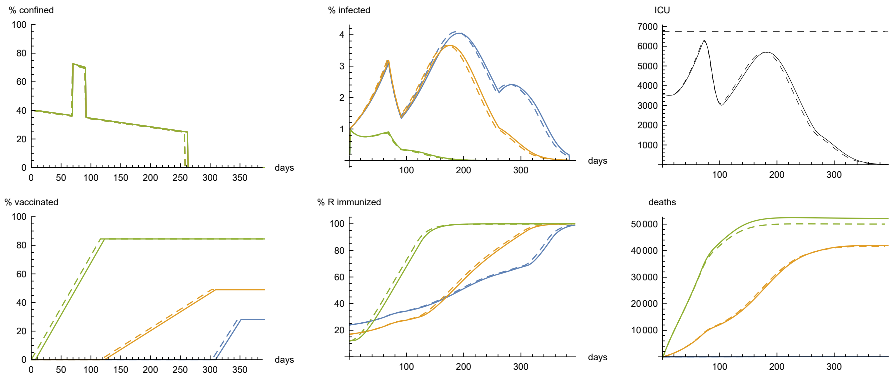


Figure 6: Dynamics of the pandemic under 100k vaccinations per day delayed to start on day 7. Dashed curves correspond to the dynamics under the benchmark vaccination speed of 100k vaccinations per day started on day 0.

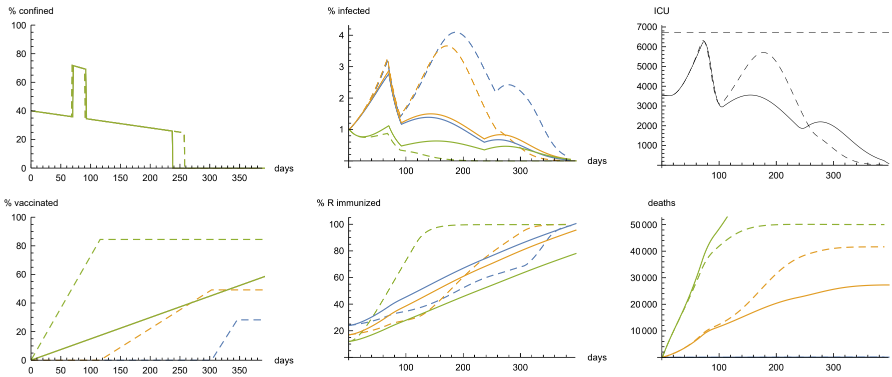


Figure 7: Dynamics of the pandemic under the 100k vaccinations per day when the vaccine is randomly distributed.

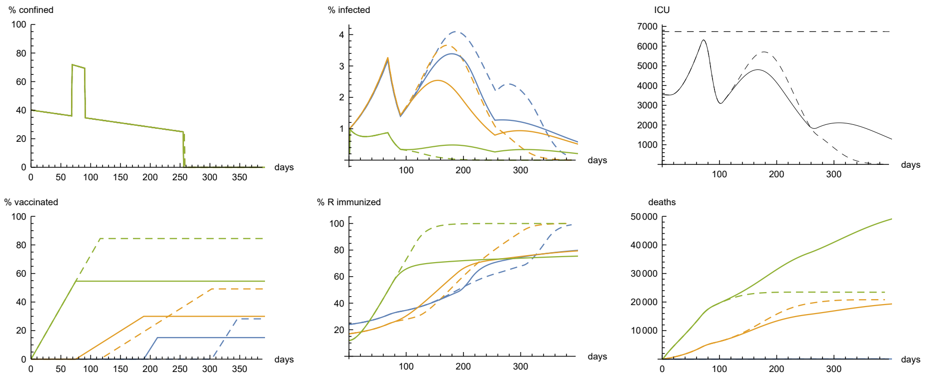


Figure 8: Dynamics of the pandemic under the 100k vaccinations per day with 30% anti-vaxxers in the population.

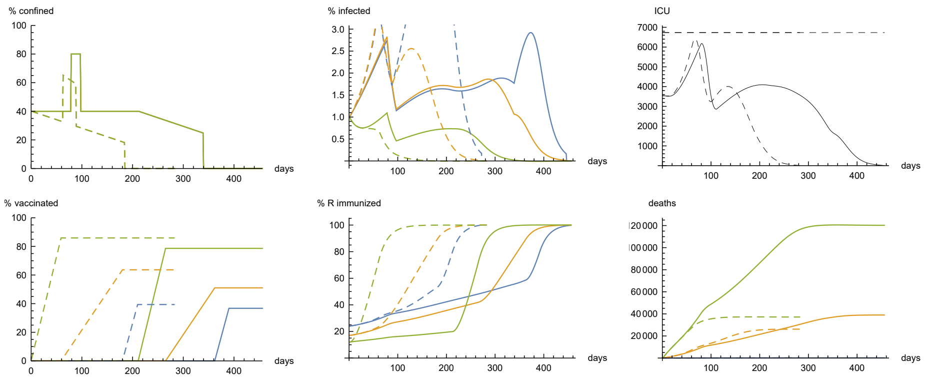


Figure 9: Dynamics of the pandemic in the thought experiment of vaccine nationalism. The importing country (plain curves) starts its vaccination campaign on day 211 after the producing country (dashed curve) has fully vaccinated its population.

CEPR PRESS

Covid Economics Issue 74, 30 March 2021

COVID-19 rental eviction moratoria and household well-being[1]

Xudong An,[2] Stuart A. Gabriel[3] and Nitzan Tzur-Ilan[4]

Date submitted: 12 March 2021; Date accepted: 18 March 2021

We investigate the impact of 2020 COVID-19 rental eviction moratoria on household well-being. Analysis of new panel data indicates that eviction moratoria reduced evictions and resulted in redirection of scarce household financial resources to immediate consumption needs, notably including food and grocery spending. We also find that eviction moratoria reduced household food insecurity and mental stress, with larger effects evidenced among African American households. Findings suggest broad salutary effects of eviction moratoria during a period of widespread virus and economic distress.

Covid Economics 74, 30 March 2021: 25-70

1 We thank Emily Benfer, Chris Finger, Gary Painter, and Bill Spaniel for helpful discussions and comments. We also thank the seminar participants at Kellogg for helpful suggestions. Stuart Gabriel and Nitzan Tzur-Ilan are grateful to the UCLA Ziman Center for Real Estate's Rosalinde and Arthur Gilbert Program in Real Estate, Finance and Urban Economics for research funding and to Kartik Agarwal and Susu Zhu for excellent research assistance. The views expressed in this paper are solely those of the authors and do not necessarily reflect he views of the Federal Reserve Bank of Philadelphia or the Federal Reserve System.

2 Federal Reserve Bank of Philadelphia.
3 UCLA Anderson School of Management.
4 Northwestern University and Bank of Israel.

I. Introduction

In the wake of the COVID-19 pandemic and related disruption to economic activity, weekly jobless claims in March 2020 skyrocketed to 7 million, roughly 10 times that of peak levels recorded during the 2000s global financial crisis.[1] To assure shelter of idled households and to damp virus spread, many state and local governments in the U.S. enacted moratoria on tenant eviction.[2] In this paper, we apply new data on state and local COVID-19 rental eviction moratoria to evaluate the effects of those measures on household well-being, notably including consumer spending and debt, food insecurity, and mental health outcomes.

Moratoria on rental eviction may have conferred a broad set of benefits on vulnerable households and the local economy. Upon onset of the pandemic, the share of affordability-constrained renters, defined as households paying more than one-half of their income on rent, jumped to one-half of all renter households.[3] Further, renter households had little wherewithal to withstand COVID-related employment shocks, given an average renter household net worth of only \$5,000.[4] Therefore, moratoria on eviction and related deferral of rent may have provided treated households with financial and mental relief in the form of positive shocks to household liquidity. Renters benefiting from such interventions could re-direct scarce resources to other immediate consumption needs, notably including food purchases.[5]

[1]Bureau of Labor Statistics, U.S. Department of Labor, March 20, 2020.

[2]Sheen et al. (2020) suggest that policies to stem evictions are an important component of COVID-19 public health control. See also Jowers et al. (2020).

[3]See, Census Household Pulse Survey. According to the survey, in December 2020, nearly 30 million adults lived in households where there wasn't enough to eat, up 28% relative to prior to the pandemic. In Louisiana, a full one in five people faced food scarcity, the survey showed, with the numbers being even more dire among African American Americans.

[4]See, Federal Reserve Board Survey of Consumer Finance. This is not only a U.S. phenomenon; Ater et al. (2020) show that the Covid-19 pandemic caused Israeli households suffering a larger income cut, or those lacking sufficient liquid assets, to pay less of their rent.

[5]Rosen et al. (2020) find that rent-burdened households are more likely to have cutbacks on food, health and medicine, clothing, and transportation than non-rent-burdened households. A large literature has found consumption responses to income and liquidity shocks. See, e.g., Johnson et al. (2006), Agarwal et al. (2007),

Covid Economics 74, 30 March 2021: 25-70

Eviction moratoria similarly assured renters of continued shelter during a period of elevated COVID-19 virus diffusion, likely easing mental stress and anxiety among treated households.[6]

COVID-19 eviction moratoria were implemented by state and local government in a haphazard manner throughout the March-August 2020 period. For example, among states that enacted eviction moratoria, California was among the first to implement such measures in March 2020 while Virginia did not enact a state-level eviction moratorium until July. Separate from state-level enactment of eviction moratoria, similar measures were sometimes adopted at the county level at different times. The staggered implementation of rental eviction moratoria at both state and county levels provide us an opportunity to identify the impact of those interventions on households using panel data.[7]

We collect data related to household well-being from numerous sources. We assemble a zip code by month panel of credit card usage information using the Federal Reserve confidential supervisory data; also, we obtain county by week data on consumer spending by category including food and grocery spending from the Opportunity Insight Economic Tracker (Opportunity Insight) database compiled by Chetty et al. (2020). We also compile a state by week panel of food insecurity and mental health information from the Census COVID-19 Household Pulse Survey. Finally, we construct a state-level panel of food insecurity measures using search query data from Google. We comprise panels on renter eviction moratoria at state and local levels using data scraped from government websites and from the Eviction Lab at Princeton University. Together with information on local housing and labor markets

and DiMaggio et al. (2017).

[6]Rental eviction moratoria similarly may impose financial hardship on landlords. In a related paper, Ambrose et al. (2020) assess variation in eviction risk associated with source of landlord mortgage finance and related opportunity for borrower forbearance in the case of GSE-backed loans. We leave the full welfare analysis of rental eviction moratoria to another paper.

[7]As discussed below, the 2020 CARES Act also included a limited 120-day federal eviction moratorium which commenced in March 2020. However, the federal policy intervention was limited to renters who participated in federal housing assistance programs or lived in a property with a federally-backed mortgage.

Covid Economics 74, 30 March 2021: 25-70

Covid Economics 74, 30 March 2021: 25-70

and other controls, we run treatment intensity difference-in-differences regressions to assess the causal effects of rental eviction moratoria on household spending, food insecurity and mental health outcomes.

Results using zip code-level credit card data show that state rental eviction moratoria led to both elevated credit card spending and related debt payoff. We also show a small but significant positive impact of moratoria on rental eviction on borrowers' credit score. We further distinguish between renters and homeowners to help our causal inference as renters, not homeowners, were the target beneficiaries of the eviction moratoria. To do so, we divide zip codes into those with high versus low renter share of households, based on U.S. Census data. If the relations we find between renter protection measures and credit card outcomes are causal, one would expect a larger impact among predominantly renter zip codes. We also take into consideration the share of population under financial distress (and thus at risk of eviction) as eviction moratoria are targeted to those households. Our results confirm the causal relation.

The impact of state eviction moratorium on credit card spending and payment is economically significant. Based on our estimates, a 12-month eviction moratorium is associated with a 16 and 14 percent increase in credit card spending and payment, respectively, with larger effects estimated for targeted high renter share zip codes.

We corroborate and provide further disaggregation by spending category of state eviction moratoria using the Opportunity Insight data. Model specification is consistent with that of the zip code analysis. We find sizable spending effects in certain categories of spending including accommodation and food service and retail with and without grocery. A one week of eviction moratorium is associated with a 1 percent increase in food service spending and a 0.9 percent increase in grocery spending.

Covid Economics 74, 30 March 2021: 25-70

Consistent with above findings of elevated food and grocery spending in the wake of enactment of state eviction moratoria, our results show that eviction moratoria reduce the incidence of household food insecurity. Based on outcome terms from the state by week Census COVID-19 Household Pulse Survey, we find an additional week of enactment of state eviction moratoria is associated with a 2 percent decline in subsequent self-reporting of food insecurity among African Americans (compared to an average of 21 percent that reported food insecure). State eviction moratoria also result in a decline in food bank utilization. Further, using Google search query data, we find that state-level search query for such terms as "Food Stamps" and "Food Banks Near Me" was significantly reduced in the wake of enactment of state eviction moratoria.

Finally, we utilized the Census COVID-19 Household Pulse Survey to assess the effects of state eviction moratoria on indicators of mental health. As indicated by the survey, about 4 in 10 adults in the U.S. reported symptoms of anxiety or depressive disorder in the wake of onset of the COVID-19 pandemic, up from 1 in 10 adults who reported these symptoms during 2019.[8] Our results suggest that state-level rental eviction moratoria significantly reduced the incidence of emotional stress as reported in the survey, measured by such indicators as "feeling anxious", "can't stop worrying", and "feeling down". Results are especially pronounced among African American households.

Substantial recent literature provides evidence of adverse societal and household economic effects associated with rental housing eviction. Desmond (2012), Desmond and Kimbro (2015), and Desmond (2016)) show large negative effects of evictions on employment, homelessness, and future housing stability. Collinson and Reed (2018) and Currie and Tekin (2015) find that housing instability is associated with unfavorable health outcomes. Prior to

[8] See Panchal et al. (2020).

our paper, few studies provided evidence of consumption, food insecurity, and mental health effects of moratoria on rental evictions.[9]

Research also shows disproportionate rent-burdens and risks of eviction among communities of color. Greenberg et al. (2016) show that African American and Latinx households comprise roughly four-fifths of those facing eviction. The Census COVID-19 Household Pulse Survey, dated August 7 2020, indicates that nearly one-half of African American and Hispanic renters had slight or no confidence in their ability to pay the next month's rent on time, a figure that was twice as high as white renters. Moreover, 26 percent of African American renters and 25 percent of Hispanic renters reported being unable to pay rent the prior month, compared to 13 percent of white renters.[10] Consistent with the above, our findings indicate that rental market interventions more substantially reduced food insecurity and mental distress among African American households.

Among the rapidly growing body of work studying the impact of the COVID-19 pandemic on the economy, Eichenbaum et al. (2020), Jones et al. (2020) and Elenev, Landvoigt, and Nieuwerburgh (Elenev et al.) provide macroeconomic frameworks for studying the pandemic and related government responses. A large number of researchers explore the impact of the pandemic on employment and household consumption (see, e.g., Bartik et al. (2020); Baker et al. (2020); Chetty et al. (2020) among others). Cherry et al. (2020) and An et al. (2021) investigate how mortgage forbearance affects the consumer debt markets. Granja et al. (2020), Agarwal et al. (2020) and others study the impact of the federal Paycheck Protection Program (PPP) on small businesses. Our paper is among the first to describe

[9]Gabriel et al. (2021) provide evidence of beneficial effects of California 2000s financial crisis foreclosure moratoria on housing and local economies. Also, substantial literature studies the costs and benefits of other rental market interventions notably including rent control. See, e.g., Favilukis et al. (2019); Diamond et al. (2019); Sims (2007) and Glaeser and Luttmer (2003).

[10]More generally, there is substantial concern that the costs of the pandemic are being borne disproportionately by minority and lower-income groups. See, e.g., Chetty et al. (2020) and Mongey et al. (2020).

the temporal and geographic incidence of 2020 COVID-19 rental policy interventions and to provide evidence of their household and local economic treatment effects.

The remainder of the paper is organized as follows. We provide background and summary information on COVID-19 rental eviction moratoria in the next section; in Section III, we explain our data and methodology. Results are reported in Section IV, followed by concluding remarks in Section V.

II. COVID-19 Rental Eviction Moratoria

The Eviction Lab at Princeton University (hereinafter Eviction Lab) compiles information on state and county incidence of COVID-19 "eviction moratoria which bar landlords from serving tenants with a notice to quit and filing an eviction action for nonpayment of rent" (Benfer et al. (2020)). In addition to information from that source, we used web scraping and test parsing protocols to conduct an automated search over the period of analysis of COVID-19 rent policies at state-level governor, court, and legislation websites for all states in the U.S. Rental eviction moratoria panel information from collected from the web scraping exericse and the Eviction Lab site were highly consistent. Figure 1 maps treatment incidence for U.S. states and counties for specific timeframes during the study period. We also provide a dynamic mapping of the state eviction moratoria treatment panels over the March – August study period (See `https://covid19evictionmoratoria.anderson.ucla.edu/map/`).[11]

During our period of analysis, the federal eviction moratorium as specified by the CARES Act was limited only to renters who received federal housing assistance or lived in a property

[11]The website includes information on four different rental market policy treatment terms: eviction moratoria, caps on rent increase, limitations on reporting delinquent tenants to credit bureaus, prohibitions on utility disconnection. during the period of analysis, imposition of eviction moratoria varied widely in duration and timing among states and counties in the U.S.

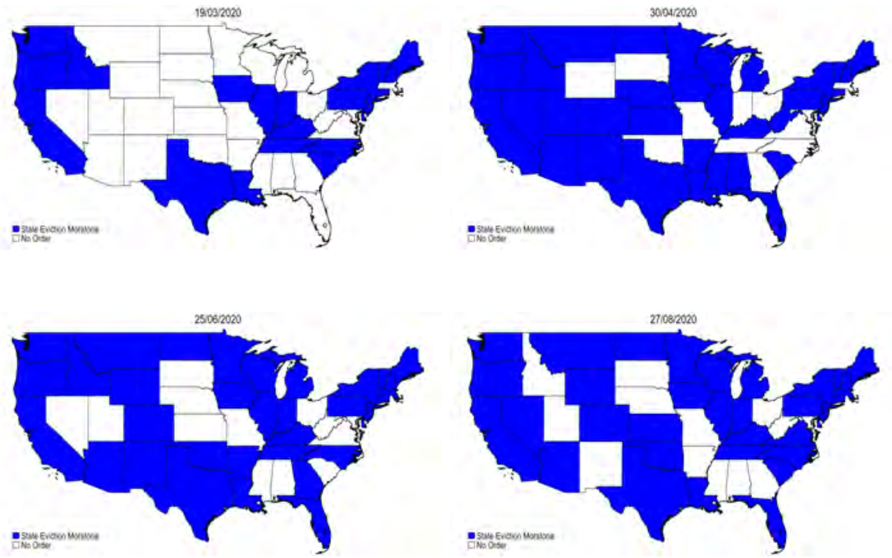


Figure 1. Dynamic Maps of Eviction Moratoria for U.S. States

Notes: The figure describes the geographic and temporal incidence of eviction moratoria using a series of dynamic treatment maps at the state-level. The maps are updated on an ongoing basis and are available at the following website: https://covid19evictionmoratoria.anderson.ucla.edu/map/. Eviction Moratoria Refers to implementation of eviction moratorium in specific locations due to the COVID-19 pandemic. Data sources include: The Eviction Lab at Princeton University, Emily Benfer at Wake Forest University, and authors' own calculations.

Covid Economics 74, 30 March 2021: 25-70

with a federally-backed mortgage.[12] Indeed, the Federal Reserve Bank of Atlanta estimated that the CARES Act moratorium covered between 28 to 46 percent of occupied rental units

[12]The CARES Act moratorium covered tenants who receive assistance through most federal housing programs, including public housing, the Housing Choice Voucher program, Low Income Housing Tax Credit properties, and rural housing programs administered through the U.S. Department of Agriculture (USDA). Also included in the protections were renters in homes with mortgages owned, securitized, or insured by Fannie Mae, Freddie Mac, the Department of Housing and Urban Development (HUD), USDA, or other federal agencies. For more information, please see U.S. Congress CARES Act, 2020. "Temporary Moratorium on Eviction Filings," Section 4024.

nationally, leaving as many as 31 million renter households without federal eviction protection.[13] In the context of limited federal renter protection under the CARES Act, many states and counties issued moratoria on rental evictions, ranging from a few weeks to several months. During March 2020, 38 U.S. states including California, Florida, Texas, New York and the District of Columbia issued eviction moratorium. Massachusetts and 5 other states enacted eviction moratoria in April. Virginia enacted such a rental market treatment in July. Some of the states, including Alabama, Mississippi and Nebraska, concluded the eviction moratorium by the end of May. Arkansas, Idaho and New Mexico discontinued treatment in June. Seven states never implemented eviction moratorium.

In addition to the federal and state eviction moratorium, many counties and cities implemented local eviction moratorium. Sometimes local ordinances were issued in states that failed to enact eviction moratoria. Elsewhere, the local ordinances often appeared redundant to those imposed by state treatments. Indeed, a myriad of explanations are ascribed to the passage of local eviction moratoria in treated states, notably including differences in timing of measures, efforts by local authorities to raise awareness of such measures among both landlords and tenants, and to establish local jurisdiction for purposes of local enforcement of such ordinances (Benfer et al. (2020)). Among the 626 counties in the eviction lab dataset, 94 counties implemented eviction moratoria, of which 25 are in California. Below we separately identify and estimate the effects of state and local treatment.

Commencing September of 2020, the Centers for Disease Control and Prevention (CDC) broadened the federal eviction moratorium to effectively protect all of the nation's 43 million rental households through December 2020. In the wake of the issuance of the CDC ordinance,

[13] See, Federal Reserve Bank of Atlanta, "Housing Policy Impact: Federal Eviction Protection Coverage and the Need for Better Data", by Sarah Stein and Nisha Sutaria.

Covid Economics 74, 30 March 2021: 25-70

CEPR PRESS

state and local treatment largely became redundant.[14] Hence we limit our study period to March-August 2020.

III. Data and Research Design

A. Data Sources

A primary source of data for this study is the Federal Reserve Y-14M regulatory report. That report contains detailed information on the asset portfolios of bank holding companies (BHCs) required to participate in Comprehensive Capital Analysis and Review and Dodd Frank Act Stress Tests. The Federal Reserve dataset contains about 50 billion records for over 500 million anonymised credit card accounts in the U.S. The data cover over 80 percent of the market and well represent the universe of credit cards outstanding. The monthly report at the account-level contains detailed information about borrowers' credit card purchases, cash withdrawal, transfer, convenience checks, payment, balance, interest charges and fees, and the like. It also contains updated borrower credit score and other borrower characteristics.[15]

For purposes of our study, we aggregate the account level credit card data to the zip code-level and form a zip code by month panel. We focus on three outcomes, including credit card spending, credit card payment and credit score. To compute credit card spending, we include purchases using credit cards, cash withdrawals and convenience checks but exclude balance transfers so as to avoid double counting. In order to account for seasonality, we calculate year-over-year changes of the three outcome terms, the first two as percentage changes and the last as change in credit score points. We exclude zip codes with fewer than 100 accounts

[14]For further details, see the Federal Register https://www.federalregister.gov/documents/2020/09/04/2020-19654/temporary-halt-in-residential-evictions-to-prevent-the-further-spread-of-COVID-19.

[15]We work with a 1 percent random sample of the data.

Covid Economics 74, 30 March 2021: 25-70

Covid Economics 74, 30 March 2021: 25-70

in 2020 to ensure that the change statistics are not affected by outliers. We merge eviction moratorium data and other macroeconomic controls such as unemployment rate and house price index (HPI) to our credit card data using geographic identifiers such as county FIPS and state name, depending on the level of granularity of the macro variables.

As suggested above, the paper seeks to assess the effects of eviction moratoria on a wide array of indicators of household spending and well-being. To that end, we also use the real-time Opportunity Insight Economic Tracker (hereinafter Opportunity Insight) data from Chetty et al. (2020) that measure consumer spending. These data are compiled largely based on aggregated and anonymised information on credit and debit card spending collected by Affinity Solutions Inc.[16] The Opportunity Insight data are not as granular in geography as the Federal Reserve data in that they are available only at the state- or county-level. However, a distinct advantage of the Opportunity Insight data is that, at the state-level, they contain measures of consumption by category of spending, including non-durable spending, spending on grocery and food store, spending on health care, and the like. The data are seasonally-adjusted in that year-over-year changes are calculated. The seasonally-adjusted series are then compared to the pre-COVID-19 levels in the first four weeks of 2020 (January 4-31).

To assess the effect of rental policy interventions on food insecurity and mental health disorders we compiled information from the Census COVID-19 Household Pulse Survey. That Survey commenced on April 23, 2020 and sought to provide insights into household social and economic COVID-19 pandemic effects. The Survey collected information on a weekly basis for 10 consecutive weeks on food sufficiency and security. We define "food

[16] Affinity Solutions Inc is a company that aggregates consumer credit and debit card spending information to support a variety of financial service products, such as loyalty programs for banks. Affinity Solutions captures nearly 10% of debit and credit card spending in the U.S.

Covid Economics 74, 30 March 2021: 25-70

insecurity" as the share of survey respondents that indicated that they sometimes or often don't have enough food to eat (in the past 7 days). We also use search query data from Google Trends to develop a broad-based and real-time search indicators related to food insecurity. [17] As of October 2020, Google accounted for 62% of all US internet searches.[18] Hence, internet queries through Google are representative of the US internet population. Google Trends reports the search frequency for a given search term relative to all other search terms in the form of a Search Volume Index (SVI).[19] We begin by considering food insecurity related keywords, such as "food" in combination with the word '"help" or "assistance". This process led to three key search terms, including "Food Stamps", "Food Assistance", "Food Banks Near Me". Regarding indicators of household mental health, the National Center for Health Statistics (NCHS) partnered with the Census Bureau to include three questions in the 2020 weekly Household Pulse Survey that ask about symptoms of anxiety or depression. The three mental health outcome terms include "feeling anxious", "can't stop worrying", and "feeling down". For each of the three indicators, we define the percentage of people who replied that they experience this feeling more than half the days or nearly everyday over the last seven days.

B. Summary Statistics

Table I presents summary statistics of those variables (see Table A.1 for detailed definition of each variable). Panel A reports summary statistics for the eviction filing and state and county eviction moratoria, implemented in the US as a response to the COVID-19 pandemic. The mean number of eviction filings among cities in the U.S. on April 23 2020 was 63; eviction

[17] https://trends.google.com/trends/

[18] As measured by statista. Further, according to the Pew Research Center, 92% of online adults use search engines, See http://www.pewinternet.org/Reports/2011/Search- and- email/Report.aspx.

[19] For more information, see Chauvet et al. (2016)

filings rose to 139 on July 9. As of April 23, 40 states had implemented eviction moratoria.

Panel B reports the Federal Reserve Y-14M variables, including credit card spending, payment, and credit score. Our credit card data sample from the Federal Reserve contains 46,064 monthly observations for 9,870 zip codes for April-August 2020. The sample includes all 50 states and the District of Columbia. Due to the pandemic and related shutdown, there is a large reduction in credit card spending. The average year-over-year (YoY) spending declined about -14% from April to August 2020. Credit card payment also declined year-over-year. These trends are also depicted in Figure 2. Panel A of the figure shows a large decline in spending in April followed by a slow recovery through the summer months. Panel B shows significant variations across states in credit card spending. Finally, in Appendix Figure A.1, we plot the distribution of the zip code-level credit card spending and payment changes. The time-series spending patterns as well as cross zip code variations are clearly evidenced in the density plots.

Panel C reports the change in various categories of consumer spending relative to January 2020,[20] as reported by Opportunity Insight (Chetty et al. (2020)). The trends in the main categories are depicted in Figure 3 for selected a few states and Washington DC.

Covid Economics 74, 30 March 2021: 25-70

[20]Seasonally adjusted credit/debit card spending relative to January 4-31 2020, in annual terms

Table I Summary Statistics

	March-August 2020				
	Obs	Mean	Std. Dev.	Min	Max
	(1)	(2)	(3)	(4)	(5)
Panel A - Eviction Moratoria					
County Eviction Filing	1,148	125	212	0	1,890
State Evic. Mor.	1,326	0.75	0.43	0	1
County Evic. Mor.	16,016	0.09	0.28	0	1
Panel B - Federal Reserve Y-14M: Credit Cards					
Number of credit card accounts	9,697	391	278	100	2,495
Spending change	45,835	-13.96	24.86	-56.65	65.33
Payment change	45,832	-3.71	25.91	-48.21	80.98
Score change	36,038	3.19	4.67	-67.62	31.57
Panel C - Opportunity Insight Database					
County Spending	41,392	-10.11	16.10	-118	38.7
State food service spending	1,326	-39.42	16.67	-95	4.96
State merchandise stores	1,326	-15.53	17.05	-63.3	28.1
State grocery spending	1,326	13.88	12.36	-53.8	103
State health care	1,326	-26.18	21.12	-109	126
State transportation	1,326	-52.8	13.68	-98.3	1.11
Retail with grocery	1,326	7.13	9.02	-26.9	35.7
Retail no grocery	1,326	4.13	12.27	-35	34
Durable	1,326	-108.2	29.22	-200.1	29.11
Non-durable	1,326	-67.27	50.3	-268.1	92.98
Panel D - Census Pulse Survey: Food Insecurity					
Food insecurity	612	9.45	2.9	2.65	20.4
Food insecurity Hispanic	504	16.8	8.5	0.76	54.6
Food insecurity Black	434	21.4	11.2	3.26	85.2
Food banks	612	2.22	1.23	0.13	8.75

Covid Economics 74, 30 March 2021: 25-70

Summary Statistics - Cont.

	March-August 2020				
	Obs	Mean	Std. Dev.	Min	Max
	(1)	(2)	(3)	(4)	(5)
Panel E - Google Search Query					
Food Stamps	1,326	40.5	22.8	0	100
Food Assistance	1,170	23.9	28.0	0	100
Food Banks	1,170	20.45	25.5	0	100
Help Food	1,326	37.1	26.9	0	100
Panel F - Census Pulse Survey: Mental Health					
Feeling Anxious	612	29.4	4.21	18.4	42.7
Feeling Anxious Hispanic	604	33.5	12.2	7.01	82.2
Feeling Anxious Black	530	31	12	2.55	90.8
Cant Stop Worrying	612	23.8	4.24	13.2	37.1
Cant Stop Worrying Hispanic	602	28.4	11.8	2.95	80.5
Cant Stop Worrying Black	521	28.7	11.7	1.05	88.6
Feeling Down	612	20.8	3.88	11	34.1
Feeling Down Hispanic	593	25.4	11.4	2.13	92.8
Feeling Down Black	503	24.3	11.1	2.12	77.5
Panel G - Macro Variables					
County unemp. rate	4,163	10.44	4.01	2.8	34.4
County HPA	4,163	4.56	2.88	-8.37	15.64
State DPI change	255	4.58	3.28	0.51	12.41

Notes: This table reports the summary statistics of the variables used in the paper. Panel A reports summary statistics for the eviction filing and state and county eviction moratoria, implemented in the US as a response to the COVID-19 pandemic. Panel B reports the Federal Reserve Y-14 Regulatory Report variables, including credit card spending, payment, and credit score. These variables are winsorized at the 1^{st} and 99^{th} percentiles. Panel C reports the change in various categories of consumer spending relative to January 2020, seasonally adjusted credit/debit card spending relative to January 4-31 2020, as was documented at Opportunity Insight (Chetty et al. (2020)). Panel D and E report from the Census Pulse Survey measures of food insecurity and mental health. Panel F reports Google search query variables, and finally Panel G reports macroeconomic variables. See Appendix Table A.1 for variable definitions. Data sources include: The Eviction Lab at Princeton University, the Federal Reserve Y-14M, the Opportunity Insight Economic Tracker, the Census Pulse Survey, and Google.

Covid Economics 74, 30 March 2021: 25-70

Covid Economics 74, 30 March 2021: 25-70

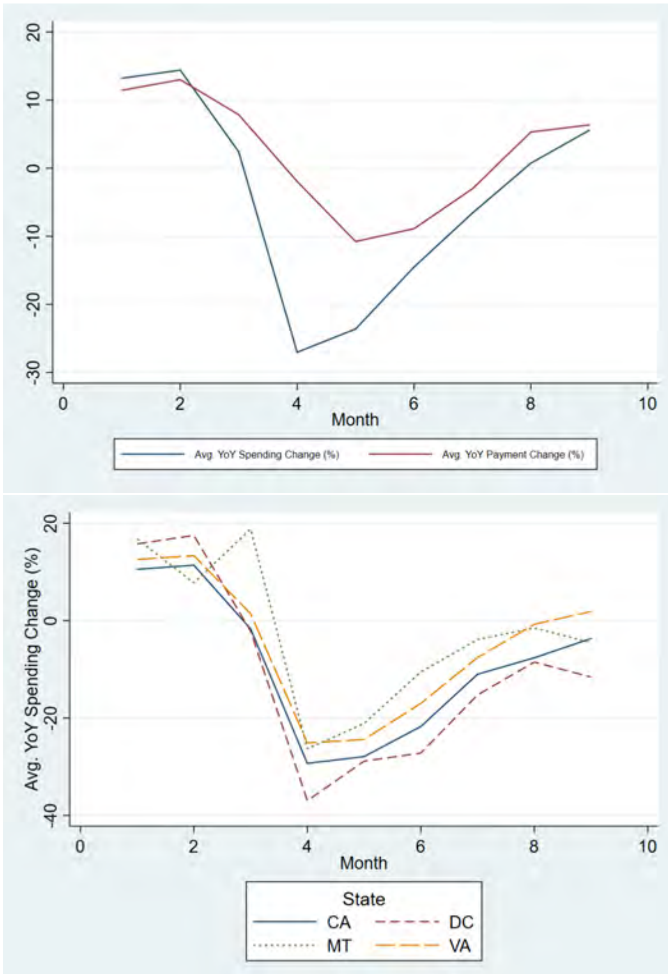


Figure 2. Credit Card Spending and Payment Year-Over-Year Changes

Notes: The figure describes the average year-over-year changes in zip code-level credit card spending and payment. Panel A shows the averages of a national sample of zip codes and Panel B shows the averages by state for a selected number of states. We exclude zip codes with fewer than 100 credit card accounts in our data as well as those outside of Metropolitan Statistical Areas (MSAs) to minimize outlier impact. Data source is the Federal Reserve Y-14M.

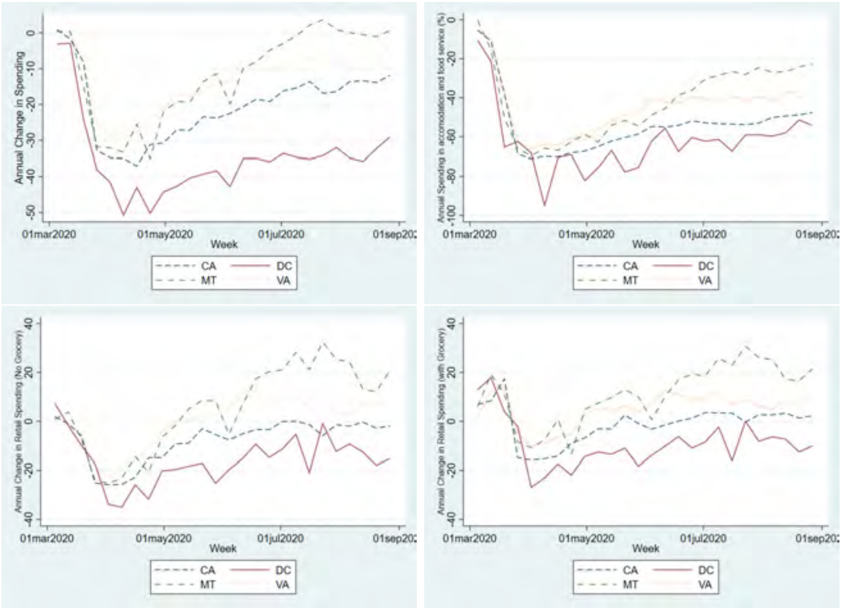


Figure 3. Spending by Categories Year-Over-Year Change

Notes: The figure describes the average year-over-year changes in state spending by categories. Panel A shows the averages change by week on overall spending for a selected number of states and Panel B shows the averages change by week in accommodation and food service for a selected number of states. Panel C shows the annual averages change by week on retail spending (no grocery) for a selected number of states and Panel D shows the annual averages change by week on retail spending (with grocery). Data source is the Opportunity Insight Economic Trackers.

Covid Economics 74, 30 March 2021: 25-70

CEPR PRESS

Panels D and E report summary information on food insecurity and population mental health and by race from the COVID-19 Census Pulse Survey. Panel F reports summary information on food insecurity search query from Google Trends. The Google indices indicate an increase in search for terms related to food insecurity throughout the March to August 2020 study period.

As a first step in the analysis, we seek to assess the reasonableness of the eviction moratorium data by correlating state eviction moratoria and reductions in eviction filings. Our information on eviction filings is obtained from the Eviction Tracking System of the Eviction Lab dataset as described above (see Benfer et al. (2021)). As shown in Appendix Table A.2 we separately assess the effects of state and county eviction moratoria on eviction filings in the 27 U.S. cities covered in the Eviction Lab data. Our regressions include county-level labor and housing market controls as well as county and week fixed effects. The county-level eviction moratoria regressions alternatively employ MSA by week fixed effects. Column 1 in Table A.2 shows that an additional week of state eviction moratoria treatment (lagged in two weeks) is associated with a decline of 129 eviction filings compared to a state-weekly average of 125 eviction filings. A difference-in-differences (DID) regression shown in Column 2 suggests that the reduction of eviction filings is mostly in high renter share counties, which is intuitive. Here *Target* is an indicator that the county is ranked in the top quartile in terms of both renter share and unemployment rate.[21]

As described above, certain counties implemented eviction moratoria even in the presence of similar state-wide policy treatment. In columns 3 and 4 of Table A.2 , we seek to ascertain whether there is an incremental benefit to county-level policy. To address that question, we

[21] To derive a clean identification of the effect of state eviction moratorium, in the first two columns, we comprise the sample to include only those states (state-week) where no county-level eviction moratorium was in place. For each state, we move the implementation dates by two weeks, such that the focus variable is lagged by two weeks.

Covid Economics 74, 30 March 2021: 25-70

select places where both state- and county-level eviction moratoria were in place and re-run our models. Column 3 of Table A.2 shows that an additional week of county eviction moratoria (in already treated states) is associated with a decline of 80 eviction filings compared to a state- weekly average of 125 eviction filings. However, the DID results shown in Column 4 fail to indicate significant incremental effects of county eviction moratoria among targeted high renter share counties. Overall, imposition of eviction moratoria had the intended effect of reducing eviction filings during a period of pandemic distress.

Covid Economics 74, 30 March 2021: 25-70

C. Empirical Strategy

We employ a panel data model with fixed effects to identify the relation between eviction moratorium and household well-being. Our observations are at zip code-, county-, or state-level and our outcome variables vary by month or week. Given sample structure, we estimate the following model:

$$Y_{it} = \alpha + \beta V_{it} + X'_{it}\gamma + \tau_t + \zeta_i + \varepsilon_{it}, \tag{1}$$

where Y_{it} stands for the outcome in zip code/county/state i at time t, V_{it} is an indicator of the treatment, eviction moratorium, in geography i and period t; and X_{it} is a matrix of time- and space-varying control variables such as unemployment rate and house price appreciation. τ_t and ζ_i are time- and geography- fixed effects. Finally, ε_{it} stands for the error term, which are assumed to be clustered at the state- or county-level. The coefficient β is the treatment effect of eviction moratoria.

Eviction moratoria specifically target renter populations, especially those that are having rental payment difficulties. Therefore, we leverage the contrast between renters and homeowners to aid in identification. In that regard, in addition to the baseline model we ex-

Covid Economics 74, 30 March 2021: 25-70

plained above, we estimate the following treatment intensity difference-in-differences (DID) regression:

$$Y_{it} = \alpha + \beta_1 V_{it} + \beta_2 V_{it} R_i + \beta_3 R_i + X'_{it}\gamma + \tau_t + \zeta_i + \varepsilon_{it}, \tag{2}$$

where R_i is a treatment intensity indicator and it is based on the local renter share and unemployment rate as a proxy for the share of local population in financial distress. More specifically, R_i is a dummy variable for zip codes in the top two quartiles in terms of both renter share and unemployment rate in April, the first peak of the COVID-19 pandemic.[22] Note that the impact of R_i is absorbed by the fixed effects in the regression. In this DID setting, eviction moratorium is the treatment, and areas with high renter share and high financial distress are more intensively "treated". β_2 is the lower-bound estimate of the treatment effect. This augmented specification helps our inference of the causal impact as renters (especially those in financial distress), not homeowners, are the target beneficiaries of the eviction moratoria intervention. This same econometric structure is utilized in analysis of Opportunity Insights and other outcome terms at the county and state levels.

IV. Results

A. Credit Card Spending, Payment and Credit Score

We first present results based on the Federal Reserve Y-14M credit card data. Our sample is a zip code by month panel of year-over- year changes in credit card spending, payment, and borrower credit score.[23] The data span April to August of 2020. Table II contains

[22] See, e.g., "Three peaks: How the coronavirus pandemic is evolving in each state," NBC News, November 12, 2020.

[23] The unit of observation is zip code month.

estimates of the impact of state-level eviction moratoria. Our focus variable is an indicator of presence of a state-level eviction moratoria in the zip code during a particular month. We lag the focus variable by two weeks.[24]

In column 1, we show the baseline model results for credit card spending. The positive coefficient of the *State Evic. Mor.* term indicates that the presence of a state eviction moratorium is associated with elevated zip code credit card spending. Zip codes are heterogeneous in demographic structure and economic conditions. Hence, we include zip code-fixed effects to control for cross-sectional variations in these and other factors. We also include a month-fixed effect to control for time variation in economic or other conditions (note that possible seasonality is addressed via our focus on year-over-year changes in the spending term), In addition, we include two county-level and time variant drivers of zip code spending, including those that proxy for fluctuations in household income and wealth. Those factors are the county-level unemployment rate and one-quarter lagged house price appreciation (HPA). Unemployment status is a major factor that affects household income and related propensity to spend and service debt. HPA provides a proxy for fluctuations in capacity to spend out of housing wealth.[25]

[24] To identify the effects of state eviction moratorium, we comprise a sample of only those states (state-month) where no county-level eviction moratorium was in place.

[25] As shown in column 1, local unemployment rates are negatively associated with spending growth. HPA is estimated with a positive sign but is insignificant.

Covid Economics 74, 30 March 2021: 25-70

Table II Effects of State-level Eviction Moratoria on Credit Card Utilization

	Zip Code by Month Panel					
	Spending Change		Payment Change		Score Change	
	(1)	(2)	(3)	(4)	(5)	(6)
State Evic. Mor.	1.867*	1.458	0.249	-0.610	-0.131	-0.216
	(0.988)	(1.036)	(1.353)	(1.440)	(0.170)	(0.176)
State Evic. Mor.×Target		1.356**		1.199*		0.341***
		(0.583)		(0.707)		(0.116)
County unemp. rate	-0.401***	-0.459***	-0.276	-0.328*	-0.016	-0.031
	(0.136)	(0.131)	(0.186)	(0.173)	(0.035)	(0.034)
County HPA 1Q lag	0.006	-0.006	-0.181	-0.191	0.017	0.013
	(0.110)	(0.108)	(0.134)	(0.137)	(0.029)	(0.029)
Spending change 1M lag			0.162**	0.162**	-0.001	-0.001
			(0.060)	(0.060)	(0.002)	(0.002)
Payment change					0.004***	0.004***
					(0.001)	(0.001)
Constant	-10.259***	-9.527***	3.183	3.828	3.444***	3.631***
	(1.523)	(1.482)	(2.351)	(2.298)	(0.442)	(0.436)
Dep Var Mean	-13.00	-13.00	-3.02	-3.02	3.21	3.21
Zip Code FE	X	X	X	X	X	X
Month FE	X	X	X	X	X	X
N	20,996	20,996	20,650	20,650	16,477	16,477
R2	0.5788	0.5790	0.4887	0.4888	0.8457	0.8459

Notes: This table presents our estimates of the impact of state-level eviction moratorium on consumer credit card spending, payment and credit score based on zip code by month panel data of YoY changes of the outcome variables. Our focus variable here is an indicator of whether the state in which the zip code is located had an eviction moratorium in place during a particular month. For each state, In the spending and payment regression, we lag the eviction moratorium indicators by two weeks, so we end up with spending and payment data from April to August to reflect the impact of eviction moratorium between late March and early August. For the credit score regressions, we lag the eviction moratorium indicators by two months so the credit score data are from May to September to reflect the impact of eviction moratorium from March to July. To derive a clean identification of the effect of state eviction moratorium, we comprise the sample to include only those states (state-week) where no county-level eviction moratorium was in place. We also exclude zip codes with fewer than 100 credit card accounts in our data as well as those outside of MSAs to minimize outlier impact. About 4,000 zip codes remain in these regressions. Data sources include: The Federal Reserve Y14M, BLS, BEA, and the Census. Robust standard errors in parentheses with error terms clustered at the state-level; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Column 1 estimates the average rental eviction moratorium treatment effect. Note that COVID-19 eviction moratoria sought to target unemployed renter households experiencing difficulties in payment of rent. Hence, our target group is defined as those zip codes in the upper half of renter share with high levels of unemployment in April 2020. The focus variable is an interaction of *State Evic. Mor.* with the *Target* indicator. Results of the treatment intensity difference-in-differences (DID) analysis indicate a positive and significant effect of state eviction moratoria on credit card spending among targeted zip codes. The regression includes controls for county unemployment rate, lagged HPA and zip code- and month-fixed effects. The estimated credit card spending effect of state-level eviction moratorium is also economically significant. The one-month target zip code treatment effect is 1.356 percent, meaning that a 12-month treatment effect amounts to about 16 percent ($1.356 \times 12 = 16$). To put this into perspective, the average year-over-year decline in credit card spending in April is 25 percent, and the 75th percentile is 38 percent.

In Appendix Figure A.2, we show results of the parallel trend test. We shift the moratoria implementation ("event") dates by a defined number of weeks for each state and then re-run the DID regression. Results indicate that there exists a parallel trend between treatment and control groups prior to the actual event date, validating our assumption of no pre-trend in the DID analysis.

We now turn to credit card payments. Here our specification also includes lagged spending to account for the fact that households typically increase debt paydown in the wake of an increase in prior month's spending. Column 3 shows results of estimation of the baseline model while column 4 shows results of the difference-in-differences (DID) analysis of eviction moratoria among targeted high renter share zip codes. While the average treatment effect is not statistically significant, the estimated coefficient for eviction moratoria treatment in

Covid Economics 74, 30 March 2021: 25-70

Covid Economics 74, 30 March 2021: 25-70

targeted areas is positive and significant, indicating elevated debt payoff among targeted zip codes in states implementing eviction moratoria. The payment effect of state eviction moratoria among targeted zones is also economically significant: a 12-month eviction moratorium is associated with a 14 percent increase credit card debt paydown.[26]

Finally, the last two columns of Table II show the estimated impact of state eviction moratorium on borrowers' credit score. Given that credit score is typically viewed as a lagging indicator of borrowers' credit usage and performance, we use two-month lead credit score. Hence we study changes in borrowers' credit score two months subsequent to the implementation of eviction moratoria. The model specification is similar to those of the spending and payment regressions, except that we now include lagged spending and payment as added controls. As shown, while the average treatment effect is insignificant, we estimate a positive and statistically significant effect of eviction moratoria in target zip codes. The magnitude of the effect is relatively small: a 12-month treatment of state-level eviction moratorium results in a 4 point increase in credit score.[27]

As described above, certain counties implemented eviction moratoria even in the presence of similar state-wide policy treatment. In those cases, we seek to ascertain whether there was an incremental benefit to the county-level interventions. To address that question, we select places that enacted state-level eviction moratoria and then re-estimated our models so as to assess the effects of added country treatment.[28] As shown in Appendix Table A.3 ,

[26]Consistent with our priors, lagged spending growth is estimated with a positive and significant coefficient.

[27]During the pandemic study period, government provided emergency income support to households including stimulus checks and added unemployment benefits, many of whom are the credit card borrowers that we study in this paper. To account for the potential impact of transfer income on credit card spending and payment, we included real disposable income as an additional control and re-estimated all models. Results are robust are highly consistent with what we present in Table II.

[28]Given that the treatment effect of interest is now at the county-level, we use MSA by month-fixed effects to account for variations in economic and other factors both across MSAs and over time. These fixed effects also absorb the state-level treatment effects, so the coefficient of the county-level eviction moratorium captures the incremental effect of the county-level policy.

the estimated treatment terms are not statistically significant, suggesting little incremental effect of county-level treatment among states that enacted rental eviction moratoria.

B. Consumer Spending by Category

We seek to expand the above credit card spending analyses using data from the Opportunity Insight database assembled by Chetty et al. (2020). The Opportunity Insight data are not as granular in geography as the Federal Reserve data, but an advantage of that dataset is that it covers both credit and debit cards. In addition, the Opportunity Insight data enable disaggregation of household spending by category of consumption.

Before we move on to detailed spending categories, we compare the aggregate spending effects as reflected in the Opportunity Insight data and in the Federal Reserve data. To facilitate comparison, our model timeframe and specification consistent with that of the credit card zip code analysis.

In Appendix Table A.4 , Column 1 shows that an additional week of state eviction moratorium is associated with an increase of overall annual spending of 1.2 percent. This compared to an overall decline in yearly spending of 23 percent (see Table I). Results displayed in column 2 indicate that a one-week state treatment effect among policy targeted counties is associated with an annual spending increase of 1.7 percent.[29] Overall, results of the Opportunity Insights data serve to corroborate analysis of Federal Reserve credit card data in estimating positive and significant salutary effects of state pandemic rental eviction moratoria on household consumption spending.

The disaggregation of household spending by category in the Opportunity Insights data

[29]In columns 3 and 4 of Table A.4 , we undertake assessment analogous to the above of incremental effects of county-level eviction moratoria on county level spending. Consistent with the credit card analysis, results of the baseline Opportunity Insights model fail to provide evidence of significant increments in household consumption spending among counties also adopting eviction moratoria.

allows us to test for effects of the role of eviction moratoria in supporting immediate and pressing household consumption needs, notably including nondurable retail and food consumption. As suggested above, deferral of household rent payments as provided by the eviction moratoria may have enabled re-direction of scarce household financial resources to immediate consumption needs. Here we would expect to see asymmetric effects of policy intervention with more beneficial treatment effects estimated for non-durable categories.

Results of this analysis are presented in Table III. There we report on the impact of state-level eviction moratoria on state spending by category. As evident, model specification is similar to those above. Definition of spending category is described in a note to Table III and is in accordance to the Opportunity Insight data. Overall, results of disaggregation of spending by category provides new insights as are consistent with hypotheses. As evidenced in the pattern of coefficients on the treatment term, in general household spending is significantly boosted by eviction moratoria treatment in the various retail, grocery, and food service categories, indicating broad unanticipated effects of the policy treatment in supporting household food needs. Table III shows that a state eviction moratoria is associated with an annual increase in spending on food service (column 1) by 1 percent, with a 0.9 percent increase in grocery spending (column 3), and an annual increase in non-durable spending (column 9) by 1.4 percent.

Covid Economics 74, 30 March 2021: 25-70

Covid Economics 74, 30 March 2021: 25-70

Table III Effects of State-Level Eviction Moratoria on Consumption by Category

	Food Service Spending	Merchandise Stores	Grocery Spending	Health Care	Transportation	Retail with Grocery	Retail No Grocery	Durable	Non Durable
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
State Evic. Mor.	0.991*	0.860*	0.917*	1.632	-0.241	0.992*	1.382*	-0.663	1.373*
	(0.530)	(0.522)	(0.526)	(2.026)	(0.527)	(0.590)	(0.712)	(1.484)	(0.712)
Unemp. rate IV	-0.067	-0.338	-0.356	-0.103	-0.055	-0.167	-0.517	-0.081	-0.018
	(0.062)	(0.418)	(0.220)	(0.187)	(0.061)	(0.115)	(0.398)	(0.481)	(0.062)
HPA	0.002	0.161	0.812	0.405	0.647	0.363	0.916	0.269	0.346
	(0.537)	(0.260)	(0.611)	(0.248)	(0.640)	(0.531)	(0.638)	(0.658)	(0.717)
Constant	-9.570***	-11.215***	11.887***	1.007	-3.206***	-7.640***	35.822***	-7.640***	3.235
	(0.678)	(2.499)	(0.722)	(0.852)	(0.849)	(0.508)	(6.112)	(0.656)	(2.525)
County FE	X	X	X	X	X	X	X	X	X
Week FE	X	X	X	X	X	X	X	X	X
N	1,122	1,122	1,122	1,122	1,122	1,122	1,122	1,122	1,122
R2	0.849	0.901	0.873	0.606	0.756	0.966	0.886	0.756	0.606

Notes: This table presents our estimates of the impact of state-level eviction moratoria on state spending by categories, relative to its level in January 2020, seasonally adjust; relative to 2019, e.g., the change in card spending in the second week in April is calculated as ((Spending for April 8 through April 14 2020) - (Spending for April 8 through April 14 2019)) - ((Spending for January 4 through January 31 2020) - (Spending for January 4 - January 31 2019)). Nondurable goods include wholesale trade, agriculture, forestry and hunting, general merchandise, apparel and accessories, health and personal care stores, and grocery stores. We follow Chetty et al. (2020) definition of durable goods as the following groups: motor vehicles, sporting and hobby goods, home improvement centers, consumer electronics, and telecommunications equipment. Data Sources include: Eviction Lab, and Opportunity Insight database compiled by Chetty et al. (2020). Robust standard errors in parentheses with error terms clustered at the state-level; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C. Food Insecurity

The period of the COVID-19 pandemic similarly was marked by widespread media reports of food insecurity among populations substantially adversely affected by virus economic fallout. As indicated above, rental eviction moratoria and related deferral of rent payments enabled re-direction of household scare financial resources to food and grocery spending. In so doing, the rental eviction policy treatment may have helped to alleviate household food insecurity.[30] In this section, we employ new pandemic period survey research data from the Census Bureau to directly assess the effects of eviction moratoria on survey-based measures of food insecurity. Our survey-based measures come from the Household Pulse Survey, an entirely new survey intended to measure the effect of the pandemic on the well-being of households. Our paper uses the data collected for Phase 1 of the Household Pulse Survey, which commenced on April 23, 2020 and concluded on July 21, 2020.[31] Specifically, we assess survey responses whereby households declare that in the prior 7 days they "Sometimes do not have enough food to eat" or "Often do not have enough food to eat". We evaluate state-level survey responses over the April 23 2020 through July 9 2020 period. Responses to the food insecurity questions were also provided only for Hispanic or Latino and for African American households.

[30]Rosen et al 2020 survey almost 800 households in Los Angeles in 2019 to examine the impact of housing affordability constraints on Los Angeles renters. They find that rent-burdened households are more likely to have reduced food consumption than non-rent-burdened households, especially among Latino and Black families.

[31]The Household Pulse Survey was a 20-minute online survey studying how the coronavirus pandemic impacted households across the country from a social and economic perspective. The survey asked questions about how education, employment, food security, health, housing, social security benefits, household spending, consumer spending associated with stimulus payments, intention to receive a COVID-19 vaccination, and transportation were affected by the ongoing crisis. For more information, see https://www.census.gov/programs-surveys/household-pulse-survey.html. Data collection for Phase 2 of the Household Pulse Survey began on August 19, 2020. As this paper undertakes analysis of eviction moratoria treatment effects through the end of August, 2020, we focus only on the initial phase of the survey.

Covid Economics 74, 30 March 2021: 25-70

In panel A of Table IV we use information from the Census Pulse survey and report the results of regressions of state eviction moratoria on food insecurity. We define "food insecurity" as the share of respondees who over the past 7 days declared that they sometimes or often didn't have enough food to eat. We include week fixed effects to control for time variation in overall economic or other conditions. We also include state fixed effects to control for related cross-sectional variations. In addition, we include two state-level and time variant drivers of food insecurity, namely the state-level unemployment rate and the one-quarter lagged rate of house price appreciation (HPA), to proxy for cross-state and over time fluctuations in income and wealth. Column 1 of Table IV estimates the average rental eviction moratorium treatment effect (lagged in two weeks) on food insecurity. The estimated coefficient is negative but not statistically significant. In column 2, we focus on food insecurity among the sampled African American population. There the estimated effect is negative and statistically significant; an additional week of rental eviction moratoria treatment is associated with a decline of 2 percent in the number of African American households that declared as food insecured. On average, over the 10 weeks of the Census Pulse Survey, 21 percent of African American households declared that in the prior 7 days they "Sometimes do not have enough food to eat" or "Often do not have enough food to eat". Results do not yield a significant effect of rental policy treatment on either food insecurity among Hispanic households or in household use of food banks.[32]

[32]As indicated in the survey as those households that use "Food pantry or food bank as provider of free groceries or free meal/Total, in the last 7 days.

Covid Economics 74, 30 March 2021: 25-70

Covid Economics 74, 30 March 2021: 25-70

Table IVEffects of State-level Rental Eviction Moratoria on Food Insecurity

Panel A - Census Pulse Survey				
	Insecurity All	Insecurity Black	Insecurity Hispanic	Food Banks
	(1)	(2)	(3)	(4)
State Evic. Mor.	-1.906	-1.958*	1.581	-2.227
	(2.712)	(1.053)	(2.712)	(2.655)
County unemp. rate IV	0.001	0.114	0.013	-0.003
	(0.040)	(0.186)	(0.021)	(0.040)
Constant	1.160***	1.277***	1.213***	1.218***
	(0.245)	(0.233)	(0.231)	(0.218)
County FE	X	X	X	X
Week FE	X	X	X	X
N	612	612	612	612
R2	0.112	0.109	0.112	0.114

Panel B - Google Trends				
	Food Stamps	Food Assistance	Food Banks Near Me	Help Food
	(1)	(2)	(3)	(4)
State Evic. Mor.	-3.401*	-2.723	-5.124*	-1.819
	(1.789)	(2.790)	(2.697)	(2.457)
County unemp. rate IV	0.127	0.109	-0.093	-0.326
	(0.276)	(0.426)	(0.401)	(0.351)
Constant	68.904***	15.213***	36.413***	38.137***
	(4.256)	(3.843)	(3.724)	(3.469)
County FE	X	X	X	X
Week FE	X	X	X	X
N	1,122	1,122	1,122	1,122
R2	0.301	0.022	0.090	0.023

Notes: This table reports the results from regressions of state eviction moratoria on food insecurity. In panel A, We define "food insecurity" as the percentage of people that declared that sometimes or often they don't have enough food to eat (in the past 7 days). Columns 1 reports results on overall food insecurity and columns 2 and 3 report results on food insecurity among Hispanic and Black, respectively. Columns 4 reports results on the percentage of people that use food pantry or food bank as provider of free groceries or free meal, in the last 7 days. The data is from the Census Pulse survey from 4/23/2020 to 7/9/2020. In panel B, we use Google data to collect sensitive information directly from individuals seeking assistance via internet search on food insecurity. While these and related searches are derived from all households, a universe that includes both owners and renters, the bulk of such searches likely emanate from lower-income household, which is correlated with renters. We infer that when a user seeks help via a Google search. Data sources include: Eviction Lab, Google Trends, and Census Pulse Survey. Robust standard errors in parentheses with error terms clustered at the state-level; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Covid Economics 74, 30 March 2021: 25-70

We seek to corroborate effects of rental eviction moratoria on food insecurity using search query information downloaded from Google Trends. That data allow us to develop real-time indicators of food insecurity.[33] As of October 2020, Google accounted for 62 percent of all US internet searches.[34] Hence, internet queries through Google are representative of the US internet population. Google Trends reports the search frequency for a given search term relative to all other search terms in the form of a Search Volume Index (SVI).[35] We begin by considering food insecurity keywords, such as "food" in combination with the word "help." This process leads to 3 key search terms, including "Food Stamps", "Food Assistance", "Food Banks Near Me", "Help Food".

In panel B of Table IV report the results from regressions of eviction moratoria on food insecurity, using related search query terms from Google Trends, controlling for unemployment rate, and week and state fixed effect. Columns 1 and 3 of Table IV show that state eviction moratoria significantly reduce Google search for "Food Stamps" and "Food Banks Near Me". An additional week of a state eviction moratorium reduces Google search query for "Food Stamps" by 3.4, relative to an average SVI for that term of 40.5 between March to August 2020. Similarly, an additional week of state eviction moratoria reduce the amount of Google search of "Food Banks Near Me" by 5.1, relative to an average Google search for that term of 20.5 between March to August 2020.

D. Mental Health

The Census Household Pulse Survey partnered with the National Center for Health Statistics to monitor changes in population mental health in the wake of the COVID-19

[33] https://trends.google.com/trends/

[34] As measured by statista. Further- more, according to the Pew Research Center, 92 percent of online adults use search engines, See http://www.pewinternet.org/Reports/2011/Search- and- email/Report.aspx.

[35] For more information, see Chauvet et al. (2016)

pandemic. Indeed, a myriad of anecdotal reports suggested broad-based and elevated deterioration in mental health in the wake of the COVID-19 pandemic. Table I provides summary information from the Census Pulse Survey indicated that on average some 30 percent of households felt depressed or down during the pandemic survey period. Indeed, fear of eviction and related inability to pay rent may have contributed to elevated anxiety or related deterioration in mental health. If so, those symptoms may have been relieved by a temporary stay in eviction. Specifically, the Census Pulse Survey included questions on the frequency of anxiety and depression symptoms. Our paper uses responses to three questions from the survey including frequency of "feeling nervous, anxious, or on edge for more than half the days or nearly everyday", "not being able to stop or control worrying for more than half the days or nearly everyday", and "feeling down, depressed, or hopeless for more than half the days or nearly everyday". That information was tabulated each week from April 23 2020 to July 9 2020 at the state level. The survey data also provides information on those questions separately for Hispanic and African American households.

Table V reports the results from regressions of state eviction moratoria on the survey indicators of mental health. We include a weekly fixed effect to control for time variation in the overall economic or other conditions. We also include state-level fixed effects to control for cross-sectional variations. As above, we control for state-level unemployment rate and one-quarter lagged house price appreciation (HPA). Columns 1-3 of Table V estimate the average rental eviction moratorium treatment effect (lagged in two weeks) on the share of households that reported "feeling anxious" during the pandemic. As indicated in column 3, a negative and significant treatment coefficient is estimated for African American households. Here an additional week of rental eviction moratorium is associated with a decline of 1.9 percent in the share of African American households who reported "feeling anxious". On average, Pulse

Survey results showed an increase by roughly one-third in the share of African American households who reported “feeling anxious” during the April to August 2020 pandemic period. Similarly, as shown in column 12, a negative and statistically significant rental eviction moratoria treatment effect is estimated for share of African American households “feeling down” during the pandemic study period. Results indicate that an additional week of policy treatment is associated with a reduction by 1.6 percent in the share of African American households who reported “feeling down”. As suggested in the summary information, the pandemic study period witnessed a roughly one-quarter increase in share of African American households who reported “feeling down”. Column 4 of Table V shows that eviction moratoria lower the number of households that declare they ”Cant stop worried” by 1%, compare to an overall increase of 23.8% in the amount of households that ”Cant stop worried” during the pandemic.

Covid Economics 74, 30 March 2021: 25-70

CEPR PRESS

Covid Economics 74, 30 March 2021: 25-70

Table V Effects of State-level Eviction Moratoria on Mental Health

	Feeling Anxious	Feeling Anxious Hispanic	Feeling Anxiouss Black	Cant Stop Worrying	Cant Stop Worrying Hispanic	Cant Worrying Black	Feeling Down	Feeling Down Hispanic	Feeling Down Black
	(1)	(2)	(3)	(4)	(5)	(6)	(10)	(11)	(12)
State Evic. Mor.	-2.979	-1.395	-1.866***	-0.983*	-1.330	-0.985	-0.725	-2.191	-1.627***
	(2.601)	(2.785)	(0.577)	(0.578)	(2.310)	(2.451)	(2.372)	(2.645)	(0.576)
County unemp. rate IV	0.027	0.149	0.069	-0.209	0.109	0.068	-0.001*	0.001	-0.002
	(0.060)	(0.271)	(0.057)	(0.258)	(0.318)	(0.291)	(0.001)	(0.003)	(0.003)
Constant	31.307***	39.455***	34.329***	23.899***	24.725***	26.197***	19.513***	21.700***	23.865***
	(1.215)	(4.896)	(5.508)	(1.167)	(4.803)	(5.183)	(1.146)	(4.890)	(5.119)
County FE	X	X	X	X	X	X	X	X	X
Week FE	X	X	X	X	X	X	X	X	X
N	612	612	612	612	612	612	612	612	612
R2	0.327	-0.037	-0.116	0.360	-0.053	-0.096	0.265	-0.077	-0.105

Notes: This table reports the results from regressions of eviction moratoria on four different mental health disorders, taken from the Census Pulse Survey. The four mental health outcome terms include: feeling anxious, can't stop worrying, and feeling down. For each of the three indicators, we define the percentage of people who replied that they experience this feeling more than half the days or nearly everyday over the last seven days. Data sources include: Eviction Lab and Census Pulse Survey. Robust standard errors in parentheses with error terms clustered at the state-level; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

CEPR PRESS
Covid Economics 74, 30 March 2021: 25-70

V. Conclusions and Discussion

The COVID-19 pandemic exposed an estimated 17 million U.S. households to eviction risk.[36] To assure ongoing shelter of idled households and to damp pandemic virus spread, many states and counties in the U.S. enacted rental eviction moratoria. In this paper, we apply new panel data from the 2020 pandemic period to test the effects of rental eviction moratoria on measures of household well-being including household spending and debt, food insecurity, and mental health outcomes.

Our findings suggest that COVID-19 rental eviction moratoria had broad salutary effects during a period of widespread virus and economic distress. We firstly document that pandemic eviction moratoria resulted in substantial reduction in eviction filings. Analysis of both Federal Reserve and Opportunity Insights data indicate that the imposition of rental eviction moratoria served to boost household spending, notably as regards food and grocery spending and among targeted high renter share and high unemployment neighborhoods. Eviction moratoria also reduced Census Pulse Survey measures of food insecurity and mental stress, especially among African American households. Results are further corroborated in analysis of search query data from Google.

However, the above estimated benefits associated with eviction moratoria come with a cost. Moody's Analytics estimates that upward to $70 billion in outstanding rent debt was owed to landlords at the end of 2020. Further, the housing assistance provisions of the 2021 American Rescue Plan Act cover only a small portion of those moratoria-deferred rents.

[36] See Benfer (2020). While the pandemic has focused attention on eviction risk during a period of virus and related economic exigency, it is important to note that tenant evictions are commonplace during normal times and that research clearly documents their adverse and deleterious effects on individuals and communities. For example, evictions are associated with increased violence in communities (Sampson and Sharkey, 2008), lower educational attainment (Pribesh and Downey, 1999), and lasting negative health outcomes (Dong et al., 2005).

The National Low-Income Housing Coalition estimates that the average renter household will owe $5,400 in missed payments even in the aftermath of 2021 federal assistance.[37] Also, the University of Arizona Cost of Eviction Calculator estimates that expiration of eviction moratoria could lead to emergency shelter, medical and foster care, and juvenile delinquency costs associated with evicted and newly homeless renters in the range of $62 to $129 billion.

In the absence of new measures to address widespread and accrued shortfalls in rent, large numbers of households could face housing instability, economic hardship, and adverse health outcomes. Among relief measures, numerous states have passed legislation to direct 2021 federal stimulus funds to defray some portion of qualified renter deferred rents. The federal government also has enacted programs to provide mortgage forbearance to some renter property owners. Finally, the combination of expansive fiscal and monetary stimulus will help to accelerate the economic recovery and to put renter households back to work. While our research findings demonstrate broad and not well-appreciated renter and local economic benefits of temporary eviction moratoria, substantial ongoing efforts likely will be necessary to address accrued shortfalls in rent and to keep families stably housed.

Covid Economics 74, 30 March 2021: 25-70

[37] https://nlihc.org/sites/default/files/costs-of-COVID19-evictions.pdf

CEPR PRESS

Covid Economics 74, 30 March 2021: 25-70

References

Agarwal, S., B. Ambrose, L. Lopez, and X. Xiao (2020). Did the payment protection program help small businesses? evidence from commercial mortgage-backed securities. *SSRN Working Paper 3674960*.

Agarwal, S., C. Liu, and N. Souleles (2007). Reaction of consumer spending and debt to tax rebates: Evidence from consumer credit data. *Journal of Political Economy 115*(6), 986–1019.

Ambrose, B., X. An, and L. Luis (2020). Eviction risk of rental housing: Does it matter how your landlord finances the property? *SSRN Working Paper 3745974*.

An, X., L. Cordell, L. Geng, and K. Lee (2021). Inequality in the time of covid-19: Evidence from mortgage delinquency and forbearance. *SSRN Working Paper 3789349*.

Ater, I., Y. Elster, D. Genesove, and E. Hoffmann (2020). Agreements must be kept? residential leases during covid-19.

Baker, S. R., R. A. Farrokhnia, S. Meyer, M. Pagel, and C. Yannelis (2020). How does household spending respond to an epidemic? consumption during the 2020 covid-19 pandemic. *The Review of Asset Pricing Studies 10*(4), 834–862.

Bartik, A., M. Bertrand, F. Lin, J. Rothstein, and M. Unrath (2020). Measuring the labor market at the onset of the covid-19 crisis. *NBER Working Paper 27613*.

Benfer, E. (2020). Covid-19 eviction moratoria by state, commonwealth, and territory. *Wake Forest University School of Law*. *https://docs.google.com/spreadsheets/d/e/2PACX-1vTH8dUIbfnt3X52TrY3dEHQCAm60e5nqo0Rn1rNCf15dPGeXxM9QN9UdxUfEjxwvfTKzbCbZxJMdR7X/pubhtml*.

Benfer, E. A., S. J. Greene, and M. Hagan (2020). Approaches to eviction prevention. *SSRN Working Paper 3662736*.

Benfer, E. A., D. Vlahov, M. Y. Long, E. Walker-Wells, J. Pottenger, G. Gonsalves, and D. E. Keene (2021). Eviction, health inequity, and the spread of covid-19: Housing policy as a primary pandemic mitigation strategy. *Journal of Urban Health*, 1–12.

Chauvet, M., S. Gabriel, and C. Lutz (2016). Mortgage default risk: New evidence from internet search queries. *Journal of Urban Economics 96*, 91–111.

Cherry, F. S., E. X. Jiang, G. Matvos, T. Piskorski, and A. Seru (2020). Government and private household debt relief during covid-19. *NBER Working Paper 28357*.

Chetty, R., J. Friedman, N. Hendren, M. Stepner, et al. (2020). How did covid-19 and stabilization policies affect spending and employment? a new real-time economic tracker based on private sector data. *NBER Working Paper 27431*.

Collinson, R. and D. Reed (2018). The effects of evictions on low-income households. *Unpublished Manuscript.[Google Scholar]*, 1–82.

Currie, J. and E. Tekin (2015). Is there a link between foreclosure and health? *American Economic Journal: Economic Policy 7*(1), 63–94.

Desmond, M. (2012). Eviction and the reproduction of urban poverty. *American journal of sociology 118*(1), 88–133.

Desmond, M. (2016). *Evicted: Poverty and profit in the American city.* Crown.

Desmond, M. and R. T. Kimbro (2015). Eviction's fallout: housing, hardship, and health. *Social forces 94*(1), 295–324.

Diamond, R., T. McQuade, and F. Qian (2019). The effects of rent control expansion on tenants, landlords, and inequality: Evidence from san francisco. *American Economic Review 109*(9), 3365–94.

DiMaggio, M., A. Kermani, B. Keys, T. Piskorski, R. Ramcharan, A. Seru, and V. Yao (2017). Interest rate pass-through: Mortgage rates, household consumption, and voluntary deleveraging. *American Economic Review 107*(11), 3550–3588.

Dong, M., R. F. Anda, V. J. Felitti, D. F. Williamson, S. R. Dube, D. W. Brown, and W. H. Giles (2005). Childhood residential mobility and multiple health risks during adolescence and adulthood: the hidden role of adverse childhood experiences. *Archives of pediatrics & adolescent medicine 159*(12), 1104–1110.

Eichenbaum, M. S., S. Rebelo, and M. Trabandt (2020). The macroeconomics of epidemics. *NBER Working Paper 26882.*

Elenev, V., T. Landvoigt, and S. V. Nieuwerburgh. Can the covid bailouts save the economy? *CEPR Covid Economics 17*, 101–153.

Favilukis, J., P. Mabille, and S. V. Nieuwerburgh (2019). Affordable housing and city welfare. *NBER Working Paper 25906.*

Gabriel, S., M. Iacoviello, and C. Lutz (2021). A crisis of missed opportunities? foreclosure costs and mortgage modification during the great recession. *The Review of Financial Studies 34*(2), 864–906.

Glaeser, E. L. and E. F. Luttmer (2003). The misallocation of housing under rent control. *American Economic Review 93*(4), 1027–1046.

Granja, J., C. Makridis, C. Yannelis, and E. Zwick (2020). Did the paycheck protection program hit the target? *NBER Working Paper 27095.*

Greenberg, D., C. Gershenson, and M. Desmond (2016). Discrimination in evictions: Empirical evidence and legal challenges. *Harv. CR-CLL Rev. 51*, 115.

Johnson, D. S., J. A. Parker, and N. S. Souleles (2006). Household expenditure and the income tax rebates of 2001. *American Economic Review 96*(5), 1589–1610.

Jones, C. J., T. Philippon, and V. Venkateswaran (2020). Optimal mitigation policies in a pandemic: Social distancing and working from home. *NBER Working Paper 26984*.

Jowers, K., C. Timmins, N. Bhavsar, Q. Hu, and J. Marshall (2020). Housing precarity & the covid-19 pandemic: Impacts of utility disconnection and eviction moratoria on infections and deaths across us counties. *NBER Working Paper 28394*.

Mongey, S., L. Pilossoph, and A. Weinberg (2020). Which workers bear the burden of social distancing policies. *CEPR Covid Economics 12*, 69–86.

Panchal, N., R. Kamal, K. Orgera, C. Cox, R. Garfield, L. Hamel, and P. Chidambaram (2020). The implications of covid-19 for mental health and substance use. *Kaiser family foundation*.

Pribesh, S. and D. B. Downey (1999). Why are residential and school moves associated with poor school performance? *Demography 36*(4), 521–534.

Rosen, J., S. Angst, S. D. Gregorio, and G. Painter (2020). How do renters cope with unaffordability? household-level impacts of rental cost burdens in los angeles. *USCPrice Research Brief*.

Sampson, R. J. and P. Sharkey (2008). Neighborhood selection and the social reproduction of concentrated racial inequality. *Demography 45*(1), 1–29.

Sheen, J., A. Nande, E. L. Walters, B. Adlam, A. Gheorghe, J. Shinnick, M. F. Tejeda, A. J. Greenlee, D. Schneider, A. L. Hill, et al. (2020). The effect of eviction moratoriums on the transmission of sars-cov-2. *medRxiv*.

Sims, D. P. (2007). Out of control: What can we learn from the end of massachusetts rent control? *Journal of Urban Economics 61*(1), 129–151.

Appendix

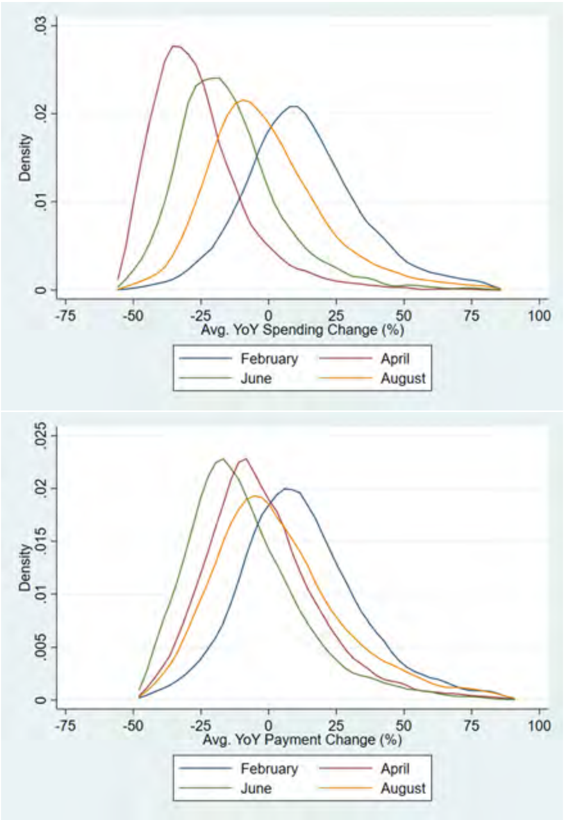


Figure A.1. Distribution of Zip Code Credit Card Spending/Payment Changes

Notes: These figures describe the kernal density of year-over-year changes in zip code-level credit card spending and payment. Panel A shows the averages of a national sample of zip codes and Panel B shows the averages by state for a selected number of states. We exclude zip codes with fewer than 100 credit card accounts in our data as well as those outside of MSAs to minimize outlier impact. Data source is the Federal Reserve Y-14M.

Covid Economics 74, 30 March 2021: 25-70

Covid Economics 74, 30 March 2021: 25-70

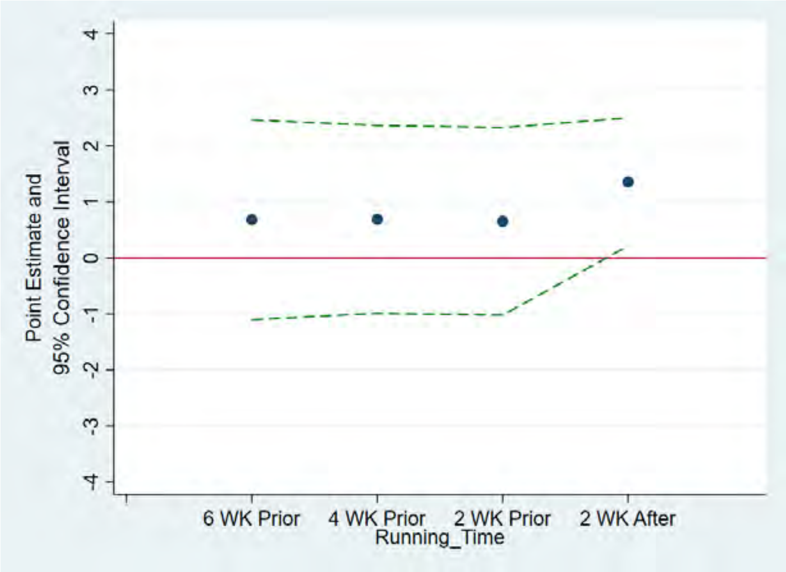


Figure A.2. Test of Parallel Trend for Credit Card Spending

Notes: This figure plots the point estimates and confidence intervals of the focus variable "State EvicMor×Target" in the regression in Table II Column 2 when we shift the "event" dates as indicated on the X-axis in the chart. See Table II for more notes. Data sources include: The Federal Reserve Y14M, BLS, BEA, and the Census.

CEPR PRESS

Table A.1 Description of the Variables

Panel A - Eviction Moratoria from Eviction Lab	
County Eviction Filings	Number of eviction cases being filed, by counties
State Eviction Moratoria	Dummy for whether the state implemented eviction moratorium during a particular month/week
County Eviction Moratoria	Dummy for whether the county implemented eviction moratorium during a particular month/week
Panel B - Federal Reserve Y-14M: Credit Cards	
Number of credit card accounts	Number of credit card account in the Y14M random sample in each zip code
Spending change	YoY change in total credit card spending in a particular zip code and month (%)
Payment change	YoY change in total credit card payment in a particular zip code and month (%)
Score change	YoY change in average credit score in a particular zip code and month
Panel C - Opportunity Insight Database	
County Spending	Seasonally adjusted county credit/debit card spending, in annual terms
State food service spending	Seasonally adjusted spending in accommodation and food service, in annual terms
State merchandise stores	Seasonally adjusted spending in general merchandise stores, apparel and accessories
State grocery spending	Seasonally adjusted spending grocery and food store, in annual terms
State health care	Seasonally adjusted spending in health care and social assistance, in annual terms
State transportation	Seasonally adjusted spending in transportation and warehousing, in annual terms
retail with grocery	Seasonally adjusted spending in retail with grocery, in annual terms
retail no grocery	Seasonally adjusted spending in retail with no grocery, in annual terms
durable	Spending in transportation and warehousing, and in arts, entertainment, and recreation
non durable	Spending in health care, grocery and food store, merchandise stores, and food service
Panel D - Census Pulse Survey: Food Insecurity	
food insecurity	% of households that answer that in the last 7 days they sometimes or often not have enough food to eat, from 4/23/2020 to 7/9/2020 for a duration of 12 weeks
food insecurity Hispanic	Food insecurity for Hispanic or Latino
food insecurity Black	Food insecurity for Black alone, not Hispanic
food banks	% of households that used, in the last 7 days, food pantry or food bank as provider of free groceries or free meal

Covid Economics 74, 30 March 2021: 25-70

CEPR PRESS

Covid Economics 74, 30 March 2021: 25-70

Description of the Variables - Cont.

Panel E - Census Pulse Survey: Mental Health	
Feeling Anxious	Frequency of feeling nervous, anxious, or on edge for more than half the days or nearly everyday as a % of total households
Feeling Anxious Hispanic	Feeling anxious for Hispanic or Latino
Feeling Anxious Black	Feeling anxious for Black
Cant Stop Worrying	Frequency of not being able to stop or control worrying for more than half the days or nearly everyday as a % of total households
Cant Stop Worrying Hispanic	Cant Stop Worrying for Hispanic or Latino
Cant Stop Worrying Black	Cant Stop Worrying for Black
Feeling Down	Frequency of feeling down, depressed, or hopeless for more than half the days or nearly everyday as a % of total households
Feeling Down Hispanic	Feeling Down for Hispanic or Latino
Feeling Down Black	Feeling Down for Black
Panel F - Google Search Query	
Food Stamps	Search Volume for ”food stamps”
Food Assistance	Search Volume for ”Food Assistance”
Help Food	Search Volume for ”Help Food”
Panel G - Macro Variables	
County unemp. rate	County unemployment rate in a particular month
County HPA	YoY change in county house price index
State DPI change	YoY change in state real disposable income

Notes: This table explains the meaning of the variables. Data source include: The Eviction Lab at Princeton University, the Federal Reserve Y-14M, the Opportunity Insight Economic Tracker, and the Census Pulse Survey.

Table A.2

Eviction Filings Regression Results

	County Eviction Filing			
	(1)	(2)	(3)	(4)
State Evic. Mor.	-129.283***	-17.560		
	(26.921)	(43.329)		
State Evic. Mor.×Target		-85.737*		
		(48.839)		
County Evic. Mor.			-80.383***	-32.265
			(30.160)	(46.111)
County Evic. Mor.×Target				-92.332
				(70.688)
County unemp. rate IV	3.656	1.590	4.093	3.175
	(6.442)	(6.420)	(16.947)	(18.387)
County HPA 1Q lag	-0.808	-3.332	-1.975	-0.348
	(7.300)	(7.308)	(16.889)	(19.402)
Constant	268.206***	232.096***	87.868	-451.628
	(70.386)	(75.209)	(96.416)	(300.133)
County FE	X	X	X	X
Week FE	X	X		
MSA×Week FE			X	X
N	261	261	261	261
R2	0.317	0.326	0.325	0.395

Notes: This table reports the results from regressions of state eviction moratoria on eviction filing. We use data from the Eviction Las, that built the Eviction Tracking System (ETS), a unique dataset that track eviction filings as they happen. The dataset includes currently 27 different cities in the US. Columns 1 and 2 report results on the effect of a state eviction moratoria, and columns 3 and 4 report results on the effect of a county eviction moratoria, controlling for county-level one-quarter lagged unemployment rate and one-quarter lagged house price appreciation (HPA), and county and week fixed effects. Data source is the Eviction Lab at Princeton University. Robust standard errors in parentheses with error terms clustered at the state- or county-level, depending on the focus variable; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

CEPR PRESS

Covid Economics 74, 30 March 2021: 25-70

Table A.3 Effects of County-level Eviction Moratoria on Credit Card Utilization

	Zip Code by Month Panel					
	Spending Change		Payment Change		Score Change	
	(1)	(2)	(3)	(4)	(5)	(6)
County Evic. Mor.	0.043	-0.135	-1.199	-1.347	-0.304	-0.344
	(0.553)	(0.651)	(1.259)	(1.294)	(0.188)	(0.226)
County Evic. Mor.×Target		0.559		0.246		0.136
		(0.786)		(1.471)		(0.257)
County unemp. rate IV	-0.053*	-0.056*	-0.062*	-0.062	-0.011**	-0.011**
	(0.031)	(0.031)	(0.037)	(0.038)	(0.005)	(0.005)
County HPA 1Q lag	0.022	0.038	-0.486**	-0.486*	-0.087*	-0.084*
	(0.221)	(0.223)	(0.245)	(0.246)	(0.050)	(0.049)
Spending change 1M lag			0.002	0.002	-0.001	-0.001
			(0.002)	(0.002)	(0.002)	(0.002)
Payment change					0.008***	0.008***
					(0.002)	(0.002)
Constant	-16.749***	-16.802***	-2.426**	-2.424**	4.081***	4.067***
	(0.979)	(0.976)	(1.090)	(1.084)	(0.245)	(0.239)
Dep Var Mean	-17.12	-17.12	-6.11	-6.11	3.40	3.40
Zip Code FE	X	X	X	X	X	X
MSA×Month FE	X	X	X	X	X	X
N	14,234	14,234	14,012	14,012	11,383	11,383
R2	0.5986	0.5986	0.5311	0.5311	0.8505	0.8505

Notes: This table presents our estimates of the incremental impact of county-level eviction moratorium on consumer credit card spending, payment and credit score based on zip code by month panel data of YoY changes of the outcome variables. Our focus variable here is an indicator of whether the county in which the zip code is located had an eviction moratorium in place during a particular month. For each state, In the spending and payment regression, we lag the eviction moratorium indicators by two weeks, so we end up with spending and payment data from April to August to reflect the impact of eviction moratorium between late March and early August. For the credit score regressions, we lag the eviction moratorium indicators by two months so the credit score data are from May to September to reflect the impact of eviction moratorium from March to July. For the identification of the incremental effect of county-level eviction moratorium, we include in these regressions zip codes where there were both state- and county-level eviction moratoria. The impact of state-level eviction moratorium is absorbed by the MSA×Month fixed effects. We also exclude zip codes with fewer than 100 credit card accounts in our data as well as those outside of MSAs to minimize outlier impact. About 4,000 zip codes remain in these regressions. Data sources include: The Federal Reserve Y14M, BLS, BEA, and the Census. Robust standard errors in parentheses with error terms clustered at the county-level; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Covid Economics 74, 30 March 2021: 25-70

Table A.4 Effects of Eviction Moratoria on Consumer Spending

	County by Week Panel			
	(1)	(2)	(3)	(4)
State Evic. Mor.	1.178***	1.167		
	(0.425)	(0.932)		
State Evic. Mor.×Target		1.673*		
		(0.918)		
County Evic. Mor.			0.214	0.066
			(0.574)	(0.897)
County Evic. Mor.×Target				0.172
				(0.447)
County unemp. rate IV	-0.049	-0.034	-0.014	-0.029
	(0.056)	(0.059)	(0.058)	(0.060)
County HPA 1Q lag	0.021	0.049	0.057	0.075*
	(0.105)	(0.040)	(0.040)	(0.041)
Constant	-3.990***	-3.199***	-4.794***	-2.318***
	(0.676)	(0.339)	(0.413)	(0.410)
County FE	X	X	X	X
Week FE	X	X		
MSA×Week FE			X	X
N	5,010	5,010	4,527	4,527
R2	0.530	0.532	0.417	0.424

Notes: This table presents our estimates of the impact of state-level and county-level eviction moratorium on county spending. The dependent variable is year-over-year changes in spending, benchmarked to pre-pandemic levels (see, Chetty et al. (2020) for more details). In column 1, we show the baseline model results for the Opportunity Insights spending term controlling for county-level one-quarter lagged unemployment rate and one-quarter lagged house price appreciation (HPA), and county and week fixed effects. Our focus variable here is an indicator of whether the state in which the county is located had an eviction moratorium in place during a particular week. For each state, we move the implementation dates by two weeks, so that the focus variable is lagged by two weeks. To derive a clean identification of the effect of state eviction moratorium, we comprise the sample to include only those states (state-week) where no county-level eviction moratorium was in place. In column 2, we focus on the target group that is defined as those counties in the upper quartile of renter share with high levels of unemployment in April 2020, using difference-in-differences regression. In columns 3 and 4 our focus variable is an indicator of whether the county had an eviction moratorium in place during a particular week, in states that had eviction moratorium in place. We move the implementation dates by two weeks, so that the focus variable is lagged by two weeks and we add an interaction term between MSAs and Week fixed effect. Data Sources include: Eviction Lab, and Opportunity Insight database compiled by Chetty et al. (2020). Robust standard errors in parentheses with error terms clustered at the state- or county-level, depending on the focus variable; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

CEPR PRESS

Did fiscal space influence Covid-19's fiscal response?

Ablam Estel Apeti,[1] Jean-Louis Combes,[2] Xavier Debrun[3] and Alexandru Minea[4]

Date submitted: 12 March 2021; Date accepted: 19 March 2021

Using a sample of 125 countries, we evaluate the effect of the pre-Covid-19 fiscal space on the size of the fiscal stimulus packages in response to the virus. We find that higher ratings and higher tax revenues (to public debt) predict the size of fiscal stimuli, while public debt (to GDP) does not. These findings vary with countries' level of economic development and the composition of fiscal support.

Covid Economics 74, 30 March 2021: 71-93

1 Université Clermont Auvergne, CNRS, IRD, CERDI.
2 Université Clermont Auvergne, CNRS, IRD, CERDI.
3 National Bank of Belgium, European Fiscal Board, and Catholic University of Louvain.
4 Université Clermont Auvergne, CNRS, IRD, CERDI; Laboratoire d'Economie d'Orléans, Université d'Orléans; Department of Economics, Carleton University.

1 Introduction

Deeply concerned about the severity and spread of the disease, the World Health Organization announced on March 11^{th} 2020 that the Covid-19 outbreak can be qualified as a pandemic. This announcement was followed by an unprecedented sequence of containment plans to curb the spread of the pandemic: the *Great Lockdown* crisis that began is expected to shrink global GDP growth by around 3% in 2020, namely well above the -0.1% decrease in 2009 associated to the Global Financial Crisis (based on World Economic Outlook data).

Taking stock of previous work on the role of fiscal policy in times of crises (see e.g. Aizenman and Jinjarak, 2010; Jordà et al., 2016; Romer and Romer, 2018; Romer and Romer, 2019), an already-large literature exploring the economic impact of the crisis (see e.g. Abiad et al., 2020; Auerbach et al., 2020; Baqaee and Farhi, 2020; Barro et al., 2020; Casado et al., 2020; Çakmaklı et al., 2020; Deb et al., 2020; ElFayoumi and Hengge, 2020; Eichenbaum et al., 2020; Faria-e Castro, 2020; Gopinath, 2020; Guerrieri et al., 2020; Jordà et al., 2020; McKibbin and Fernando, 2020;), called for immediate action from governments and international institutions, all the more that—although the second wave of the crisis seems less virulent than the first—GDP still remains well below its pre-crisis level.[1] Converging with these requests, various national fiscal stimuli plans were indeed implemented starting the first half of 2020.[2]

This paper investigates an important determinant of these fiscal stimuli, namely countries' pre-Covid fiscal space. This issue is currently under an important debate: while a (pre-Covid) established literature praises the benefits of a higher fiscal space in times of crises, more recent Covid-related studies reject these benefits. Consequently, we test the following hypothesis: were countries with higher fiscal space able to provide higher fiscal stimuli for fighting the contraction of the economy caused by the Covid?

Our answer to this question is nuanced. First, fiscal stimuli were found to be disconnected with respect to the public debt-to-GDP ratio, corroborating—in a larger sample—the conclusions of Benmelech and Tzur-Ilan (2020). However, a lower debt-to-tax rate and—particularly—higher sovereign debt ratings were significant and robust (as shown by several tests) determinants of the size of Covid-related fiscal stimuli, in line with the literature supporting the benefits of fiscal space in times of crises (see e.g. Aizenman and Jinjarak, 2010; Jordà et al., 2016; Romer and Romer, 2018; Romer and Romer, 2019). Second, while these effects were not found to display robust nonlinearities, they vary with countries' level of economic development and the type of fiscal stimuli.

Our nuanced findings may be related to the recent dynamics of public debt, whose increase during the last decade or so—mainly related to major macroeconomic shocks, e.g. the Great Recession or the Covid-19 pandemic—was fueled by persistently-weak interest rates, indepen-

1. For example, in October 2020 the IMF wrote (see Long and Ascent, 2016): *the global economy is climbing out from the depths to which it had plummeted during the Great Lockdown in April. But with the COVID-19 pandemic continuing to spread, many countries have slowed reopening and some are reinstating partial lockdowns to protect susceptible populations. While recovery in China has been faster than expected, the global economy's long ascent back to pre-pandemic levels of activity remains prone to setbacks.*

2. We disregard in this paper other stimuli for mitigating the consequences of the Covid crisis, e.g. (un)conventional monetary policies.

Covid Economics 74, 30 March 2021: 71-93

dently of the initial level of public debt. But let us not believe that such increases in public debt are not without a cost: the governments' intertemporal constraint will—sooner or later—kick in, and too large indebtedness levels, possibly together with the higher risk premia they may trigger, will shrink fiscal space and therefore reduce the possibility of fiscal maneuver in a context of endangered public finance sustainability.

The reminder of the paper is organized as follows. Section 2 presents the data, section 3 illustrates the methodology, section 4 reports our results and assesses their robustness, section 5 explores several sources of potential heterogeneity in the effect of fiscal space on Covid-related fiscal stimuli, and section 6 provides concluding remarks.

2 Data, and descriptive statistics

2.1 Data

Our data covers 125 countries of which 30 are developed and 95 are developing countries. Our dependent variable—*Covid-related fiscal policy response*—comes from the IMF's database of fiscal policy responses to Covid-19 until September 11^{th}, 2020. This variable equals the sum of the two fiscal measures taken by governments to alleviate the effect of the Covid crisis on economic activity. First, above-the-line-measures include additional spending or foregone revenues for the health sector and the non-health sector, and accelerated spending/deferred revenues. Second, liquidity support includes below-the-line-measures (i.e. equity injections, loans, asset purchase, or debt assumptions), and contingent liabilities (i.e. government guarantees, and quasi-fiscal operations).

A crucial and complicated task concerns the measure of the abstract concept of *fiscal space*. In their seminal contribution, Ghosh et al. (2013) highlight a negative correlation between public debt (in % of GDP) and fiscal space, i.e. the higher the public debt, the lower the fiscal space. Approaching fiscal space by the *public debt-to-GDP ratio*, Benmelech and Tzur-Ilan (2020) notably reject a significant impact of fiscal space on Covid-related fiscal spending using cross-section data for 85 countries.

However, we believe that there are good reasons for using alternative measures of fiscal space, particularly given its multiple facets. On the one hand, the popular contribution of Bohn (2008) highlights the importance of primary surpluses for debt sustainability; adapted to our analysis that aims at explaining Covid-related public spending, this may suggest that what equally matters is the way public debt is accommodated by fiscal revenues. Consequently, aside from the public debt-to-GDP ratio, we consider *public debt as a ratio of taxes* as an additional measure of fiscal space (Kose et al., 2017). On the other hand, the theoretical work of Minea and Villieu (2009, 2012), emphasizes the importance of the cost of the debt (i.e. the debt burden) in the government's budget constraint accountancy, due to its crowding-out effects; adapted to our analysis, this may suggest that—rather than a high public debt-to-GDP ratio—it is the cost of indebtedness that may better seize fiscal space, particularly given its ability to account for potential risk premia (Blanchard, 2019), which may signal an increasing danger on

Covid Economics 74, 30 March 2021: 71-93

debt sustainability and therefore shrinking fiscal space. Consequently, we equally measure fiscal space using foreign currency long-term *sovereign debt ratings* from Kose et al. (2017) to capture countries' ability to access finance on international markets. To tackle reversed causality issues, all our three measures of fiscal space—namely, public debt-to-GDP, public debt-to-taxes, and sovereign debt ratings—are measured in 2019, i.e. *prior to the Covid pandemic.*

2.2 Descriptive statistics

Given the violence of the Covid crisis, the average fiscal stimulus is around 7% of GDP in our sample, namely already more important than the total fiscal package implemented after the Global Financial Crisis (GFC). For example, in the United States the Covid-related fiscal stimulus topped already to 14.31% of GDP (against 5.9% of GDP after the GFC), and could further increase given that the US is one of the the most affected countries in the world (see https://www.worldometers.info/coronavirus/?). [3]

Closer to the goal of our analysis, Figure 1 reports Covid-related fiscal measures (in % of GDP) for relatively low and high values of our various measures of fiscal space, defined using the median value of the sample for each fiscal space variable.

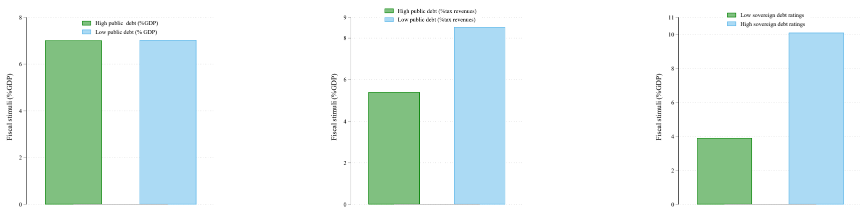


Figure 1 – *Fiscal stimuli (% of GDP) by level of fiscal space*

Table 1 – Fiscal stimuli (% of GDP) by level of fiscal space

Low debt-to-GDP	7.029	Low debt-to-tax	8.530	Low debt ratings	3.901
High debt-to-GDP	7.014	High debt-to-tax	5.391	High debt ratings	10.092
T-test (equal averages)	0.014	T-test (equal averages)	-2.843	T-test (equal averages)	-6.344
P-value	0.989	P-value	0.005	P-value	0.000

As illustrated by Figure 1—and confirmed by statistical tests of equality of the averages between low and high values in Table 1—while fiscal stimuli do not seem to vary with respect to the public debt-to-GDP ratio, they are statistically higher in the presence of a higher fiscal space indicated by either lower public debt-to-tax ratios or higher sovereign debt ratings. Keeping these simple statistics in mind, in the following we develop a more formal analysis.

3. Similarly, the fiscal stimulus in Spain equals 17.7% of GDP (against 3.7% during the GFC), and 7.5% of GDP in China (against 4.8% of GDP during the GFC; see Prasad and Sorkin, 2009; Auerbach et al., 2010, or Aizenman and Jinjarak, 2010, for analyses on the GFC).

Covid Economics 74, 30 March 2021: 71-93

3 Methodology

3.1 The model

We estimate the effect of fiscal space on fiscal stimuli using a cross-section model

$$Fiscal\_stimulus_i = \beta_0 + \beta_1 Fiscal\_space_i + \beta_{2j} X_i^j + \varepsilon_i, \tag{1}$$

with $Fiscal\_stimulus_i$ the fiscal stimulus (in % of GDP) of country i due to Covid-19, $Fiscal\_space_i$ the pre-Covid fiscal space measure in country i, X_i^j the vector of j control variables, and ε_i the error term.

The selection of the control variables, namely: GDP per capita (in log), infection fatality rate (IFR) proxied by the case fatality rate (CFR), population density (in log), and inflation, is guided by Aizenman and Jinjarak (2010) and Benmelech and Tzur-Ilan (2020), while democracy is included to capture potential political budget cycles and transparency in the crisis management. The parameter of interest is β_1: to confirm our hypothesis, β_1 should be statistically-significant and indicate a favorable effect of higher pre-Covid fiscal space on fiscal stimuli.

3.2 Identification

A traditional regression that aims at capturing the effect of fiscal space in period $t-1$ on public spending in period t would suffer from an endogeneity bias arising from reversed causality: public spending in $t-1$ can hardly be considered not to have influenced fiscal space in $t-1$, which would require an appropriate instrumentation strategy to purge this reversed causality.

However, our analysis is not likely to be influenced by such a reversed-causality issue: since our public spending variable contains *exclusively* Covid-related public spending, it captures only the "surprise" public spending fully driven by an exogenous shock, i.e. the unexpected Covid pandemic. Put simpler, since 2020 Covid-related spending were fully unexpected, they cannot act on the 2019 fiscal space. From a broader perspective, our analysis can be compared with natural experiment studies that equally draw upon unexpected variation to establish a causal effect, such as climate shocks (for example, unusual drought phenomena), (mostly-)unexpected institutional reversals (for example, the fall of communist regimes in Central and Eastern Europe), and so forth. Besides, since we tackle a possible omitted-variable bias through our vector of control variables—that includes in particular key potential determinants of Covid fiscal stimuli, such as the infection fatality rate—we can, with some comfort, state that our simple OLS estimations provide a causal effect in this particular case.

Covid Economics 74, 30 March 2021: 71-93

4 Results

4.1 Baseline results

Our baseline results are presented in Table 2. The naive regression reported in column [1] reveals a lack of significant association between fiscal space measured by the public debt-to-GDP ratio and fiscal stimuli. To protect this effect from a potential omitted-variable bias, we include in regression [2] the entire set of control variables. Although control variables present the expected sign and are mostly significant (in particular, a higher level of economic development captured by GDP per capita, the magnitude of the shock of the virus captured by IFR, and higher levels of democracy are associated with higher fiscal stimuli), the effect of the pre-Covid public debt-to-GDP ratio on Covid-related fiscal stimuli remains statistically not significant. Consequently, we confirm that the results of Benmelech and Tzur-Ilan (2020) still hold when increasing the number of countries by up to almost 50%.

Table 2 – Pre-Covid fiscal space and Covid-related fiscal stimuli

Fiscal stimuli (%GDP)	[1]	[2]	Fiscal stimuli (%GDP)	[3]	[4]	Fiscal stimuli (%GDP)	[5]	[6]
Debt-to-GDP ratio (log)	0.1302	0.1054	*Debt-to-tax ratio* (log)	-2.3388***	-1.6920**	*Sovereign debt ratings*	0.8059***	0.5871***
	(0.7615)	(0.8621)		(0.6718)	(0.6765)		(0.0916)	(0.1235)
GDP per capita (log)		1.6153***	GDP per capita (log)		1.6661***	GDP per capita (log)		-0.1547
		(0.5409)			(0.5286)			(0.5426)
Inf. fatality rate (IFR)		0.5540***	Inf. fatality rate (IFR)		0.5837***	Inf. fatality rate (IFR)		0.5006***
		(0.1879)			(0.1801)			(0.1734)
Pop. density (log)		0.1397	Pop. density (log)		0.3584	Pop. density (log)		0.2437
		(0.4209)			(0.4444)			(0.3817)
Index Democrat.		0.1568***	Index Democrat.		0.1002*	Index Democrat.		0.1618***
		(0.0583)			(0.0583)			(0.0549)
Inflation		-0.0122	Inflation		-0.0204	Inflation		0.0129
		(0.0281)			(0.0299)			(0.0278)
Constant	6.4941**	-12.5966*	Constant	20.243***	-3.0103	Constant	-2.3423**	-3.7236
	(2.9359)	(6.7647)		(3.9432)	(6.3693)		(0.9533)	(4.8037)
Observations	124	107	Observations	123	107	Observations	125	107

Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

In the following, given the various facets of fiscal space, we consider alternative measures of it. First, regressions [3]-[4] consider public debt as a ratio of taxes (instead of GDP). Interestingly, a higher public debt-to-tax ratio is associated with a lower fiscal stimuli on average, an effect that remains statistically-significant when introducing the vector of control variables (whose effect is comparable to our previous estimations). In particular, although purging the effects of other fiscal stimuli determinants reduces the magnitude of the impact of the debt-to-tax ratio, its size remains economically important: a one standard deviation increase in the (log of) debt-to-tax ratio reduces on average fiscal stimuli by 1.42 percentage points, namely a decrease of around 20% relative to the mean fiscal stimuli value.

Second, regressions [5]-[6] consider sovereign debt ratings. Both the unconditional and conditional—upon the vector of control variables—effect of sovereign debt ratings on fiscal stimuli is statistically-significant, and—although weaker in the latter case— economicallymeaningful. Based on regression [6], a one standard deviation increase in sovereign debt ratings raises on average fiscal stimuli by 3.01 percentage points, or around 43% relative to their mean value.

To summarize, in light of our baseline estimations we share the conclusion of Benmelech and Tzur-Ilan (2020) on the lack of significant effect of public debt-to-GDP on fiscal stimuli. However, when using other measures of fiscal space, namely the public debt-to-tax ratio or sovereign debt ratings, we reveal that a larger fiscal space was a significant determinant of the fiscal stimuli implemented in response to the Covid, consistent with previous evidence on the importance of the fiscal space for Governments' policy (see e.g. Aizenman and Jinjarak, 2010; Jordà et al., 2016; Romer and Romer, 2018; Romer and Romer, 2019).

4.2 Robustness

We consider several alternative specifications of our baseline model.

First, we expand our vector of control variables and include additional potential determinants of fiscal stimuli, namely: a fixed exchange rate dummy, a stringency index capturing the severity of the containment measures, the share of the population above 65 years, government expenditure, an index of government fractionalization capturing government fragmentation, the presence of elections, and the presence of fiscal rules. Estimations in Table 3 show that these additional control variables do not significantly influence fiscal stimuli, with the notable exception of the positive effect of the share of the population above 65 years old—consistent with the particularly-important impact of the Covid on this segment of the population. More importantly, we observe a lack of significant effect of the debt-to-GDP ratio on fiscal stimuli, and a significant and negative (positive) effect of the debt-to-tax ratio (sovereign debt ratings). Consequently, accounting for several additional control variables confirms our baseline findings.

Second, we alter our sample by excluding various groups of countries, namely: (*i*) the Euro zone countries that are subject to fiscal constraints that may influence their fiscal space (e.g. various types of supra-national and national fiscal rules); (*ii*) major oil exporters that benefit of natural rents that may affect their fiscal space; and (*iii*) heavily indebted poor countries (HIPC) that present poor fiscal conditions that may influence markets' view of their fiscal space. Table 4 illustrates a non-significant effect of the public debt-to-GDP ratio, and a favorable effect of a lower debt-to-tax ratio (although with some loss of precision when excluding major oil exporters), or a higher sovereign debt rating on fiscal stimuli, consistent with our baseline estimations.

Third, we take a closer look at our dependent variable, namely fiscal stimuli. Compared with our baseline estimations in which we include all Covid-related public spending, we follow Benmelech and Tzur-Ilan (2020) and exclude from this general measure government guarantees. The results reported in Table A2 in the Appendix are—irrespective of the retained specification, namely naive, with the vector of main, and then additional controls, or when restraining the sample—consistent with our baseline findings: contrary to the lack of significance of the effect of public debt-to-GDP, a higher fiscal space signaled by a lower public debt-to-tax ratio or a

Covid Economics 74, 30 March 2021: 71-93

Table 3 – Pre-Covid fiscal space and Covid-related fiscal stimuli: Additional controls

Dependent variable Fiscal stimuli (% of GDP)	[1] Add Fix Exchange	[2] Add Stringency Index	[3] Add Above 65 yrs	[4] Add Total Gov. Exp.	[5] Add Gov. Fraction.	[6] Add Election	[7] Add Fiscal Rule
Debt-to-GDP ratio (log)	0.1576	0.0741	0.0577	0.0870	0.3971	0.1725	0.1536
	(0.8374)	(0.8848)	(0.8672)	(0.8864)	(0.8735)	(0.8506)	(0.8558)
Additional Control	-1.4148	0.0173	0.2162*	0.0224	-2.3441	1.4348	0.9167
	(1.0131)	(0.0305)	(0.1143)	(0.0719)	(1.9474)	(1.2728)	(0.9893)
Main Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	107	104	107	107	102	104	107
Debt-to-tax ratio (log)	-1.6048**	-1.7088**	-1.5184**	-1.7526**	-1.4066**	-1.5505**	-1.6337**
	(0.6810)	(0.6841)	(0.6985)	(0.7063)	(0.6734)	(0.6684)	(0.6993)
Additional Control	-1.1990	0.0244	0.1633	0.0395	-2.6003	1.2912	0.6071
	(1.0003)	(0.0301)	(0.1211)	(0.0663)	(1.9474)	(1.2180)	(1.0081)
Main Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	107	104	107	107	102	104	107
Sovereign debt ratings	0.5667***	0.6352***	0.5894***	0.5945***	0.5645***	0.5729***	0.5823***
	(0.1210)	(0.1219)	(0.1208)	(0.1259)	(0.1227)	(0.1208)	(0.1273)
Additional Control	-0.4988	0.0414	0.2209*	0.0384	-2.9562	1.1377	0.1557
	(0.9215)	(0.0267)	(0.1133)	(0.0643)	(1.8801)	(1.0911)	(0.9241)
Main Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	107	104	107	107	102	104	107

Unreported constant included. Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table 4 – Pre-Covid fiscal space and Covid-related fiscal stimuli: Altering the sample

Dependent variable Fiscal stimuli (% GDP)	[1] Excl. Euro	[2] Excl. Oil exp.	[3] Excl. HIPC	[4] Excl. Euro	[5] Excl. Oil exp.	[6] Excl. HIPC	[7] Excl. Euro	[8] Excl. Oil exp.	[9] Excl. HIPC
Debt-to-GDP ratio (log)	0.0318	-0.2767	-0.2480						
	(1.1035)	(0.9486)	(0.8695)						
Debt-to-tax ratio (log)				-1.9777**	-1.4404	-2.0118***			
				(0.7811)	(0.8716)	(0.6915)			
Sovereign debt ratings							0.6628***	0.6309***	0.5855***
							(0.1385)	(0.1269)	(0.1291)
Main Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	92	97	94	92	97	94	92	97	94

Unreported constant included. Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Covid Economics 74, 30 March 2021: 71-93

higher sovereign rating is associated with higher fiscal stimuli on average.

Finally, Benmelech and Tzur-Ilan (2020) notably reveal that outliers play a fundamental role in the accuracy of their estimates of the effect of the public debt-to-GDP ratio on fiscal policy spending: excluding Japan turns the coefficient into not significant. Capitalizing on this lesson, we *excluded* in our baseline estimations those countries that present too high debt *or* fiscal stimuli, namely: Germany, Italy, and Japan.

However, given the importance of outliers, we imagined two additional tests. On the one hand, we performed our baseline regressions with these three countries included. Estimations in Table A3 in the Appendix confirm our findings for the debt-to-GDP ratio and sovereign ratings, but reveal that the significance of the debt-to-tax ratio is fragile with respect to these three countries. Due to these findings, we decided—on the other hand—to exclude top and bottom 10% of increasingly-ordered debt-to-GDP observations. Estimations in Table 5 show that while the top 10% observations seem to drive to some extent the results for the variable public debt-to-tax (the coefficient is no longer significant as the p-value equals 0.161), our baseline findings are unchanged irrespective of the measure of fiscal space when excluding the bottom 10% observations, i.e. a non-significant, negative, and positive impact of public debt-to-GDP, public debt-to-tax, and sovereign ratings, respectively.

Table 5 – Pre-Covid fiscal space and Covid-related fiscal stimuli: Outliers

Dependent variable	[1]	[2]	[3]	[4]	[5]	[6]
Fiscal stimuli (% of GDP)	Drop top 10% debt-to-GDP obs.			Drop bottom 10% debt-to-GDP obs.		
Debt-to-GDP ratio (log)	0.1054			-0.1799		
	(0.8621)			(1.2983)		
Debt-to-tax ratio (log)		-1.4796			-1.5706*	
		(1.0472)			(0.7907)	
Sovereign debt ratings			0.5344***			0.6219***
			(0.1337)			(0.1818)
Main Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	107	96	96	94	98	96

Unreported constant included. Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Overall, the robustness analysis delivers two messages: the debt-to-GDP ratio was not a determinant of fiscal stimuli, contrary to the robust impact of sovereign ratings on fiscal stimuli; and, while the debt-to-tax ratio influences fiscal stimuli, the fact that its significance may be altered by some outliers suggest that we take a closer look at possible heterogeneities in the effect of fiscal space on Covid-related fiscal stimuli.

5 Heterogeneity

We investigate in this section if the effect of fiscal space on Covid-related fiscal stimuli may be subject to heterogeneity. We focus on three stances that are closely related to our analysis: the level of economic development, the initial level of fiscal space, and various disaggregated

Covid Economics 74, 30 March 2021: 71-93

types of Covid-related fiscal stimuli.

5.1 The level of economic development

Using the IMF's classification of countries, simple statistics reported in Table 6 reveal that developed countries were more affected by Covid-19 than developing countries, i.e. a statistically higher average infection fatality rate of 5.31% against 2.95%, and responded with statistically higher fiscal stimuli (14.24% of GDP against 4.74% of GDP).

Table 6 – Descriptive statistics: developed *versus* developing countries

	Fiscal stimuli	IFR	Debt-to-GDP (log)	Debt-to-tax (log)	Debt ratings
Developed countries	14.235	5.305	4.023	5.429	17.618
Developing countries	4.744	2.953	3.821	5.752	9.725
T-test	-9.492	-3.546	-1.344	1.851	-9.732
P-value	0.000	0.000	0.182	0.067	0.000

However, such differences in fiscal stimuli may be equally driven by differences in fiscal space. As shown by the right-hand side part of Table 6, although debt-to-GDP ratios were statistically equal on average, developed countries present a higher fiscal space signaled by a slightly lower public debt-to-tax ratio (5.43 versus 5.75) and higher sovereign debt ratings (17.62 versus 9.73). Fueled by these simple statistics, below we explore this intuition of a differentiated relationship between fiscal space and fiscal stimuli in developed versus developing countries.

Table 7 – Heterogeneity: developed *versus* developing countries

Dependent variable Fiscal stimuli (% GDP)	[1] Developing	[2] Developed	Dependent variable Fiscal stimuli (% GDP)	[3] Developing	[4] Developed	Dependent variable Fiscal stimuli (% GDP)	[5] Developing	[6] Developed
Debt-to-GDP (log)	-0.5608	-1.6672	*Debt-to-tax* (log)	-1.9150***	-2.3615	*Sovereign debt ratings*	0.3993**	0.7858**
	(0.9552)	(1.8168)		(0.6957)	(1.9184)		(0.1623)	(0.2914)
Main Controls	Yes	Yes	Main Controls	Yes	Yes	Main Controls	Yes	Yes
Observations	79	28	Observations	79	28	Observations	79	28
Dep. var.: Fiscal stimuli *w/o Gov. Guarantees* (%GDP)	[1] Developing	[2] Developed	Dep. var.: Fiscal stimuli *w/o Gov. Guarantees* (%GDP)	[3] Developing	[4] Developed	Dep. var.: Fiscal stimuli *w/o Gov. Guarantees* (%GDP)	[5] Developing	[6] Developed
Debt-to-GDP (log)	-0.4072	-1.2927	*Debt-to-tax* (log)	-1.5089**	-1.8778	*Sovereign debt ratings*	0.2810**	0.8874**
	(0.7843)	(1.3840)		(0.5832)	(1.5706)		(0.1219)	(0.3660)
Main Controls	Yes	Yes	Main Controls	Yes	Yes	Main Controls	Yes	Yes
Observations	79	28	Observations	79	28	Observations	79	28
Dep. var.: Fiscal stimuli *with outliers included* (%GDP)	[1] Developing	[2] Developed	Dep. var.: Fiscal stimuli *with outliers included* (%GDP)	[3] Developing	[4] Developed	Dep. var.: Fiscal stimuli *with outliers included* (%GDP)	[5] Developing	[6] Developed
Debt-to-GDP (log)	-0.5608	2.5905	*Debt-to-tax* (log)	-1.9150***	2.5197	*Sovereign debt ratings*	0.3993**	0.3922
	(0.9552)	(2.9330)		(0.6957)	(2.8012)		(0.1623)	(0.6095)
Main Controls	Yes	Yes	Main Controls	Yes	Yes	Main Controls	Yes	Yes
Observations	79	31	Observations	79	31	Observations	79	31

Unreported constant included. Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

The first two columns of the top of Table 7 show that the public debt-to-GDP ratio is not significantly associated with fiscal stimuli. Regarding the public debt-to-taxes, the subsequent two columns reveal an interesting heterogeneity: while a lower public debt-to-tax ratio significantly increases fiscal stimuli in developing countries (with a higher magnitude than the baseline effect for the full sample), it is not a significant determinant of fiscal stimuli in developed countries. Lastly, although fiscal stimuli significantly responded in both developing and developed countries to sovereign debt ratings, the magnitude of the effect is higher in absolute terms in

Covid Economics 74, 30 March 2021: 71-93

the latter: a one standard deviation increase in fiscal space is associated on average with a higher fiscal stimulus of 4.03 percentage points in developed countries (i.e. around 28% of their mean), namely twice—in absolute terms—compared with the increase of only 2.05 percentage points in developing countries (i.e. around 43% of their mean).

These findings remain fairly stable if we modify our measure of fiscal stimuli to exclude government guarantees (i.e. the effect is never significant for debt-to-GDP, significantly only in developing countries for debt-to-tax, and stronger in developed countries for sovereign ratings, see the middle of Table 7), or if we introduce the three outlier countries in the sample (except for an imprecise estimation of the effect of sovereign ratings in developed countries, see the bottom of Table 7).

Consequently, except for the debt-to-GDP ratio, estimations seem to support a differentiated effect of the fiscal space on fiscal stimuli in developed versus developing countries: a lower debt-to-tax ratio significantly increases fiscal space only in the later, and—although they significantly increase fiscal space in both developed and developing countries—higher sovereign debt ratings are on average associated with a stronger (in absolute terms) effect in the former.

5.2 The initial level of fiscal space

Our previous estimations revealed that in some cases outliers may influence our findings. An appealing way to better account for the presence of outliers is to allow for nonlinearities. For example, Minea and Villieu (2012) and Ghosh et al. (2013) illustrate theoretically and empirically the importance of debt-driven nonlinearities in the effect of deficits on economic growth, and fiscal reaction functions, respectively. Taking stock of these findings, we extend our model to include the square of each of our fiscal space measure, in order to search for potential nonlinearities in the impact of fiscal space on Covid-related fiscal stimuli driven by the initial level of the fiscal space measure.

We present estimations for all three fiscal space measures, augmented with all the specifications considered in the robustness section. According to the top of Table 8, both coefficients of the public debt-to-GDP terms are not significant when considering the naive or the baseline specification, adding subsequent controls, or restricting the sample; adding to our baseline findings, it comes that the public debt-to-GDP ratio was not a robust determinant of fiscal stimuli. Moreover, a comparable lack of nonlinear effects of the public debt-to-tax ratio is suggested by the middle of Table 8, irrespective of the assumed specification; consequently, it appears that the effect of the debt-to-tax ratio is likely linear as illustrated by our baseline results. Lastly, as shown by the bottom of Table 8, except for some significant and positive squared terms when restricting the sample (by excluding euro countries and major oil exporters) suggesting an acceleration of the favorable effect of sovereign ratings on fiscal stimuli as the former increase, estimations mostly reject a robust nonlinear impact of sovereign debt ratings. [4]

4. Comparable results arise if we exclude government guarantees from our measure of fiscal stimuli; see Table A4 in the Appendix.

Table 8 – Heterogeneity: the initial fiscal space level

Fiscal stimuli (% of GDP)	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Debt-to-GDP (log)	-1.8399**	0.7503	-0.6800	0.4657	2.0185	1.2331	-1.8273	0.6566	0.7219	-0.4316	1.0309	1.7895
	(0.7363)	(6.2260)	(6.1092)	(6.1504)	(6.1089)	(6.5221)	(6.6599)	(6.2227)	(6.2201)	(10.8558)	(6.6912)	(6.1878)
Debt-to-GDP (log) *squared*	0.3618	-0.0852	0.1107	-0.0517	-0.2592	-0.1516	0.2967	-0.0640	-0.0751	0.0608	-0.1716	-0.2706
	(0.2410)	(0.8584)	(0.8433)	(0.8488)	(0.8372)	(0.9003)	(0.9274)	(0.8604)	(0.8545)	(1.4632)	(0.9140)	(0.8493)
Main Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
Altering the Sample	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes
Observations	124	107	107	104	107	107	102	104	107	92	97	94
Fiscal stimuli (% of GDP)	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Debt-to-tax (log)	0.9340	1.0621	0.0766	0.6185	1.0208	3.1296	0.1722	1.6909	0.8380	-1.8235	1.5795	0.5402
	(0.9849)	(4.6676)	(4.7862)	(4.6632)	(4.8772)	(4.9409)	(4.7955)	(4.5474)	(4.8223)	(6.2304)	(6.9750)	(4.8221)
Debt-to-tax (log) *squared*	-0.3221***	-0.2342	-0.1433	-0.1976	-0.2161	-0.4177	-0.1344	-0.2754	-0.2105	-0.0128	-0.2680	-0.2172
	(0.1093)	(0.3669)	(0.3768)	(0.3639)	(0.3811)	(0.4017)	(0.3736)	(0.3598)	(0.3804)	(0.4759)	(0.5971)	(0.3831)
Main Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
Altering the Sample	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes
Observations	123	107	107	104	107	107	102	104	107	92	97	94
Fiscal stimuli (% of GDP)	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Debt ratings	-0.2452	0.0451	0.0424	-0.0187	-0.1720	0.0583	0.0646	0.1584	0.0003	-0.2347	-0.3121	0.3026
	(0.3740)	(0.4455)	(0.4454)	(0.4425)	(0.4418)	(0.4470)	(0.4439)	(0.4684)	(0.4564)	(0.4550)	(0.4085)	(0.4779)
Debt ratings squared	0.0414***	0.0224	0.0218	0.0273	0.0315	0.0222	0.0206	0.0172	0.0238	0.0380*	0.0386**	0.0118
	(0.0155)	(0.0195)	(0.0196)	(0.0196)	(0.0195)	(0.0197)	(0.0195)	(0.0203)	(0.0198)	(0.0203)	(0.0176)	(0.0214)
Main Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
Altering the Sample	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes
Observations	125	107	107	104	107	107	102	104	107	92	97	94

Note: The *main controls* are those from Table 2. The *additional controls* are those from Table 3 in the same order. The *altering of the sample* is the one from Table 4 in the same order. Unreported constant included. Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

5.3 Disaggregated types of fiscal stimuli

Finally, in search for channels that may explain the effect of fiscal space on fiscal stimuli, we perform estimations when decomposing fiscal stimuli into their various types in Table 9, namely: additional spending or foregone revenues for the health sector (HS, column [1]); additional spending or foregone revenues for the non-health sector (NHS, column [2]); accelerated spending/deferred revenues (AS/DR, column [3]); equity injections, loans, asset purchase, or debt assumptions (EI/L/AP/DA, column [4]); government guarantees (GG, column [5]); and quasi-fiscal operations (QFO, column [6]).

The results can be summarized as follows. The public debt-to-GDP ratio is never a significant determinant of the various types of fiscal stimuli, consistent with our baseline results (see the top of Table 9). Next, the favorable effect of a lower public debt-to-tax ratio is driven by a significant response of accelerated spending/deferred revenues (column [3]), and by equity injections, loans, asset purchase, or debt assumptions (column [4]) types of fiscal stimuli (see the middle of Table 9). Lastly, the positive impact of higher sovereign debt ratings on fiscal stimuli in our baseline estimations is related to the significant responses of additional spending or foregone revenues for the non-health sector (column [2]), and of accelerated spending/deferred revenues (column [3]) types of fiscal stimuli (see the bottom of Table 9).

In addition, we explore the presence of possible nonlinearities driven by the initial level of

Table 9 – Heterogeneity: Disaggregated types of fiscal stimuli

Disaggregated fiscal stimuli (% of GDP)	[1] HS	[2] NHS	[3] AS/DR	[4] EI/L/AP/DA	[5] GG	[6] QFO
Debt-to-GDP (log)	-0.0538	0.8162	-1.0430	-0.2051	0.0672	0.6173
	(0.0971)	(0.6284)	(0.6878)	(0.4121)	(0.7234)	(0.4167)
Main Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	91	91	44	55	56	24

Disaggregated fiscal stimuli (% of GDP)	[1] HS	[2] NHS	[3] AS/DR	[4] EI/L/AP/DA	[5] GG	[6] QFO
Debt-to-tax (log)	-0.0796	-0.3701	-0.9903*	-0.3925*	-0.1129	-0.1144
	(0.1010)	(0.6636)	(0.4939)	(0.2242)	(0.5011)	(0.3320)
Main Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	91	91	44	55	56	24

Disaggregated fiscal stimuli (% of GDP)	[1] HS	[2] NHS	[3] AS/DR	[4] EI/L/AP/DA	[5] GG	[6] QFO
Sovereign debt ratings	0.0069	0.3457***	0.1422**	0.0184	0.0796	0.0742
	(0.0177)	(0.1040)	(0.0653)	(0.0494)	(0.1063)	(0.0757)
Main Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	91	91	44	55	56	24

Note: Columns [1]-[6] include respectively additional spending or foregone revenues for the health sector (% GDP), additional spending or foregone revenues for the non-health sector (% GDP), accelerated spending / deferred revenues (% GDP), equity injections, loans, asset purchase, or debt assumptions (% GDP), government guarantees (% GDP), and quasi-fiscal operations (% GDP). Unreported constant included. Robust standard errors in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Covid Economics 74, 30 March 2021: 71-93

each measure of fiscal space on the various disaggregated types of fiscal stimuli. As shown by Table 10, a favorable effect of a lower public debt-to-GDP on equity injections, loans, asset purchase, or debt assumptions (column [4]) is at work only below a debt ratio estimated around 43% (i.e. a U-shape effect). Besides, a lower debt-to-tax ratio is associated with higher accelerated spending/deferred revenues (column [3]) below a debt-to-tax ratio estimated around 1152% (i.e. a U-shape effect), and with higher government guarantees (column [5]) above a threshold estimated around 305% (i.e. a bell-shape effect). In addition, the favorable effect of higher sovereign debt ratings on additional spending or foregone revenue for the non-health sector (column [2]), or accelerated spending/deferred revenues (column [3]) is at work above sovereign ratings thresholds estimated at 6.96 and 8.71 respectively (i.e. a U-shape effect), and below a sovereign debt ratings threshold estimated at 12.99 (i.e. a bell-shape effect) on government guarantees (column [5]) .

The results from the linear and nonlinear estimations of the impact of the different measures of fiscal space on the various types of fiscal stimuli—summarized in Table 11—provide insights on the channels that drive our findings. First, consistent with the lack of a significant effect for aggregated fiscal stimuli, the public debt-to-GDP ratio is never a significant determinant of disaggregated fiscal stimuli, except for a favorable effect of lower debt on equity injections, loans, asset purchase or debt assumptions (column [3]) but only for low enough debt ratios—roughly for 40% of observations.

Second, the aggregated effect of the debt-to-tax ratio is supported by its favorable impact on most types of fiscal stimuli. Lower debt-to-tax ratios significantly improve (i) at all debt-to-tax levels the equity injections, loans, asset purchase, or debt assumptions (EI/L/AP/DA,

Covid Economics 74, 30 March 2021: 71-93

Table 10 – Heterogeneity: Nonlinearity with disaggregated types of fiscal stimuli

Nonlinear Disag. fiscal stimuli	[1] HS	[2] NHS	[3] AS/DR	[4] EI/L/AP/DA	[5] GG	[6] QFO
Debt-to-GDP (log)	0.0983	-1.2428	-10.7147	-8.3691***	4.9897	-1.4426
	(0.6984)	(4.2772)	(8.5474)	(1.9110)	(3.4273)	(6.3509)
Debt-to-GDP (log) *squared*	-0.0199	0.2694	1.2014	1.1110***	-0.6532	0.2751
	(0.0917)	(0.5813)	(1.0335)	(0.2866)	(0.4967)	(0.8102)
Main Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	91	91	44	55	56	24
Nonlinear Disag. fiscal stimuli	[1] HS	[2] NHS	[3] AS/DR	[4] EI/L/AP/DA	[5] GG	[6] QFO
Debt-to-tax (log)	0.6635	0.5477	-7.1336*	-2.3831	4.2743**	3.4435
	(0.4908)	(3.8319)	(3.7466)	(1.5130)	(1.9048)	(2.2217)
Debt-to-tax (log) *squared*	-0.0638*	-0.0789	0.5060*	0.1703	-0.3737**	-0.2753
	(0.0363)	(0.2949)	(0.2850)	(0.1285)	(0.1453)	(0.1609)
Main Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	91	91	44	55	56	24
Nonlinear Disag. fiscal stimuli	[1] HS	[2] NHS	[3] AS/DR	[4] EI/L/AP/DA	[5] GG	[6] QFO
Sovereign debt ratings	-0.0056	-0.4717*	-0.4614*	-0.1555	0.8732***	-0.2997
	(0.0469)	(0.2750)	(0.2416)	(0.1266)	(0.3082)	(0.3851)
Sovereign debt ratings squared	0.0005	0.0339**	0.0265**	0.0075	-0.0336**	0.0162
	(0.0019)	(0.0136)	(0.0120)	(0.0053)	(0.0141)	(0.0152)
Main Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	91	91	44	55	56	24

Note: Columns [1]-[6] include respectively additional spending or foregone revenues for the health sector (% GDP), additional spending or foregone revenues for the non-health sector (% GDP), accelerated spending / deferred revenues (% GDP), equity injections, loans, asset purchase, or debt assumptions (% GDP), government guarantees (% GDP), and quasi-fiscal operations (% GDP). Unreported constant included. Robust standard errors in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

column [4]), and—even in an accelerated way—the additional spending or foregone revenues for the health sector (HS, column [1]); and (*ii*) for most debt-to-tax levels, namely for roughly 98% of observations, the accelerated spending/deferred revenues (AS/DR, column [3]), and for roughly 41% of observations for government guarantees (GG, column [5]).

Finally, the robust impact of higher sovereign debt ratings on aggregated fiscal stimuli is explained by its favorable effect at most ratings levels on additional spending or foregone revenues for the non-health sector (NHS, column [2]), namely for roughly 86% of observations; on accelerated spending/deferred revenues (AS/DR, column [3]) for roughly 70% of observations; and on government guarantees (GG, column [5]) for roughly 46% of observations.

Table 11 – Heterogeneity: A summary for disaggregated types of fiscal stimuli

Disaggregated fiscal stimuli	[1] HS	[2] NHS	[3] AS/DR	[4] EI/L/AP/DA	[5] GG	[6] QFO
Debt-to-GDP (log)	ns	ns	ns	U-shape	ns	ns
Threshold	—	—	—	43%	—	—
Higher FSpace → Higher FStimuli	—	—	—	below 43%	—	—
% Observations	—	—	—	40%	—	—
Disaggregated fiscal stimuli	[1] HS	[2] NHS	[3] AS/DR	[4] EI/L/AP/DA	[5] GG	[6] QFO
Debt-to-tax (log)	acceleration	ns	U-shape	negative	bell-shape	ns
Threshold	—	—	1152%	—	305%	—
Higher FSpace → Higher FStimuli	always	—	below 1152%	always	above 305%	—
% Observations	all	—	98%	all	41%	—
Disaggregated fiscal stimuli	[1] HS	[2] NHS	[3] AS/DR	[4] EI/L/AP/DA	[5] GG	[6] QFO
Sovereign debt ratings	ns	U-shape	U-shape	ns	bell-shape	ns
Threshold	—	6.96	8.71	—	12.99	—
Higher FSpace → Higher FStimuli	—	above 6.96	above 8.71	—	below 12.99	—
% Observations	—	86%	70%	—	46%	—

ns=not significant.

We can summarize our findings for disaggregated types of fiscal stimuli as follows:

(i) a higher fiscal space—signaled by lower debt-to-tax ratios or higher sovereign debt ratings—was a significant determinant on average of *accelerated spending/deferred revenues* at all debt-to-tax levels (except one country) and most sovereign debt ratings levels (for example, this was the case for e.g. Canada, the UK, or the US, with reversed effects due to too low ratings for e.g. Argentina, Greece, or Tunisia);

(ii) countries with lower debt-to-tax ratios were on average—irrespective of the debt-to-tax level—capable of significantly increasing their *additional spending or foregone revenues for the health sector*, and their *equity injections, loans, asset purchase, or debt assumptions*;

(iii) countries with higher sovereign debt ratings were on average—in most cases—capable of significantly increasing their *additional spending or foregone revenues for the non-health sector* (for example, this was the case for e.g. Australia, France, or New Zealand, with reversed effects due to too low ratings for e.g. Gabon, Moldova, or Zambia); and

(iv) a higher fiscal space allowed to significantly increase *government guarantees* only when debt-to-taxes were high enough (around 41% of observations; for example, for e.g. Belgium, Spain, or Portugal) and when sovereign debt ratings were low enough (around 46% of observa-

Covid Economics 74, 30 March 2021: 71-93

tions; for example, for Honduras, Senegal, or Turkey).

However, this *unfavorable* effect of a higher fiscal space on government guarantees for *most countries* does not alter our main results: as illustrated by estimations reported in the robustness (see Table A2 in the Appendix) and heterogeneity sections (see Table A4 in the Appendix and Table 7), our findings still hold when *excluding government guarantees* from the accountancy of the aggregated measure of fiscal stimuli.

6 Concluding remarks

In response to the dramatic consequences of the Covid-19 *Great Lockdown* crisis, many countries around the world implemented fiscal stimuli. Capitalizing on the literature emphasizing the benefits of fiscal space for fiscal policy in times of crises, this paper investigated the role of the pre-Covid fiscal space as a determinant of national Covid-related fiscal stimuli.

Estimations performed on a large sample of 125 countries revealed the following. First, whether pre-Covid fiscal space was a significant determinant of fiscal stimuli varies with the precise measure of fiscal space. On the one hand, Governments seem to have neglected—by and large—their indebtedness levels when having decided the amount of their national fiscal stimuli. On the other hand, however, the degree to which public debt is backed up by fiscal revenues, and particularly the ratings of their sovereign debts were found to be significant predictors of the magnitude of national fiscal stimuli, a result that survived several robustness tests (e.g. when adding various control variables, excluding various groups of countries, or controlling for outliers). Second, these results are found to vary with respect to the level of economic development, and the precise type of fiscal stimulus. Regarding the latter, a higher fiscal space measured by lower debt-to-tax ratios or higher sovereign debt ratings was found to affect both accelerated spending/deferred revenues and government guarantees types of fiscal stimuli.

Consequently, we see several takeaways of our analysis. While our findings confirm in a larger panel of countries the disconnection between public debt-to-GDP and fiscal stimuli illustrated by Benmelech and Tzur-Ilan (2020), we equally provide robust support for fiscal space as a key determinant of the size of Covid-related fiscal stimuli: countries with lower debt-to-tax ratios or higher sovereign ratings are on average significantly more capable of implementing larger fiscal packages to fight the detrimental consequences of the Covid crisis. Next, the size of fiscal stimuli was significantly larger in developing countries with lower pre-Covid debt-to-tax ratios or higher sovereign debt ratings; however, the magnitude of the favorable effect of higher sovereign debt ratings was—in absolute terms—twice higher in developed countries compared with developing countries. Lastly, having a larger fiscal space was found to unevenly support the various types of national fiscal stimuli.

These various types of conditionality in the favorable effect of fiscal space on Governments' national fiscal stimuli require future work on the determinants of fiscal stimuli (including the various dimensions of fiscal space) in a more dynamic setup that may exploit data from the following periods, should—against the *strong* desire of the authors of this study—such Covid-related fiscal stimuli still prove necessary in the future.

Covid Economics 74, 30 March 2021: 71-93

References

Abiad, A., Arao, R. M., and Dagli, S. (2020). The economic impact of the covid-19 outbreak on developing asia. *ADB Briefs 128, Asian Development Bank.*

Aizenman, J. and Jinjarak, Y. (2010). De facto fiscal space and fiscal stimulus: Definition and assessment. *NBER Working Paper 16539, National Bureau of Economic Research, Cambridge, MA.*

Auerbach, A. J., Gale, W. G., and Harris, B. H. (2010). Activist fiscal policy. *Journal of Economic Perspectives*, 24(4):141–64.

Auerbach, A. J., Gorodnichenko, Y., and Murphy, D. (2020). Fiscal policy and covid19 restrictions in a demand-determined economy. *NBER Working Paper 27366, National Bureau of Economic Research, Cambridge, MA.*

Baqaee, D. and Farhi, E. (2020). Supply and demand in disaggregated keynesian economies with an application to the covid-19 crisis. *NBER Working Paper 27152, National Bureau of Economic Research, Cambridge, MA.*

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 26866, National Bureau of Economic Research, Cambridge, MA.*

Benmelech, E. and Tzur-Ilan, N. (2020). The determinants of fiscal and monetary policies during the covid-19 crisis. *NBER Working Paper 27461, National Bureau of Economic Research, Cambridge, MA.*

Blanchard, O. (2019). Public debt and low interest rates. *American Economic Review*, 109(4):1197–1229.

Bohn, H. (2008). The sustainability of fiscal policy in the united states. *published in: Reinhard Neck and Jan-Egbert Sturm, Sustainability of Public Debt, MIT Press 2008*, pages 15–49.

Çakmaklı, C., Demiralp, S., Kalemli-Özcan, S., Yesiltas, S., and Yildirim, M. A. (2020). Covid-19 and emerging markets: an epidemiological model with international production networks and capital flows. *NBER Working Paper 27191, National Bureau of Economic Research, Cambridge, MA.*

Casado, M. G., Glennon, B., Lane, J., McQuown, D., Rich, D., and Weinberg, B. A. (2020). The effect of fiscal stimulus: Evidence from covid-19. *NBER Working Paper 27576, National Bureau of Economic Research, Cambridge, MA.*

Deb, P., Furceri, D., Ostry, J. D., and Tawk, N. (2020). The economic effects of covid-19 containment measures. *CEPR Discussion Paper No. DP15087.*

Covid Economics 74, 30 March 2021: 71-93

Eichenbaum, M. S., Rebelo, S., and Trabandt, M. (2020). The macroeconomics of epidemics. *NBER Working Paper 26882, National Bureau of Economic Research, Cambridge, MA.*

ElFayoumi, K. and Hengge, M. (2020). Capital markets, covid-19 and policy measures. *COVID-19 and Policy Measures 45: 32-64.*

Faria-e Castro, M. (2020). Fiscal policy during a pandemic. *Covid Economics 2, 67-101.*

Ghosh, A. R., Kim, J. I., Mendoza, E. G., Ostry, J. D., and Qureshi, M. S. (2013). Fiscal fatigue, fiscal space and debt sustainability in advanced economies. *The Economic Journal*, 123(566):F4–F30.

Gopinath, G. (2020). The great lockdown: Worst economic downturn since the great depression. *IMF Blog, 14 April.*

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 26918, National Bureau of Economic Research, Cambridge, MA.*

Ilzetzki, E., Reinhart, C. M., and Rogoff, K. S. (2017). Exchange arrangements entering the 21st century: Which anchor will hold? *NBER Working Paper 23135, National Bureau of Economic Research, Cambridge, MA.*

Jordà, Ò., Schularick, M., and Taylor, A. M. (2016). Sovereigns versus banks: credit, crises, and consequences. *Journal of the European Economic Association*, 14(1):45–79.

Jordà, Ò., Singh, S. R., and Taylor, A. M. (2020). Longer-run economic consequences of pandemics. *Covid Economics 1, 1-15.*

Kose, M. A., Kurlat, S., Ohnsorge, F., and Sugawara, N. (2017). *A cross-country database of fiscal space*. Policy Research Working Paper 8157, World Bank, Washington, DC.

Long, A. and Ascent, D. (2016). World economic outlook. *International Monetary Fund (IMF): Washington*, pages –203.

Max Roser, Hannah Ritchie, E. O.-O. and Hasell, J. (2020). Coronavirus pandemic (covid-19). *Our World in Data*. https://ourworldindata.org/coronavirus.

McKibbin, W. and Fernando, R. (2020). The economic impact of covid-19. *In: R. Baldwin and B. W. di Mauro (Eds.), Economics in the Time of COVID-19, London, UK: CEPR Press*, pages 45–51.

Minea, A. and Villieu, P. (2009). Borrowing to finance public investment? the 'golden rule of public finance'reconsidered in an endogenous growth setting. *Fiscal Studies*, 30(1):103–133.

Minea, A. and Villieu, P. (2012). Persistent deficit, growth, and indeterminacy. *Macroeconomic Dynamics*, 16(S2):267–283.

Covid Economics 74, 30 March 2021: 71-93

Prasad, E. and Sorkin, I. (2009). Assessing the g-20 economic stimulus plans: A deeper look. *Brookings Institution*.

Romer, C. D. and Romer, D. H. (2018). Phillips lecture–why some times are different: Macroeconomic policy and the aftermath of financial crises. *Economica*, 85(337):1–40.

Romer, C. D. and Romer, D. H. (2019). Fiscal space and the aftermath of financial crises: how it matters and why. *NBER Working Paper 25768, National Bureau of Economic Research, Cambridge, MA.*

Teorell, J., Dahlberg, S., Holmberg, S., Rothstein, B., Alvarado Pachon, N., and Axelsson, S. (2020). *The Quality of Government Standard Dataset, version Jan20*. University of Gothenburg. The Quality of Government Institute. doi = 10.18157/qogstdjan20, url = http://www.qog.pol.gu.se.

Covid Economics 74, 30 March 2021: 71-93

APPENDIX

Table A1 – Descriptive statistics of major variables

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Fiscal stimuli (% GDP)	125	7.0214	6.2591	0.0000	25.9096
Public debt (%GDP) in log	124	3.8699	0.7174	-1.3155	5.1885
Public debt (%GDP)	124	56.7739	29.8841	0.2684	179.2009
Public debt (% tax revenues) in log	123	5,6736	0,8392	0,7259	8,4150
Public debt (% tax revenues)	123	402.6337	489.7068	2.0666	4514.0840
Sovereign debt ratings	125	11.6196	5.1314	2.0575	21
Additional spending or foregone revenues for health sector (%GDP)	107	0.6514	0.5873	0.0359	3.9059
Additional spending or foregone revenues for non-health sector (%GDP)	107	3.5117	3.2378	0.0000	19.1857
Accelerated spending / deferred revenue (%GDP)	51	1.6094	1.8748	0.0000	7.8782
Equity injections, loans, asset purchase or debt assumptions (%GDP)	63	0.7397	0.9386	0.0000	4.7050
Government guarantees (%GDP)	64	3.6797	3.9044	0.0000	16.5153
Quasi-fiscal operations (%GDP)	28	1.2594	1.6005	0.0000	6.5789
Infection fatality rate (IFR)	120	3.5409	3.2960	0.0813	17.3023
GDP per capita (log)	116	9.0189	1.2930	6.1379	11.6039
Population density (log)	116	4.2013	1.3875	0.5037	8.7603
Index of Democratization	121	15.0763	10.8916	0.0000	39.4048
Inflation	118	13.0710	19.4301	1.1066	112.7968

Table A2 – Alternative definition of fiscal stimuli: Without Government Guarantees

Fiscal stimuli w/o Gov. Guarantees (% GDP)	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Debt-to-tax (log)	-0.3299	0.0431	0.0956	0.0138	0.0001	0.0545	0.2958	0.0725	0.0939	0.2932	-0.2736	-0.1781
	(0.5583)	(0.7616)	(0.7512)	(0.7808)	(0.7585)	(0.7775)	(0.7829)	(0.7472)	(0.7579)	(1.0093)	(0.8454)	(0.7767)
Main Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
Altering the Sample	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes
Observations	124	107	107	104	107	107	102	104	107	92	97	94

Fiscal stimuli w/o Gov. Guarantees (% GDP)	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[11]	[12]	[13]
Debt-to-tax (log)	-1.8006***	-1.4843**	-1.3941**	-1.5060**	-1.3267**	-1.4852**	-1.2714**	-1.3982**	-1.4170**	-1.5881**	-1.3081	-1.7097***
	(0.4666)	(0.6070)	(0.6214)	(0.6122)	(0.6158)	(0.6408)	(0.6221)	(0.5944)	(0.6266)	(0.6990)	(0.8114)	(0.6283)
Main Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
Altering the Sample	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes
Observations	123	107	107	104	107	107	102	104	107	92	97	94

Fiscal stimuli w/o Gov. Guarantees (% GDP)	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[11]	[12]	[13]
Debt ratings	0.4996***	0.4581***	0.4281***	0.4891***	0.4602***	0.4578***	0.4356***	0.4489***	0.4463***	0.5152***	0.4985***	0.4583***
	(0.0743)	(0.1137)	(0.1080)	(0.1138)	(0.1098)	(0.1129)	(0.1138)	(0.1096)	(0.1189)	(0.1257)	(0.1239)	(0.1174)
Main Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
Altering the Sample	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes
Observations	125	107	107	104	107	107	102	104	107	92	97	94

Note: The *main controls* are those from Table 2. The *additional controls* are those from Table 3 in the same order. The *altering of the sample* is the one from Table 4 in the same order. Unreported constant included. Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table A3 – Accounting for country outliers: Germany, Italy, and Japan

Fiscal stimuli (% GDP)	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Debt-to-GDP (log)	1.4687	1.6548	1.6662	1.6492	1.3461	1.6334	1.9841	1.7600	1.7042	1.8524	1.5019	1.3402
	(1.3610)	(1.4435)	(1.4016)	(1.4804)	(1.2384)	(1.4636)	(1.4569)	(1.4644)	(1.4393)	(1.9089)	(1.6133)	(1.4879)
Main Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
Altering the Sample	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes
Observations	127	110	110	107	110	110	105	107	110	93	100	97

Fiscal stimuli (% GDP)	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Debt-to-tax (log)	-1.5674*	-0.3007	-0.2237	-0.3031	-0.0255	-0.3563	0.0419	-0.1100	-0.2091	-0.7549	0.2553	-0.6060
	(0.8644)	(1.1535)	(1.1555)	(1.1821)	(1.1316)	(1.1914)	(1.1691)	(1.1604)	(1.1850)	(1.3730)	(1.4491)	(1.1693)
Main Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
Altering the Sample	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes
Observations	126	110	110	107	110	110	105	107	110	93	100	97

Fiscal stimuli (% GDP)	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Debt ratings	0.9237***	0.5963***	0.5754***	0.6267***	0.5965***	0.6052***	0.5756***	0.5767***	0.5862***	0.6695***	0.6423***	0.5858***
	(0.1158)	(0.1658)	(0.1783)	(0.1687)	(0.1642)	(0.1684)	(0.1673)	(0.1570)	(0.1707)	(0.1308)	(0.1837)	(0.1737)
Main Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
Altering the Sample	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes
Observations	128	110	110	107	110	110	105	107	110	93	100	97

Note: The *main controls* are those from Table 2. The *additional controls* are those from Table 3 in the same order. The *altering of the sample* is the one from Table 4 in the same order. Unreported constant included. Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table A4 – Accounting for non-linearity: Without Government Guarantees

Fiscal stimuli w/o Gov. Guar. (% GDP)	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Debt-to-GDP (log)	-1.8654***	-0.8810	-2.3489	-0.6638	0.2459	-1.1919	-3.4654	-1.0209	-0.9110	-2.9502	-1.0213	0.1008
	(0.5358)	(5.1567)	(5.2167)	(5.1806)	(4.9424)	(5.4316)	(5.3215)	(5.2010)	(5.1203)	(9.9163)	(5.6664)	(5.1593)
Debt-to-GDP (log) *squared*	0.2820	0.1221	0.3232	0.0895	-0.0325	0.1648	0.5016	0.1445	0.1328	0.4252	0.0981	-0.0370
	(0.1741)	(0.7092)	(0.7172)	(0.7113)	(0.6834)	(0.7576)	(0.7362)	(0.7140)	(0.7015)	(1.3372)	(0.7740)	(0.7103)
Main Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
Altering the Sample	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes
Observations	124	107	107	104	107	107	102	104	107	92	97	94

Fiscal stimuli w/o Gov. Guar. (% GDP)	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Debt-to-tax (log)	-0.7635	-0.6461	-1.7167	-0.7313	-0.6839	-0.4866	-1.1963	-0.2702	-0.9202	-2.0226	-0.7570	-0.7505
	(0.7459)	(4.1554)	(4.2471)	(4.2373)	(4.2822)	(4.3260)	(4.4349)	(4.1306)	(4.3277)	(5.7286)	(6.5266)	(4.2172)
Debt-to-tax (log) *squared*	-0.1021	-0.0713	0.0275	-0.0658	-0.0547	-0.0854	-0.0064	-0.0958	-0.0423	0.0362	-0.0489	-0.0816
	(0.0847)	(0.3228)	(0.3294)	(0.3286)	(0.3302)	(0.3461)	(0.3438)	(0.3229)	(0.3373)	(0.4359)	(0.5623)	(0.3285)
Main Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
Altering the Sample	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes
Observations	123	107	107	104	107	107	102	104	107	92	97	94

Fiscal stimuli w/o Gov. Guar. (% GDP)	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[11]	[12]	[13]
Sovereign debt ratings	-0.3236	-0.1862	-0.2080	-0.1241	-0.5789*	-0.1898	-0.2157	-0.1117	-0.2925	-0.2255	-0.4924	0.0050
	(0.3358)	(0.4059)	(0.3952)	(0.4403)	(0.3244)	(0.4083)	(0.4105)	(0.4253)	(0.3956)	(0.5089)	(0.3911)	(0.5006)
Sovereign debt ratings squared	0.0345**	0.0273	0.0259	0.0250	0.0433***	0.0274	0.0275	0.0240	0.0305*	0.0317	0.0412**	0.0196
	(0.0135)	(0.0177)	(0.0177)	(0.0197)	(0.0148)	(0.0178)	(0.0180)	(0.0183)	(0.0172)	(0.0226)	(0.0163)	(0.0219)
Main Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
Altering the Sample	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes
Observations	128	110	110	107	110	110	105	107	110	93	100	97

Note: The *main controls* are those from Table 2. The *additional controls* are those from Table 3 in the same order. The *altering of the sample* is the one from Table 4 in the same order. Unreported constant included. Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Sources, and definitions of the data

Fiscal stimuli (% GDP): COVID-19 total fiscal measures over GDP (*until September 11, 2020*). *Source*: IMF(2020)

Additional spending or foregone revenues for the non-health sector (%GDP) (*until September 11, 2020*): detail definition—see IMF's database of fiscal policy responses to COVID-19. *Source*: IMF (2020)

Additional spending or foregone revenues for health sector (%GDP) (until September 11, 2020): detail definition—see IMF's database of fiscal policy responses to COVID-19. *Source*: IMF(2020)

Accelerated spending/deferred revenues (%GDP) (until September 11, 2020): detail definition—see IMF's database of fiscal policy responses to COVID-19. *Source*: IMF (2020)

Equity injections, loans, asset purchase, or debt assumptions (%GDP) (until September 11, 2020): detail definition—see IMF's database of fiscal policy responses to COVID-19. *Source*: IMF (2020)

Government guarantees (%GDP) (until September 11, 2020): detail definition—see IMF's database of fiscal policy responses to COVID-19. *Source*: IMF (2020)

Quasi-fiscal operations (%GDP) (until September 11, 2020): detail definition—see IMF's database of fiscal policy responses to COVID-19. *Source*: IMF (2020)

Public debt (%GDP): Public debt over GDP. It is measured before the Covid-19 crisis. *Source*: Kose et al. (2017)

Public debt (% tax): Public debt over average tax revenues. It is measured before the Covid-19 crisis. *Source*: Kose et al. (2017)

Sovereign debt ratings: Foreign currency long-term sovereign debt ratings. It is measured before the Covid-19 crisis. *Source*: Kose et al. (2017)

Infection fatality rate (IFR): Infection fatality rate (until September 11, 2020). *Source*: Authors' calculations based on Max Roser and Hasell (2020)

GDP per capita (log): logarithm of GDP per capita. It is measured before the Covid-19 crisis. *Source*: World Development Indicators (WDI)

Population density (log): logarithm of population density (people per sq. km of land area). It is measured before the Covid-19 crisis. *Source*: WDI

Index of democratization: index of democratization. It is measured before the Covid-19 crisis. *Source*: Teorell et al. (2020)

Inflation: inflation, average consumer prices (Percent change). It is measured before the Covid-19 crisis. *Source*: WDI

Fixed exchange rate: dummy variable equal to 1 if a country is classified as having a fixed exchange rate regime, and 0 otherwise. It is measured before the Covid-19 crisis. *Source*: Ilzetzki et al. (2017)

Stringency index: this is a composite measure based on nine response indicators (until September 11, 2020) including school closures, workplace closures, and travel bans, re-scaled to a value from 0 to 100 (100 = strictest). If policies vary at the sub-national level, the index is

Covid Economics 74, 30 March 2021: 71-93

shown as the response level of the strictest sub-region. *Source*: Max Roser and Hasell (2020)

Aged 65 older: People aged 65 years or older (until September 11, 2020). *Source*: Max Roser and Hasell (2020)

General government total expenditure (%GDP): general government total expenditure (%GDP). Total expenditure consists of total expense and the net acquisition of nonfinancial assets. It is measured before the Covid-19 crisis. *Source*: IMF World Economic Outlook

Government Fractionalization Index: government fractionalization index. It is measured before the Covid-19 crisis. *Source*: Database of Political Institutions (DPI)

Election years: presidential or legislative Election held. It is measured before the Covid-19 crisis. *Source*: DPI

Fiscal rules: dummy variable equal to 1 if a country had in place a numerical limit on fiscal aggregates (expenditure, revenue, budget balance, debt) and 0 otherwise. It is measured before the Covid-19 crisis. *Source*: IMF Fiscal Rules Dataset

Covid Economics 74, 30 March 2021: 71-93

Covid Economics **Issue 74, 30 March 2021**

Smart containment: Lessons from countries with past experience[1]

Alexandra Fotiou[2] and Andresa Lagerborg[3]

Date submitted: 18 March 2021; Date accepted: 24 March 2021

Following the Great Lockdown in 2020, it is important to take stock of lessons learned. How effective have different containment measures been in slowing the spread of Covid-19? Have containment measures been costly in terms of economic growth, fiscal balances, and accumulated debt? This paper finds that countries with previous SARS experience acted fast and "smart", and were able to contain the virus by relying mainly on public health measures —testing, contact tracing, and public information campaigns— rather than stay-at-home requirements. Using past coronavirus outbreaks as an instrumental variable, we show that countries with past experience were able to contain the virus in a smart way, reducing transmission and deaths while also experiencing higher economic growth in 2020.

Covid Economics 74, 30 March 2021: 94-141

1 We thank Raphael Espinoza, Paolo Mauro, Joni Mayfield, Catherine Pattill , Paulo Medas, and members of the FAD Fiscal Policy and Surveillance division, and Katja Funke and Manabu Nose for useful suggestions. We would also like to thank Yuan Xiang for excellent research assistance. The views expressed in this paper are those of the authors and do not necessarily represent the views of the IMF, its Executive Board, or IMF management.

2 Economist, International Monetary Fund.
3 Economist, International Monetary Fund.

CEPR PRESS

1 Introduction

Covid-19 has had a profound impact around the globe. The human cost of the pandemic has intensified at an alarming rate, with significant outbreaks in almost every part of the world. In order to save lives, governments have responded with unprecedented measures to prevent the virus from spreading. Responses have ranged from broad lockdowns and stay-at-home orders to more targeted and smarter strategies.

Besides the alarming human cost, the pandemic has hit economies through multiple channels. Global growth in 2020 recorded the worst economic fallout since the Great Depression. As the IMF's Managing Director Kristalina Georgieva pointed out during her Curtain raiser speech for the 2020 Spring Meetings: in January, a positive per capita income growth was expected in over 160 countries in 2020; by April, the picture had reversed and over 170 countries were projected to experience negative per capita income growth.

This paper assesses the effectiveness of containment measures in suppressing the Covid-19 virus and saving lives, in a cost-effective way. First, we study the impact of containment measures implemented in over 150 countries and attempt to identify which measures and strategies were more effective. Second, we explore the economic costs/benefits of containing the pandemic and the effect of containment measures on output, fiscal balances and government debt. As countries calibrate their policies in the aftermath of the Great Lockdown amid fears of future waves and future epidemics, lessons can be drawn across countries about what approaches worked best, in order to overcome this historical crisis and minimize the human and economic cost of future crises. Learning from countries that successfully curbed the virus, we propose a smart strategy of *testing*, *contact tracing*, and *public information campaigns* and targeted stringency early on.

Several studies find that containment measures have been effective in flattening the pandemic curve (e.g. Cowling et al., 2020), especially when implemented early and resulted in effectively reducing mobility (e.g. Deb et al., 2020b).[1] Our analysis is complementary to this literature and adds to it by focusing on identifying differences in the strategies employed by countries who were highly successful in containing the Covid-19 pandemic.

Many countries were proactive when the health shock hit, responding rapidly to contain the spread of the virus and offset the economic impact of the pandemic.

[1]On the theoretical front, several recent papers use standard epidemiological models to examine the role of different measures, such as quarantines and testing (e.g. Forslid and Herzing, 2020, Brotherhood et al., 2020).

Covid Economics 74, 30 March 2021: 94-141

Some countries were more successful than others and responded in a "smarter" and more cost-effective way. Our analysis suggests that country success stories in containing Covid-19 have largely stemmed from acting with early stringency measures (e.g. monitoring international travel) and applying strong health measures (e.g. wide-scale testing, contact tracing, and public information campaigns). For example, Asian countries with previous experience in containing SARS outbreaks - namely Hong Kong SAR, Taiwan Province of China, Singapore, and Vietnam[2] - acted very quickly with these strong health system measures and targeted stringency, focusing on measures such as international travel controls, school closures, and cancellation of public events, while they did not impose quicker or stricter stay-at-home orders, closures of workplaces and transport, or restrictions on gatherings and internal mobility.[3]

Our analysis takes into account the timing of containment measures by differentiating between countries that implemented stronger containment measures on average and those that implemented containment measures early on, defined as the measures in place at the time when the country reached 100 reported Covid-19 cases.[4] Our analysis also compares the use of different containment measures, distinguishing between those that relied on stringency (e.g. lockdowns, closures, and other restrictions on mobility) compared to public health measures.

We present evidence that lower deaths and more successful containment of Covid-19 in 2020 (as measured by age-adjusted mortality rates) are associated with less stringent containment measures on average throughout the year. By contrast, more successful countries had stronger public health measures. We also show that stringency measures implemented early on helped curb deaths during a large part of the year, although this is not significant in explaining death rates recorded by the end of the year.

Does saving lives imply higher economic and fiscal costs? While many leading scholars and policymakers clearly communicated that saving lives is the utmost priority (Baldwin and di Mauro, 2020), doing "whatever it takes" can impose large costs through lower output and revenues, as well as additional fiscal support in

[2]While Canada also experienced a past SARS outbreak, the country's Covid-19 containment measures were enacted with a comparative lag.

[3]As Chinazzi et al. (2020) show within a global metapopulation disease model, one needs to account for a combination of both travel restrictions and other types of measures to project the contribution of travel restrictions to the spread of the virus.

[4]Deb et al. (2020b) study the effectiveness of early containment defined as the timing at which a measure was first implemented, known in epidemiological terms as the public health response time (PHRT). In comparison, our measure not only accounts for the timing, but also accounts for the intensity/ rigidity of containment. Another difference is that they explicitly exclude international travel restrictions from the measures they analyze, while we find suggestive evidence that this measure is important and was one of the main strategies used early on by countries with success in containing the virus. We thus include it in our analysis.

Covid Economics 74, 30 March 2021: 94-141

Covid Economics 74, 30 March 2021: 94-141

the effort to protect the most economically vulnerable. Flattening the infection curve can result in considerable macroeconomic damage, with studies estimating a 10 percent output loss from reduced economic activity and an equivalent fiscal cost (Gourinchas, 2020). Based on survey data, Coibion et al. (2020) study how lockdown measures affected households' spending decisions and expectations and report that 50 percent of survey participants incurred income losses (averaging 5,293 U.S. dollars) and wealth losses (averaging 33,482 U.S. dollars), which affected their spending decisions. Using daily data of Nitrogen Dioxide (NO_2) emissions as a proxy for economic activity, Deb et al. (2020a) find that containment measures have resulted in a loss of about 15 percent for industrial production over a 30-day horizon.

Our work contributes to the literature that assesses to what extent there exists a trade-off between saving lives and livelihoods, and the heterogeneous role played by different containment measures. Kaplan et al. (2020) estimate the trade-off between lower death rates and higher economic welfare costs implied by indiscriminate versus partial lockdown measures, tracing what they call the 'pandemic possibility frontier' (PPF). The authors note, however, that they do not evaluate other containment policies that may potentially further flatten or shift inward the PPF, such as contact tracing, widespread testing, border closures, and mandatory quarantines" and suggest this as an important task for future work.[5]

We find that lower deaths and more successful containment of Covid-19 are associated with better growth outcomes in 2020 without impacting countries' fiscal balances. Rather, lower death rates are associated with higher primary balances in 2020 and reduced debt levels in the medium run. However, these results may confound good policy with good luck. To address possible endogeneity concerns and estimate the effect of "smart" types of containment, we employ a two-stage-least-squares approach, where past experience in containing coronavirus epidemics is used as an instrument for death rates. The first stage regression reveals that past experience is associated with significantly lower death rates, controlling for countries' income level, and the F-statistic shows that our instrument is strong. In the second stage, we estimate the impact of lower Covid-19 deaths, instrumented by past experience, on economic performance. Our estimates confirm a positive impact on economic growth in 2020. Results are robust to controlling for the age structure of the population and Covid-19 fiscal support measures, among other sensitivity tests.

[5] Deb et al. (2020a) find 'preliminary evidence' that stay-at-home requirements and workplace closures are the costliest in economic terms but also the most effective in curbing infections and deaths, while school closures and international travel appear to be less costly but less successful in lowering COVID-19 infections, but emphasize that results should be treated with caution since many of these measures were often introduced simultaneously.

Covid Economics 74, 30 March 2021: 94-141

Finally, we consider the fact that countries with less experience in containing epidemics, often those less prepared to implement effective testing policies and contact tracing, in many cases resorted to stronger stringency measures over a longer period of time as a way to save lives. Such measures are likely to have reduced deaths while implying a trade-off for economic growth. We show that, in fact, countries with stricter containment measures, on average, experienced lower GDP growth. Interaction effects reveal that Covid-19 death rates are negatively related with economic growth, especially when average stringency measures were high.

Overall, the key implication of our analysis is that there is not necessarily a trade-off between saving lives and saving the economy. Countries in the Asian region with past SARS experience serve as an example: they were effective in containing Covid-19 and mitigating lockdown-associated economic costs due to a common smart strategy marked by targeted stringency and mass testing, contact tracing, and public information campaigns.

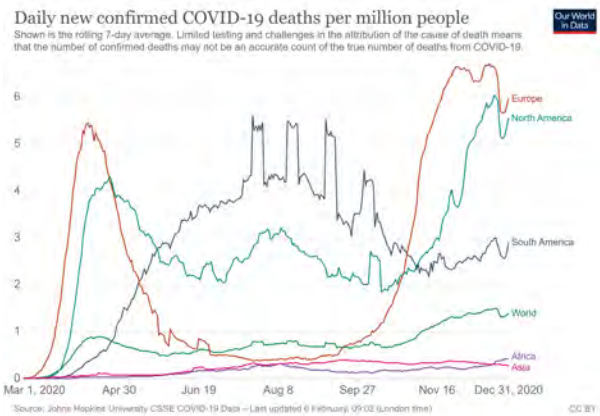
Our findings add to the literature of smart containment strategies that point to targeted lockdowns and selective quarantine (e.g. Eichenbaum et al., 2020, Favero et al., 2020, Acemoglu et al., 2020). As Andrabi et al. (2020) highlight, a smart containment strategy should be underpinned by data and contact tracing together with testing and authorities promoting voluntary compliance and trust. Dewatripont et al. (2020) propose a two-test approach to identify workers that are immune and non infectious, in line with Berger et al. (2020) who discuss the importance of testing and targeted quarantine polices. Baldwin (2020) presents the "Singapore model" —test, track, and trust— to motivate his proposal of a "big bazooka" of testing packages.

The remainder of the paper is organized as follows. Section 2 provides a narrative discussion of countries that successfully contained the Covid-19 pandemic. Section 3 describes the data used in the empirical analysis. Section 4 presents the empirical methodology, results, and policy lessons. Finally, Section 5 concludes.

2 Narrative Discussion of Success Stories

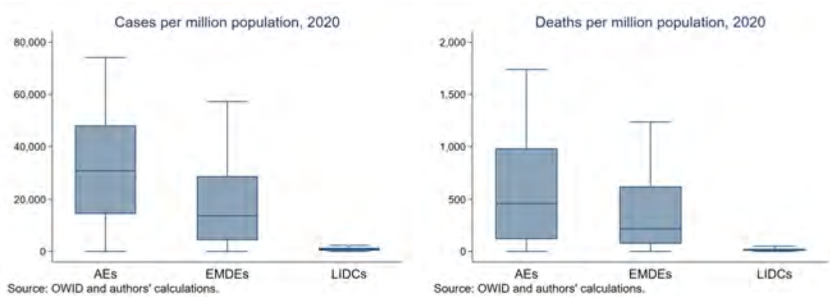
Figure 1 plots recorded Covid-19 deaths per million inhabitants by regions of the world. By this metric, Asia and Africa have been highly successful in containing the pandemic. While the reasons are still speculative, population age structure is likely a significant part of the story.

Figure 1: Global Waves of Covid-19 in 2020



More generally, recorded cases and deaths have been substantially lower in lower income countries (Figure 2), partly due to lack of widespread testing, but also because of their younger populations and the strong association between mortality and symptomatic cases and age. However, several Asian countries with relatively older populations and mass testing have been exceptionally successful in containing the spread of Covid-19. One possible explanation is their past experience in containing epidemics.

Figure 2: Covid-19 Incidence by Income Group



Before the current Covid-19 pandemic, three historically important epidemics had occurred since 2000: severe acute respiratory syndrome (SARS) in 2003, Middle East respiratory syndrome (MERS) in 2013, and Ebola virus disease (EVD) in 2014. The first two were caused by coronaviruses and the third by ebolavirus. All three were eventually contained largely through public health interventions. In particular, SARS was contained mainly through case detection and isolation, quarantine of close contacts, and enhanced infection control measures in settings where care was provided to infected people.

Covid Economics 74, 30 March 2021: 94-141

- SARS resulted in 8,000 recorded cases, including 774 deaths, with Mainland China, Hong Kong SAR, Taiwan Province of China, Canada, Singapore, and Vietnam experiencing significant outbreaks (over 50 cases in each).
- MERS caused over 2,500 cases and 881 recorded deaths, with the largest outbreaks affecting Saudi Arabia, South Korea, and United Arab Emirates (over 50 cases in each).
- The 2014-2016 Ebola outbreak in West Africa is estimated to have caused over 25,000 cases and 11,000 deaths. Significant outbreaks occurred in Guinea, Liberia, and Sierra Leone. In 2018, another large outbreak occurred in the Democratic Republic of Congo, with over 2,000 confirmed and probable cases reported and 1,357 deaths.

Countries with recent past pandemic experiences have been relatively successful in containing Covid-19 deaths. Countries with past SARS experience in particular saw low cases and deaths per capita, especially considering their population age structure and widespread testing. Countries with past MERS experience had low mortality but much larger outbreaks as measured by the number of cases. Testing was also less prevalent in the lower income countries previously hit by Ebola, and their younger populations helped cushion the hit from the pandemic.

Table 1 ranks the top 30 countries with lowest age-adjusted death rates per capita.[6] Notably, the six main countries with previous SARS experience all rank within the top-30, except for Canada which ranks 31st.

[6] Age-adjusted death rates are calculated as the residual when regressing deaths per capita on the share of population aged 70 and above. While ideally we would also control for testing, data is not available for as wide a sample of countries. As such, we chose to consider age-adjusted death rates rather than infection rates since the latter would be likely even more dependent on countries' testing policies.

Covid Economics 74, 30 March 2021: 94-141

Covid Economics 74, 30 March 2021: 94-141

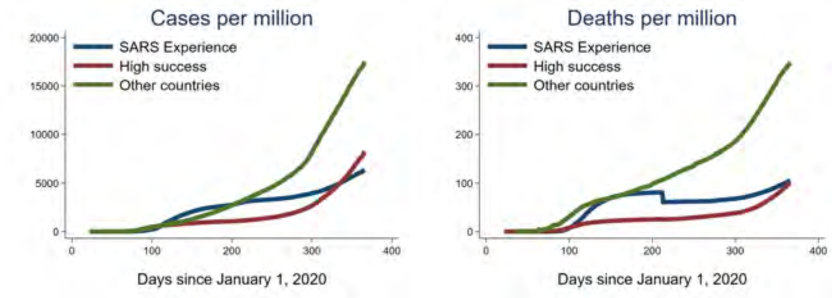
Table 1: 2020 Success Stories in Covid-19 Containment

Country	Success in Containing Covid-19: Top 30 Success in 2020: Age-Adj. Ranking	Deaths per million	Cases per million	Top 30 Success until Oct. 2020: Age-Adj. Ranking	Deaths per million	Cases per million	Pop share > age 70	Lowy's Covid Perf. Ranking	Recent Epidemic Experience
Japan	1	26	1864	1	14	801	18.5	45	
Finland	2	101	6517	6	65	2908	13.3	17	
Estonia	3	173	21100	5	55	3698	13.5	11	
Hong Kong SAR	4	20	1178	9	14	709	10.2	-	SARS
New Zealand	5	5	448	7	5	406	9.7	1	
Australia	6	36	1115	14	36	1082	10.1	8	
Uruguay	7	52	5504	8	17	899	10.4	12	
Norway	8	80	9143	15	52	3750	10.8	18	
Barbados	9	24	1333	13	24	825	9.5	-	
Taiwan Province of China	10	0	34	11	0	23	8.4	3	SARS
South Korea	11	18	1205	12	9	520	8.6	20	MERS
Germany	12	403	21013	10	125	6347	16.0	55	
Denmark	13	224	28334	27	124	8091	12.3	23	
Iceland	14	85	16862	16	35	14256	9.2	7	
Latvia	15	337	21686	2	38	3125	14.1	9	
Singapore	16	5	10016	20	5	9917	7.0	13	
Thailand	17	1	103	17	1	54	6.9	4	
Belarus	18	151	20561	29	104	10422	9.8	60	
Cyprus	19	136	25139	18	30	4985	8.6	5	
China	20	3	67	22	3	63	5.9	-	SARS
Mauritius	21	8	414	24	8	347	5.9	-	
Greece	22	464	13321	3	60	3766	14.5	32	
Sri Lanka	23	10	2022	25	1	498	5.3	10	
Vietnam	24	0	15	28	0	12	4.7	2	SARS
Jamaica	25	102	4332	35	70	3071	6.4	31	
Trinidad and Tobago	26	91	5109	62	77	4067	5.8	28	
Fiji	27	2	55	31	2	38	3.3	-	
Malaysia	28	15	3492	33	8	975	3.4	16	
Nicaragua	29	25	913	36	24	832	3.5	-	
Algeria	30	63	2272	65	45	1321	3.9	-	
Canada	31	418	15484	114	272	6288	10.8	61	SARS
Other countries with success until Oct. 2020									
Slovak Republic	69	392	32885	19	40	10562	9.2	22	
Slovenia	150	1297	58757	30	163	16502	12.9	33	
Lithuania	94	660	52145	4	56	5442	13.8	19	
Austria	102	691	40062	21	123	11650	13.7	42	
Georgia	115	628	57009	23	77	9760	10.2	-	
Croatia	132	955	51358	26	133	12013	13.1	54	
Other countries in top third of Lowy's Covid Performance Index									
Rwanda	64	7	647	53	3	397	1.6	6	
Malta	63	496	28931	32	140	13684	11.3	14	
Togo	76	8	439	73	7	282	1.5	15	
Tunisia	119	396	11773	100	111	5061	5.1	21	
Myanmar	41	49	2291	41	23	969	3.1	24	
Mozambique	53	5	596	45	3	412	1.9	26	
Malawi	61	10	344	64	10	310	1.8	27	
Zambia	89	21	1127	87	19	894	1.5	29	
Uganda	86	5	770	69	2	273	1.3	30	
Other countries with past recent epidemics									
Congo, Democratic Republic of	59	7	197	49	3	126	1.7	39	Ebola
Guinea	60	6	1045	56	5	919	1.7	-	Ebola
Liberia	71	16	352	83	16	282	1.8	-	Ebola
Sierra Leone	91	10	327	84	9	297	1.3	-	Ebola
United Arab Emirates	108	68	21013	107	50	13410	0.5	35	MERS
Saudi Arabia	114	179	10419	119	155	9975	1.8	64	MERS

This table presents the top-30 countries with lowest age-adjusted mortality rates in 2020, as well as rankings as of October 2020, and the top one-third of countries ranked according to Lowy's Covid-19 Performance Index.

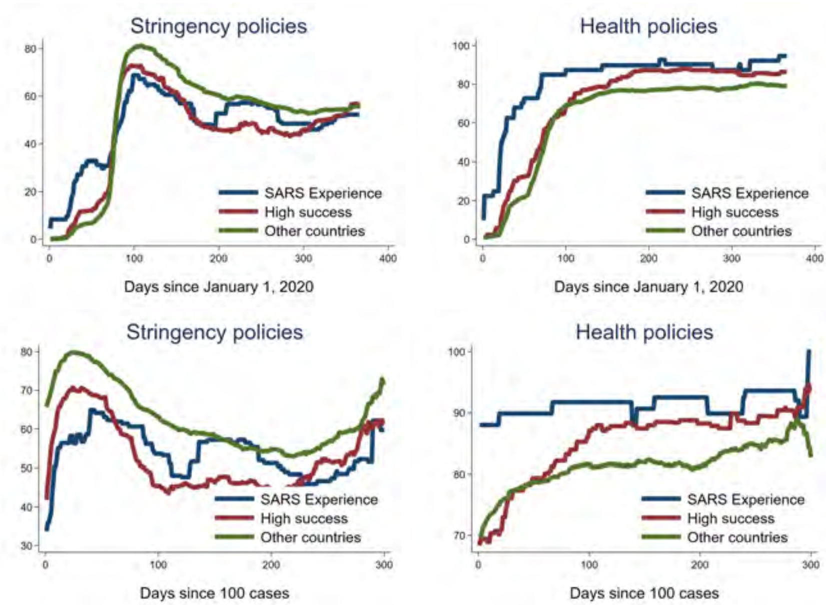
Figure 3 shows the markedly lower incidence of Covid-19 in the top-30 "high success" countries, as well as in the six countries with past SARS experience, compared to the rest of the world.

Figure 3: Covid-19 Incidence: Containment by Success Groups



Arguably, lower death rates could be a result of "good luck" rather than "good policy". For instance, perhaps countries with lower (age-adjusted) death rates were less exposed to the virus due to their geographic position, fewer connections with the rest of the world, or lower population densities reducing the speed of transmission. While these factors may have played a part, we argue that policies have played a much more important role.

Figure 4: Timeline of Containment Policies: Learning from Countries with Past SARS Experience



For example, countries with past outbreaks of SARS in the Asian region, not only acted faster but also implemented a different strategy overall. Figure 4 shows that these countries[7] implemented at least some stringency measures remarkably

[7]We exclude China from our initial discussion and the SARS average since it was the place of origin of the epidemic.

Covid Economics 74, 30 March 2021: 94-141

earlier (perhaps due to fears of importing the virus from nearby China) and also had stronger health policies throughout the year. Figure 5 shows that, differently from most other countries, countries with past SARS experience: (i) quickly imposed restrictive measures such as international travel restrictions, school closures, and cancellation of public events, (ii) were proactive in implementing stronger health policies such as public information campaigns, testing policy, and contact tracing; and (iii) relied relatively less on other measures such as stay-at-home requirements, closures of public transport, restrictions on internal mobility. Perhaps due to past experience, public information campaigning seems to have been enough for people to 'act cautiously' and reduce mobility (Figure A.1). All in all, their early and smart containment strategies, which included the rapid implementation of targeted stringency and mass testing, contact tracing, and public information campaigns, allowed these countries to successfully curb the spread of the virus, despite their geographic proximity and high interconnection with China, the country of origin of Covid-19.

One particular 'success case' that implemented this strategy is Vietnam, a country that shares a border with China, and by July 15 had only 380 cases and no deaths related to Covid-19 despite large-scale testing. The country's early response and strategic approach (with previous experience with SARS in 2003) included imposing wide-ranging social distancing measures and movement restrictions early on, mobilizing a large number of contact tracers (using a low-cost approach), and a strong public information campaign. Implementing these measures allowed Vietnam to successfully contain the virus, much more so than the Philippines, which has approximately the same population and similar proximity to China, but which imposed various containment measures with a comparative delay (Figure A.2). According to the Lowy Institute's Covid Performance Index, which ranks countries' performance in managing the COVID-19 pandemic in the 36 weeks following their hundredth confirmed case of the virus, Vietnam ranks 2nd place while the Philippines ranks 79th. This is despite Vietnam beginning to ease lockdown restrictions as early as April 23rd.

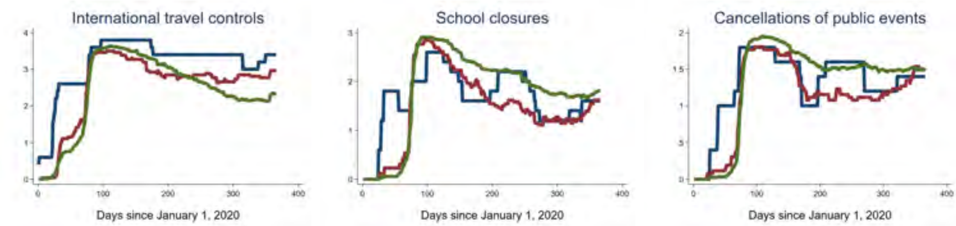
Covid Economics 74, 30 March 2021: 94-141

Covid Economics 74, 30 March 2021: 94-141

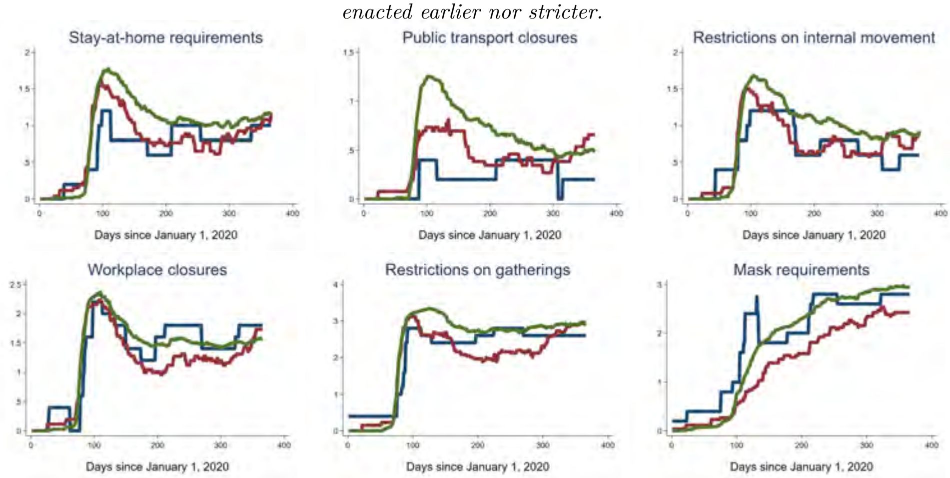
Figure 5: Timeline of Containment Measures, by Containment Success Groups

Countries with past SARS experience enacted earlier with stronger health policies (public information campaigns, testing, and contact tracing) ...

... and earlier restrictive measures such as international travel controls, school closures, and public event cancellations.



Yet, policies limiting mobility and gatherings of people (e.g. stay-at-home orders, workplace and transport closures, internal mobility and gathering restrictions) and mask requirements were not enacted earlier nor stricter.



Source: OxCGRT Database and authors' calculations.

Covid Economics 74, 30 March 2021: 94-141

Other countries with "high success" in containing (age-adjusted) Covid-19 death rates shown in Table 1, include several smaller Northern European countries (e.g. Finland, Estonia, Norway, Denmark, Iceland, Latvia), several islands in Asia (e.g. Japan, New Zealand, Australia, Fiji, Sri Lanka), the Caribbean (Barbados, Jamaica, Trinidad and Tobago), Africa (Mauritius), and Europe (Cyprus, Greece), and various other mainland countries (e.g. Uruguay, Germany, Thailand, Malaysia, Canada).[8] While it may be that these countries have their own specificities for one reason or another, note that their successful containment of Covid-19 contrasts with the experiences in neighboring countries such as in Sweden and Lithuania in Northern Europe (ranked 130th and 95th), islands such as the United Kingdom, the Bahamas, Cabo Verde, and Dominican Republic (ranked 140th, 122nd, 107th, 104th), islands in Asia such as the Philippines and Indonesia (ranked 92nd and 70th), and other neighboring mainland countries in South America (e.g. Brazil, Argentina, Paraguay, ranked 151st, 148th, and 117th), Europe (e.g. Belgium, France, Luxembourg, ranked 156th (last), 134th, and 131st), and North America (the United States, ranked 145th). These successful countries, on average, acted with somewhat earlier stringency measures compared to other countries and were able to strengthen health measures more quickly, over time converging to the health measures of countries with past SARS experience (Figure 4). In particular, they more rapidly strengthened their testing policy and also maintained stricter international travel controls throughout the year, while relaxing most domestic stringency measures compared to other countries (Figure 5). Note that at the time of 100 reported cases, these countries did not have, on average, tighter stringency measures nor stronger public health measures in place (Figure A.3). Strengthening their public health measures, such as testing and contact tracing, was a learning process as most lacked prior recent experience in using these methods to control pandemics. In contrast, countries with past SARS experience put in place stronger public health measures from the onset.

It is also worth noting that the composition of the group of successful countries in containing Covid-19 changed with subsequent waves. For example, in Europe, countries like Lithuania, the Slovak Republic, Austria, Georgia, Croatia, and Slovenia, which had been highly successful in containing the virus up until September 2020, were unable to contain its spread in the last quarter of 2020, when a second strong wave hit the continent. Figure A.4 shows the containment measures enacted by countries that had successfully contained Covid-19 until September 2020 but were unsuccessful thereafter, compared to those which remained successful throughout the remainder of the year. It appears that the former (successful only in wave 1)

[8]Note that data underreporting is a caveat of this ranking.

relaxed several stringency measures, both pertaining to international travel controls and domestic restrictions, relatively more than their counterparts that were subsequently more successful. This reduction in stringency measures, may have caused cases to surge.

3 Data and Descriptive Statistics

Our analysis draws on cross-sectional data for over 150 countries, covering the following variables:

Covid-19 Containment measures. Daily data of government measures to contain the spread of Covid-19 is obtained from the Oxford Coronavirus Government Response Tracker (OxCGRT) spanning January 1- December 31, 2020 and covering over 150 countries. The overall government response index takes into account 19 indicators on: (i) containment and closure policies (8 indicators), (ii) health system policies (7 indicators), and (iii) economic policies (4 indicators). The sub-indices include: (i) school closures, workplace closures, cancellation of public events, restrictions on gathering, public transport closures, stay-at-home requirements, restrictions on internal movement, and international travel controls; (ii) public information campaigns, testing policy, contact tracing, announced investment in healthcare, announced spending on vaccine development, facial covering requirements, and vaccination policies; and (iii) cash payments to households, freezes on financial obligations for households, announced economic stimulus spending, and international support to other countries.[9]

We make use of three main containment indicators throughout our analysis:

1. 'Overall containment measures': This is taken to be the overall 'containment and health index' reported by OxCGRT, which summarizes all containment and closure policies (8 indicators) as well as the 3 first indicators relating to health system policies (public information campaigns, testing policy, and contact tracing).

2. 'Stringency measures': This is taken to be the 'stringency index' reported by OxCGRT, which summarizes all containment and closure policies (8 indicators) as well as the first indicator relating to health system policies (public information campaigns). This indicator intends to capture policies that restrict people's movements such as closures and stay-at-home orders.

3. 'Public health measures': We construct a principal component of the 3 first indicators relating to health system policies (public information campaigns,

[9]Detailed information is available on: https://github.com/OxCGRT/covid-policy-tracker/blob/master/documentation/codebook.md#codebook-changelog

Covid Economics 74, 30 March 2021: 94-141

testing policy, and contact tracing). As such, this indicator focuses on 'smart' health measures.

We further aggregate the daily data into two main summary indicators:

1. 'Average strength' of containment measures, defined as the average value over the year (or corresponding sub-period). This does not take into account the timing of when measures were put in place.

2. 'Early strength' of containment measures, defined as the measures in place when the 100th case was recorded. This accounts for the timing of when measures were put in place.

Note that we normalize all containment indicators on a 0-1 scale.

Covid-19 death and cases. We use daily data on recorded Covid-19 cases and deaths from Our World in Data (OWID) database.[10] We complement this with data from the Coronavirus Resource Center of Johns Hopkins University, which tracks daily Covid-19 statistics from official country announcements on testing, infections, deaths and recoveries.[11].

Covid-19 containment success. We make use of Lowy Institute's Covid-19 Performance Index, which measures 98 countries' relative success in managing Covid-19 in the 36 weeks that followed countries' 100th confirmed case (based on confirmed cases and deaths, totals as well as per capita, cases as a proportion of tests, and tests per thousand people). We also construct our own ranking of containment success based on age-adjusted death rates (calculated as the residual after regressing death rates on the share of population over age 70) for our larger sample of over 150 countries.

Macroeconomic variables. Macroeconomic variables are taken from the IMF's World Economic Outlook (WEO) database, including data on: GDP per capita (in PPP USD terms), real GDP growth, real per capita GDP growth, the primary balance (as a percent of GDP), and gross public debt (as a percent of GDP). The primary data source of data is the January 2021 WEO. However, we also look into projection revisions across different vintages (October 2019, January 2020, July 2020, October 2020) of the WEO database.

Fiscal support measures. Data on Covid-19 fiscal support measures are obtained from the IMF's policy tracker on policy responses and the IMF Fiscal Monitor database of Covid-19 Fiscal Response Measures published in June 2020, October 2020, and January 2021.[12] We primarily make use of total above-the-line fiscal

[10] https://ourworldindata.org.
[11] https://coronavirus.jhu.edu/map.html
[12] https://www.imf.org/en/Topics/imf-and-covid19/Policy-Responses-to-COVID-19

Covid Economics 74, 30 March 2021: 94-141

support announcements as well as amounts implemented in 2020, where the data are measured as a percent of GDP.

Mobility. We make use of Google's Community Mobility Report data, which contains daily data on movement trends by country, across different categories of places such as retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential. We create a principal component that summarizes the different categories into an overall indicator of mobility. We also make use of Apple Map's Mobility Trends Report dataset.[13]

Health preparedness. Data on hospital beds per thousand inhabitants are obtained from Our World In Data.

Population age, size, and density. Population age, size, and density data are taken from Our World in Data.

WEO country income groups. We classify countries according to the WEO's country income groups, as advanced economies (AEs), low-income developing countries (LIDCs) and other emerging market and developing economies (EMDEs), and note relevant differences in death rates, containment measures, and macroeconomic performance across these groups. We control for these country groups throughout our analysis.

Figure 2 shows the markedly higher incidence of Covid-19 cases and deaths reported by advanced economies, followed by emerging markets, and least by low-income developing countries. This reflects differences such as reporting, testing policy, demographics, connectivity, and containment measures across the groups.

Figure A.5 shows box plots of Covid-19 containment measures according to country income groups. Stringency measures were on average stricter in emerging markets, while more stringent measures were in place earlier (at 100 cases) in developing countries. Advanced economies had stronger average health policies, whereas early health policies were similar across country groups.

Figure A.6 plots GDP growth for different WEO data vintages by country income groups. The largest economic contractions in 2020 were experienced by emerging markets, followed by advanced economies, and smallest for low-income developing countries. At the same time, primary deficits and increases in public debt were largest for advanced economies, followed by emerging markets, and smallest for low-income developing countries (Figure A.7). This is in line with the fact that Covid-19 fiscal support measures were substantially larger for advanced economies relative to developing countries, as measured by total above-the-line support as a

[13] https://www.apple.com/covid19/mobility

Covid Economics 74, 30 March 2021: 94-141

share of GDP (Figure A.8).

4 Empirical Analysis

This section presents empirical evidence on the impact of Covid-19 containment. First, we study the role of containment measures in reducing the spread and severity of the pandemic, as measured by the number of deaths per capita, focusing on the strategies employed by more successful countries. Second, we assess the effect of containing Covid-19 on the macroeconomy and countries' public finances.

4.1 The effectiveness of Covid-19 containment measures

As highlighted in the literature review above, several studies have shown that different government measures have been effective in containing the spread of Covid-19. For example, Cowling et al. (2020) show that non-pharmaceutical interventions (e.g. social distancing measures) and behavioral changes were effective in reducing the incidence of Covid-19 infections. Deb et al. (2020b) show using local projection methods that stringency measures, such as stay-at-home requirements, reduced the number of deaths, especially when implemented early and when they resulted in less mobility.

In this section, we do not intend to dispute the consensus that containment measures were successful in reducing the spread of the virus. Instead, our focus is on detecting 'smart' measures. What were the containment measures taken by countries who successfully contained the pandemic, and how did they differ from policies adopted by other countries? In particular, we highlight the importance of distinguishing between stringency measures (such as lockdown restrictions) and health policy measures (such as widespread testing and contact tracing). We also highlight the relevance of imposing containment measures early on, before the virus becomes widespread.

As a "quick-and-dirty" way to study the effectiveness of stringency measures in containing the virus, we estimate the following cross-country regression:

$$Death\ rate_i = \beta_0 + \beta_1 C_i + \beta_2 X_i + u_i \tag{1}$$

where $Death\ rate_i$ denotes the death rate per thousand inhabitants in country i, while C_i captures Covid-19 containment measures (i.e., the average level of containment measures since March 2020 and the level of containment measures implemented early on, when the country had only 100 recorded cases of Covid-19), X_i includes the set of control variables – country-specific characteristics, such as median age and health care capacity (proxied by hospital beds per capita), GDP per capita and

Covid Economics 74, 30 March 2021: 94-141

WEO country income groupings –, and β_0 and u_i denote the constant and error term, respectively.

We note that this specification does not address endogeneity concerns - a caveat inherent also in the aforementioned studies - and thus causality should be interpreted with caution. For example, it is plausible that stronger containment measures are put in place precisely because the rate of Covid-19 transmission is high, which would bias coefficient estimates of the effectiveness of containment measures in reducing deaths. As such, the regression estimates should be interpreted as correlations rather than causal relations.

Tables 2 and 3 present evidence on containment measures being associated with curbing deaths.[14] In particular, in the case where strong stringency measures are implemented early on (at the time of 100 cases) these measures are significantly associated with lower deaths up until October 2020.[15] This is consistent with others' findings (e.g. Deb et al., 2020b) that stringency measures have mattered particularly early on. Stronger overall public health measures (on average during the sample period) are also associated with lower deaths per capita. By contrast, stronger overall stringency (on average during the sample period) is positively associated with deaths per capita, likely due to an endogenous relationship whereby stringent containment measures are put in place for longer in places where the pandemic is less contained. The control variables carry the expected signs: countries with a more elderly population and lower health preparedness had higher death rates.

Table 2: Effect of Containment Measures - Average vs. Early Response, 2020 by Month

	(1) Apr. Deaths/pop	(2) May Deaths/pop	(3) Jun. Deaths/pop	(4) Jul. Deaths/pop	(5) Aug. Deaths/pop	(6) Sep. Deaths/pop	(7) Oct. Deaths/pop	(8) Nov. Deaths/pop	(9) Dec. Deaths/pop
Containment (average)	101.884	140.769	223.482**	315.315***	408.270***	467.717***	518.729***	543.993***	539.886***
	(81.086)	(93.272)	(95.011)	(97.842)	(106.272)	(115.267)	(128.018)	(158.775)	(197.570)
Containment (at 100 cases)	-77.058*	-124.338**	-187.242***	-229.402***	-252.951***	-253.912***	-244.617***	-206.642*	-161.650
	(40.723)	(52.838)	(56.464)	(62.270)	(70.726)	(79.887)	(89.327)	(109.412)	(134.740)
Median age	3.684*	4.685*	5.197*	5.106*	5.499	6.583	9.093**	19.211***	32.186***
	(1.987)	(2.462)	(2.683)	(3.044)	(3.523)	(4.016)	(4.529)	(5.570)	(6.790)
Hospital beds / 1,000 population	-9.127**	-11.870**	-13.014**	-12.567*	-12.783	-14.083	-13.872	-15.771	-19.613
	(4.531)	(5.639)	(6.155)	(7.051)	(8.130)	(9.235)	(10.383)	(12.772)	(15.373)
Log GDP per capita	-7.581	-9.631	-12.902	-20.288	-29.815	-41.427	-53.817	-93.923**	-134.268**
	(15.993)	(19.565)	(21.495)	(24.638)	(28.426)	(32.292)	(36.320)	(44.579)	(54.160)
EMDEs	-87.784***	-104.111***	-84.523**	-64.321	-43.398	-25.288	-12.785	-21.232	-24.388
	(26.245)	(32.378)	(35.409)	(40.375)	(46.620)	(52.934)	(59.514)	(73.203)	(90.340)
LIDCs	-67.461	-81.549	-67.597	-76.397	-91.706	-113.436	-129.404	-173.067	-206.126
	(49.323)	(60.296)	(65.581)	(73.046)	(84.350)	(95.942)	(108.097)	(133.317)	(164.812)
Constant	28.731	36.871	17.934	18.283	1.281	-26.082	-89.198	-256.555	-482.233*
	(79.067)	(96.775)	(106.758)	(119.868)	(139.269)	(159.798)	(181.531)	(224.674)	(277.924)
Observations	127	132	132	134	134	134	134	134	136
R-squared	0.337	0.340	0.328	0.284	0.266	0.260	0.268	0.316	0.380

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[14] Results are robust to including additional control variables e.g. population size and density.

[15] Note from Figure 1 that the period up to October 2020 corresponds to the period that all countries in our sample and different regions experienced their first Covid-19 wave.

Covid Economics 74, 30 March 2021: 94-141

CEPR PRESS

Table 3: Effect of Containment Measures - Stringency vs Health Policies, 2020 by Month

	(1) Apr. Deaths/pop	(2) May Deaths/pop	(3) Jun. Deaths/pop	(4) Jul. Deaths/pop	(5) Aug. Deaths/pop	(6) Sep. Deaths/pop	(7) Oct. Deaths/pop	(8) Nov. Deaths/pop	(9) Dec. Deaths/pop
Stringency (average)	278.327***	324.611***	368.228***	453.853***	539.422***	603.174***	665.827***	703.852***	682.713***
	(93.063)	(97.963)	(93.180)	(92.246)	(97.573)	(102.366)	(112.687)	(141.872)	(176.121)
Health policies (average)	-172.993**	-241.285**	-259.753**	-319.352**	-358.873**	-388.658**	-435.432**	-505.430**	-513.122*
	(81.060)	(106.217)	(124.504)	(146.516)	(170.177)	(188.466)	(206.574)	(251.480)	(302.976)
Stringency (at 100 cases)	-135.801***	-193.368***	-222.077***	-229.871***	-222.917***	-196.508***	-179.157**	-147.972	-92.057
	(42.304)	(53.796)	(55.913)	(59.796)	(66.070)	(72.262)	(80.058)	(100.061)	(125.434)
Health policies (at 100 cases)	68.694	80.589	28.796	-28.915	-80.928	-140.833	-142.806	-97.402	-108.476
	(66.560)	(84.515)	(93.968)	(106.406)	(119.973)	(131.239)	(144.643)	(178.684)	(222.142)
Controls:									
Median age	3.560*	4.278*	5.056*	5.213*	5.510*	6.342*	8.712**	18.402***	30.665***
	(1.953)	(2.411)	(2.603)	(2.900)	(3.321)	(3.729)	(4.201)	(5.283)	(6.576)
Hospital beds / 1,000 population	-7.532*	-7.644	-8.517	-7.439	-7.022	-7.412	-6.099	-6.805	-10.486
	(4.449)	(5.643)	(6.112)	(6.853)	(7.806)	(8.736)	(9.829)	(12.392)	(15.224)
Log GDP per capita	-6.696	-4.396	-0.830	4.734	5.040	1.885	-5.465	-41.205	-73.454
	(16.022)	(19.462)	(21.314)	(24.201)	(27.766)	(31.137)	(35.052)	(44.138)	(54.961)
EMDE dummy	-86.129***	-104.652***	-92.751***	-80.450**	-68.553	-60.216	-50.220	-57.380	-57.680
	(25.722)	(31.727)	(34.570)	(38.637)	(44.214)	(49.539)	(55.663)	(69.995)	(88.035)
LIDC dummy	-53.460	-62.430	-53.793	-55.946	-72.409	-95.887	-112.430	-154.817	-182.595
	(48.503)	(58.789)	(63.404)	(69.322)	(79.243)	(88.962)	(100.277)	(126.532)	(159.704)
Constant	-9.708	5.234	14.289	32.923	44.752	55.762	17.016	-127.143	-333.030
	(79.958)	(97.221)	(106.204)	(117.042)	(135.005)	(153.134)	(173.492)	(218.941)	(275.242)
Observations	127	132	132	134	134	134	134	134	136
R-squared	0.382	0.391	0.386	0.367	0.363	0.376	0.383	0.396	0.431

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Since many of the containment measures have often been implemented at the same time, it is difficult to disentangle between their effects. While acknowledging that their study is also subject to these caveats, Deb et al. (2020b) suggest that stay-at-home orders were among the most effective measures.[16] By contrast, we find a different subset of containment measures to be associated with higher success in containing Covid-19. Table 4 shows that most stringency measures individually are positively related with country death rates (due to reverse causality), with the exception of international travel controls, for which policies often differed from domestic measures and evidence seems to be strong in favor of reducing contagion. This is in line with narrative evidence of successful countries with past experience from the SARS coronavirus (Figure 5) that imposed international travel restrictions very early on (e.g. Taiwan Province of China, Vietnam, Hong Kong SAR, Singapore) to decrease the risk of importing the disease. We also find robust evidence in favor of strong health policies (e.g. widespread testing) being associated with lower death rates. Note that while Deb et al. (2020b) explicitly excluded international travel controls and public health policies from the measures considered in their analysis, we consistently find evidence that these seem to be among the most effective containment measures (employed the most by successful countries).

[16]The authors estimate the impact of different containment measures using local projection methods, with country fixed effects that capture country-specific characteristics (such as population age, density, etc), which we have also tried to capture in our control variables.

Covid Economics 74, 30 March 2021: 94-141

Table 4: Effect of Individual Containment Measures (One at a time), 2020

	(1)	(2)	(3)	(4)		
	Average Response		Early Response		Containment correlation	
	Deaths/pop	Deaths/pop	Deaths/pop	Deaths/pop	Average	Early
Containment measures:						
School closures	430.036***	529.049**	56.35	73.74	0.7294	0.7179
Workplace closures	400.841***	553.320***	134.890*	259.887**	0.7347	0.7727
Cancellations of public events	407.690***	602.445**	17.666	8.083	0.8171	0.7066
Restrictions on gatherings	368.835***	537.575**	116.648*	240.301**	0.7745	0.7782
Public transport closures	149.333	71.633	79.429	117.66	0.6575	0.7028
Stay-at-home requirements	199.794	118.702	116.784	191.62	0.7393	0.7468
Restrictions on internal movement	120.069	14.404	40.283	60.514	0.6509	0.7959
International travel controls	-399.315***	-508.694***	-172.312*	-301.532**	0.2625	0.702
Public information campaigns	-162.978	-422.749**	-154.511	-220.524	0.5425	0.4395
Testing policy	-358.133**	-470.073***	-244.661*	-278.107**	0.4013	0.2116
Contact tracing	-125.393	-202.928	-94.185	-105.261	0.3999	0.1163
Mask requirements	207.184	102.368	-166.234	-175.722	0.5362	0.2899
Controls:						
Overall containment	No	Yes	No	Yes		
Median age	Yes	Yes	Yes	Yes		
Hospital beds / 1000 pop	Yes	Yes	Yes	Yes		
Log GDP per capita	Yes	Yes	Yes	Yes		
WEO income groups	Yes	Yes	Yes	Yes		
Constant	Yes	Yes	Yes	Yes		

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: *t*-Test for Difference in Containment Measures (One at a time), 2020

	Average containment policies				Early containment policies			
	High success	Others	Diff.	*t*-statistic	High success	Others	Diff.	*t*-statistic
Overall containment:								
Containment policies	0.59	0.67	-0.078**	2.33	0.39	0.61	-0.219***	4.43
Stringency	0.55	0.67	-0.122***	3.27	0.41	0.65	-0.240***	4.46
Health policies	0.72	0.62	0.096***	-2.90	0.61	0.61	0.000	0.00
Individual policies:								
School closures	1.46	1.84	-0.384***	3.91	1.50	2.55	-1.048***	4.55
Workplace closures	1.16	1.35	-0.190*	1.84	0.75	1.66	-0.911***	3.84
Cancellations of public events	1.13	1.36	-0.235***	3.44	1.29	1.72	-0.432***	2.96
Restrictions on gatherings	1.94	2.39	-0.451***	3.06	1.07	2.51	-1.437***	4.33
Public transport closures	0.38	0.60	-0.218***	2.66	0.21	0.84	-0.624***	3.59
Stay-at-home requirements	0.76	0.99	-0.237**	2.32	0.54	1.15	-0.618***	2.96
Restrictions on internal moveme	0.71	0.93	-0.218**	2.33	0.43	1.21	-0.781***	4.15
International travel controls	2.61	2.40	0.208**	-2.12	2.64	3.15	-0.510*	1.91
Public information campaigns	1.72	1.67	0.057	-1.36	1.89	1.85	0.046	-0.47
Testing policy	1.83	1.45	0.379***	-3.56	1.18	1.23	-0.047	0.35
Contact tracing	1.38	1.21	0.165*	-1.78	1.25	1.24	0.008	-0.05
Mask requirements	1.43	1.86	-0.429***	3.39	0.32	0.63	-0.311	1.37
Country sample	30	124			28	125		

Table 5 presents *t*-test statistics for differences in mean containment measures between countries with high success in containing Covid-19 in 2020 (the 30 countries with lowest age-adjusted mortality rates) compared to the rest of the sample of countries. Notably, countries that were more successful in containing the pandemic did not have stronger containment measures in place early on (at the time of 100 cases), suggesting that although this was associated with lower deaths earlier on in the year, this was not the main determinant of success by the end of the year. However, they had stronger health measures, including testing policy and contact tracing, as well as stronger international travel controls in place throughout the year.

Covid Economics 74, 30 March 2021: 94-141

Their stringency policies, instead, were less strict on average throughout the year, as success in containing the virus early on meant they could subsequently relax certain stringency measures relatively more.

Table A.1 confirms these findings using regression analysis, showing that a higher success rank is associated with a lower Covid-19 death rate and also with more relaxed containment policies (especially regarding stringency measures), on average in 2020, but stronger health policies and travel controls.

Table A.2 regresses the Lowy Institute's Covid Performance Index, which measures countries' relative success in managing Covid-19 in the 36 weeks that followed countries' 100th confirmed case, on containment measures. In line with the evidence already presented, countries that were less successful in containing Covid-19 had more stringent measures in place on average (due to reverse causality), while countries with stronger health measures on average fared better in containing the virus. A similar case holds for international travel controls, which appear to have been employed more by countries that performed better in managing Covid-19. In addition, countries with more stringent measures in place early on (at 100 cases) also performed better in managing Covid-19. This confirms the relevance of early stringency measures.

4.2 Does saving lives imply higher economic and fiscal costs?

This section provides empirical evidence on the impact of lower Covid-19 deaths per capita on countries' economic outcomes. Our evidence runs against the idea that saving lives necessarily came at a higher economic and fiscal cost. First, we show that lower deaths per capita are associated with higher economic growth, without significantly impacting countries' primary balances and without being associated with significantly different fiscal support packages. Second, we show that countries with a higher success ranking (lower age-adjusted mortality rates) also experienced higher GDP growth without significantly different fiscal costs. Third, using countries' recent past experience in containing epidemics as an exogenous instrument, we confirm that containing Covid-19 deaths is associated with higher growth in 2020, without significantly impacting countries' medium-term fiscal position.

We estimate the following regression:

$$Y_{i,h} = \beta_0 + \beta_1 Death\ rate_i + \beta_2 X_i + u_i \tag{2}$$

where $Y_{i,h}$ denotes the outcome variable in country i at time horizon $h = 2020, ..., 2025$. The set of control variables X_i includes log GDP per capita in U.S. dollar PPP terms and WEO country income groups. In each regression β_0 and u_i are the constant and

Covid Economics 74, 30 March 2021: 94-141

error term, respectively.

We consider the following outcome variables from the IMF's World Economic Outlook (WEO): real GDP per capita growth rates, real GDP growth rates, the primary balance as a share of GDP, and public debt as a share of GDP. Using the January 2021 WEO vintage, we consider the actual level of these indicators in 2020 (and projections beyond then), as well as the difference versus 2019, and the WEO revisions vis-a-vis the January 2020 vintage of the WEO.[17] We also consider the impact on Covid-19 fiscal support packages using data from the IMF's Fiscal Monitor database.

The Role of Covid-19 Deaths

We find that countries with higher Covid-19 death rates experienced relatively worse economic performance, while having insignificantly different fiscal out-turns. Tables 6 and A.3 show that countries with more significant Covid-19 outbreaks, as measured by cumulative Covid-19 deaths per capita, saw: (i) larger downward growth forecast revisions for each of the WEO forecast publications in 2020, (ii) a sharper fall in growth compared to 2019, and (iii) a significantly lower realized growth rate in 2020.[18]

Table 6: GDP Per Capita Growth Revisions for 2020 - Relation with Deaths

	(1)	(2)	(3)	(4)	(5)	(6)
	2020 GDP Growth Per Capita (%)					
	Difference vs. Jan 2020 WEO Forecast				vs. 2019	Actual
WEO Edition	Apr 2020	Jul 2020	Oct 2020	Jan 2021	Jan 2021	Jan 2021
Cumulated Covid-19 deaths	-2.73*	-5.34***	-3.78***	-2.14**	-2.58***	-2.29**
	(1.38)	(1.56)	(1.32)	(0.88)	(0.88)	(0.96)
Log GDP per capita	0.36	0.08	0.41	0.86	0.71	0.97*
	(0.31)	(0.41)	(0.52)	(0.53)	(0.52)	(0.57)
EMDE dummy	1.98***	0.31	-0.89	-1.55*	-0.87	-1.09
	(0.55)	(0.73)	(0.90)	(0.93)	(0.92)	(1.01)
LIDC dummy	4.27***	2.94**	3.86**	2.60	2.51	3.63*
	(0.99)	(1.34)	(1.68)	(1.74)	(1.73)	(1.89)
Constant	-9.58***	-9.34***	-8.19***	-9.22***	-8.49***	-8.13***
	(1.22)	(1.63)	(2.06)	(2.12)	(2.10)	(2.29)
Observations	139	147	153	155	155	155
R-squared	0.33	0.27	0.28	0.17	0.16	0.18

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7 shows that higher deaths per capita were not associated with significantly different primary balances (or changes vis-a-vis previous forecasts or compared to 2019 levels).

[17] Results are robust to different vintages for the base year, e.g. considering changes vis-a-vis the October 2019 vintage of the WEO.

[18] Results are robust to including additional controls, e.g. oil exporter and commodity exporter dummies.

Table 7: Primary Balance Revisions for 2020 - Relation with Deaths

	(1)	(2)	(3)	(4)	(5)	(6)
	2020 Primary Balance (% of GDP)					
	Difference vs. Jan 2020 WEO Forecast				vs. 2019	Actual
WEO Edition	Apr 2020	Jul 2020	Oct 2020	Jan 2021	Jan 2021	Jan 2021
Cumulated Covid-19 deaths	1.245	0.657	-1.217	-0.352	-0.555	-0.390
	(2.103)	(1.756)	(1.142)	(0.751)	(0.831)	(0.951)
Log GDP per capita	-1.204**	-1.321***	-0.458	-0.552	-1.137**	-1.368**
	(0.468)	(0.459)	(0.446)	(0.441)	(0.487)	(0.558)
EMDEs	0.900	2.447***	2.148***	1.476*	1.150	-0.481
	(0.835)	(0.824)	(0.773)	(0.785)	(0.868)	(0.994)
LIDCs	1.042	2.588*	4.299***	3.649**	2.006	-0.268
	(1.489)	(1.487)	(1.433)	(1.455)	(1.610)	(1.843)
Constant	-1.946	-4.246**	-6.343***	-5.366***	-3.231	-1.919
	(1.836)	(1.805)	(1.762)	(1.767)	(1.955)	(2.238)
Observations	136	144	151	153	153	153
R-squared	0.234	0.382	0.352	0.321	0.297	0.169

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Covid Economics 74, 30 March 2021: 94-141

Table 8 shows that countries with larger Covid-19 outbreaks did not provide larger fiscal support (support actually implemented in 2020 out of the total package) (column 1) or announce larger fiscal support packages as of January 2021 nor October 2020 (columns 2-3), according to the IMF Fiscal Monitor's Covid-19 Fiscal Measures databases.[19] To further test whether the weak relationship between the size of fiscal support and countries' Covid-19 outbreaks holds across country income groups, we further interact Covid-19 death rates with a dummy for advanced economies, and find that advanced economies that experienced higher death rates actually announced relatively smaller fiscal support packages as of late 2020/early 2021.

Table 8: Covid-19 Fiscal Support Packages - Relation with Deaths

	(1)	(2)	(3)	(4)	(5)	(6)
	Covid-19 Above-the-line Fiscal Support (% of GDP)					
	Support in 2020	Total support		Support in 2020	Total support	
FM Edition	Jan 2021	Jan 2021	Oct 2020	Jan 2021	Jan 2021	Oct 2020
Covid-19 deaths	0.54	0.30	0.14	0.98	1.63	2.01**
	(0.65)	(0.89)	(0.66)	(0.87)	(1.18)	(0.85)
Covid-19 deaths x AE dummy				-1.03	-3.08*	-4.30***
				(1.32)	(1.79)	(1.29)
Log GDP per capita	0.07	-0.18	0.28	0.06	-0.23	0.21
	(0.38)	(0.51)	(0.38)	(0.38)	(0.51)	(0.37)
EMDEs	-2.72***	-4.73***	-3.49***	-3.22***	-6.25***	-5.60***
	(0.67)	(0.91)	(0.68)	(0.93)	(1.26)	(0.91)
LIDCs	-2.89**	-5.20***	-3.62***	-3.28**	-6.38***	-5.27***
	(1.23)	(1.69)	(1.25)	(1.34)	(1.81)	(1.31)
Constant	5.41***	8.35***	5.67***	5.80***	9.52***	7.31***
	(1.51)	(2.06)	(1.53)	(1.59)	(2.16)	(1.56)
Observations	147	147	146	147	147	146
R-squared	0.22	0.25	0.32	0.22	0.27	0.37

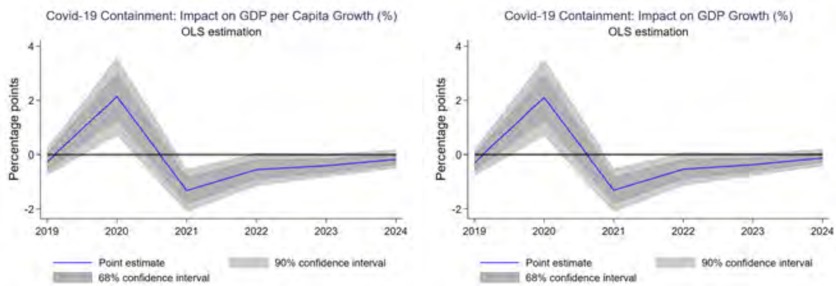
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[19] We focus on above-the-line measures because of larger data availability across countries. However, results are robust to including off-budget and below-the-line fiscal support measures as well.

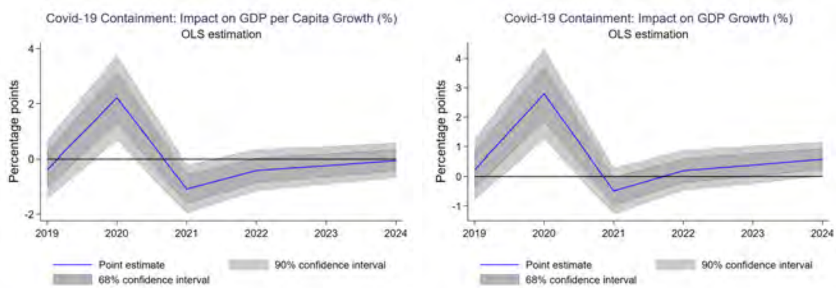
Turning to medium-term projections, reduced Covid-19 deaths are associated with higher GDP growth in 2020, but lower GDP growth in 2021, and insignificantly different economic growth projections for future years (Figure 6). Regarding effects on public finances, no significant difference is observed for primary balances nor public debt as a share of GDP throughout the forecast horizon (Figure 7).

Figure 6: OLS: Effect of Lower Deaths on Medium-Term WEO Growth Projections

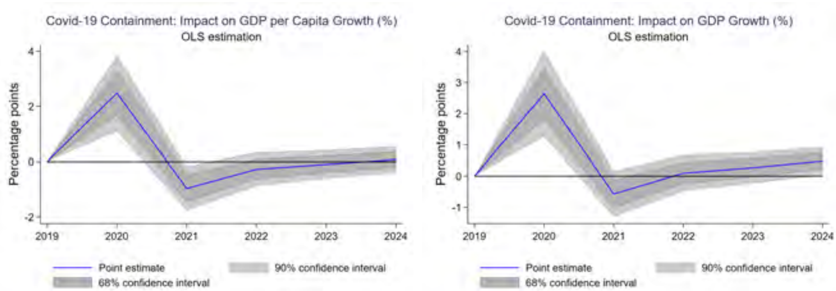
(a) Effect on WEO Projection Revisions vs Jan 2020 WEO



(b) Effect on WEO Projections, without controlling for 2019



(c) Effect on WEO Projections, controlling for 2019

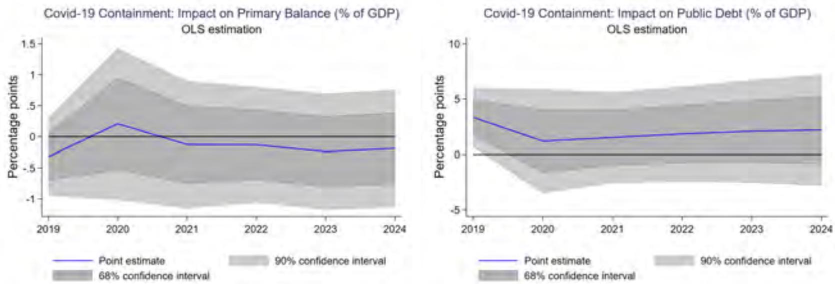


Note: This plots regression coefficients (and 68% and 90% confidence intervals) of an OLS regression of medium-term WEO revisions on Covid-19 deaths per capita, controlling for log GDP per capita and WEO income group dummies.

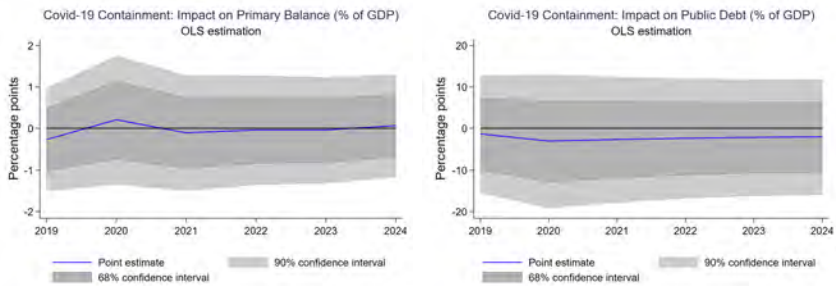
Covid Economics 74, 30 March 2021: 94-141

Figure 7: OLS: Effect of Lower Deaths on Medium-Term WEO Fiscal Projections

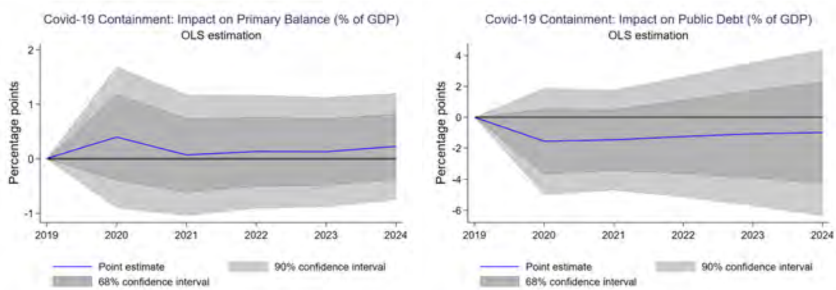
(a) Effect on WEO Projection Revisions vs Jan 2020 WEO



(b) Effect on WEO Projections, without controlling for 2019



(c) Effect on WEO Projections, controlling for 2019



Note: This plots regression coefficients (and 68% and 90% confidence intervals) of an OLS regression of medium-term WEO revisions on Covid-19 deaths per capita instrumented by past SARS experience, controlling for log GDP per capita and WEO income group dummies.

The Role of Successfully Containing Covid-19

We present similar analyses considering our Covid-19 success ranking of countries by age-adjusted mortality rates. Again, we find evidence that countries that more successfully contained Covid-19 saw higher GDP growth rates in 2020 (Table A.4) and an insignificantly different impact on their public finances in 2020 as measured by their primary balance and fiscal support as a share of GDP (Table A.5).

Turning to medium-term projections, lower age-adjusted mortality rates (higher

Covid Economics 74, 30 March 2021: 94-141

success ranking) are associated with higher GDP growth in 2020 and insignificantly different economic growth projections for 2021 and beyond (Figure A.9). Regarding effects on public finances, a borderline significantly higher primary balance is observed in 2020 and public debt is projected at significantly lower levels for most of the forecast horizon, controlling for 2019 levels (Figure A.10).

IV Approach: The Role of Past Coronavirus Experience

Yet, is better success in containing Covid-19 a product of good ('smart') containment policy or good luck? It could be that out of sheer 'luck' some countries were hit less strongly by the pandemic, and therefore experienced both lower death rates and higher growth. To estimate the impact of good policy (smart containment of Covid-19), we consider that past coronavirus epidemic experience could act as an instrument for Covid-19 death rates. We thus construct a dummy variable for the nine countries with past coronavirus pandemic experiences from SARS (Taiwan Province of China, Singapore, Vietnam, Canada, Mainland China, and Hong Kong SAR) and MERS (Saudi Arabia, South Korea, and United Arab Emirates).

We employ two-stage-least-squares (2SLS) regression methods. The first stage shows that past experience is significantly associated with lower Covid-19 deaths per capita (Table 9, column 1). Moreover, the past experience dummy passes the weak instrument test with an F-statistic of 17.6 (above the Staiger-Stock rule of thumb of 10). The second stage of the regression shows that lower Covid-19 deaths, instrumented by past experience, are associated with higher real GDP growth in 2020, and a relatively better performance compared to 2019 and compared to the outcome expected in January 2020 (Table 9, columns 2-7). Table 10 shows that lower Covid-19 deaths is also associated with lower primary balances and higher fiscal support in 2020. In other words, countries with higher success in containing Covid-19 based on past experience, also offered larger fiscal support, which may partly explain their better growth performance.

Covid Economics 74, 30 March 2021: 94-141

Table 9: 2SLS Regression: Impact of Covid-19 Containment on GDP Growth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	1st stage	2nd stage					
		2020 GDP Per Capita Growth (%)			2020 GDP Growth (%)		
	Covid-19 deaths	Actual 2020	Change vs. 2019	Revision vs. Jan 2020	Actual 2020	Change vs. 2019	Revision vs. Jan 2020
Coronavirus experience	-0.43***						
	(0.12)						
Covid-19 deaths		-5.97*	-6.37**	-6.00*	-6.88**	-6.73**	-6.35**
		(3.45)	(3.19)	(3.22)	(3.46)	(3.20)	(3.24)
Log GDP per capita	0.06	1.02*	0.78	0.93*	0.72	0.64	0.79
	(0.05)	(0.59)	(0.54)	(0.55)	(0.59)	(0.55)	(0.55)
EMDEs	-0.19**	-1.72	-1.59	-2.26**	-1.91	-1.84*	-2.60**
	(0.08)	(1.20)	(1.11)	(1.12)	(1.21)	(1.11)	(1.13)
LIDCs	-0.41***	1.93	0.72	0.79	2.16	0.15	0.13
	(0.15)	(2.49)	(2.30)	(2.32)	(2.50)	(2.31)	(2.33)
Constant	0.41**	-6.32**	-6.60**	-7.31***	-4.12	-6.04**	-6.69**
	(0.19)	(2.88)	(2.66)	(2.69)	(2.89)	(2.67)	(2.70)
Observations	156	156	156	156	156	156	156
R-squared	0.32	0.09	0.06	0.07	0.18	0.03	0.05
F-stat	17.6						

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: 2SLS Regression: Impact of Covid-19 Containment on Fiscal Position

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	1st stage	2nd stage					
		2020 Primary Balance (% of GDP)			Covid-19 Fiscal Support (% of GDP)		
	Covid-19	Actual	Change	Revision	Support in	Total package	
	deaths	2020	vs. 2019	vs. Jan 2020	2020	Jan 2021	Oct 2020
Coronavirus experience	-0.43***						
	(0.12)						
Covid-19 deaths		9.79*	5.57	4.02	-7.17**	-4.51	-2.77
		(5.49)	(4.21)	(3.61)	(3.48)	(3.69)	(2.68)
Log GDP per capita	0.06	-1.68**	-1.32**	-0.70	0.25	-0.07	0.32
	(0.05)	(0.74)	(0.57)	(0.49)	(0.52)	(0.55)	(0.40)
EMDEs	-0.19**	1.75	2.47*	2.48**	-4.14***	-5.62***	-3.92***
	(0.08)	(1.70)	(1.30)	(1.12)	(1.07)	(1.14)	(0.82)
LIDCs	-0.41***	4.62	4.93*	5.77**	-6.42***	-7.42***	-4.90***
	(0.15)	(3.49)	(2.68)	(2.30)	(2.27)	(2.42)	(1.76)
Constant	0.41**	-6.95*	-6.25**	-7.54***	9.12***	10.67***	7.05***
	(0.19)	(3.93)	(3.01)	(2.58)	(2.62)	(2.80)	(2.03)
Observations	156	154	154	154	148	148	147
R-squared	0.32	-0.45	0.05	0.18	-0.47	0.12	0.22
F-stat	17.6						

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Turning to medium-term projections, successfully containing Covid-19 deaths as a result of past experience, is associated with higher GDP growth in 2020, but not significantly different economic growth projections for future years (nor significantly different revisions to medium-term growth projections relative to the January 2020 WEO) (Figure A.11). Regarding public finances, while a lower primary balance is observed in 2020 (due to larger fiscal support), no significant difference is observed for public debt as a share of GDP (Figure A.12). In fact, if anything, the public debt path is projected to be lower (significant at the 68% level).

Our findings remain robust to various sensitivity tests (Table A.6). Results are robust to controlling for the median age of the population, which help explain death rates and improve the first-stage F-statistic (columns 1-3). The impact on growth is also robust to controlling for economic policies such as Covid-19 fiscal support measures implemented in 2020, which are important in explaining the primary balance (columns 4-6). [20]

We also test robustness of our results to variations in our instrument for past experience in containing epidemics (Table A.7). Our findings remain robust to: (i) including in our dummy instrument countries who experienced Ebola in the past, as well as (ii) considering in our instrument only countries who experienced SARS (not MERS or Ebola). Considering the wider set of past epidemics, past experience (from SARS, MERS, and Ebola) remains significantly associated with lower Covid-19 death rates, controlling for log GDP per capita and country income group dummies (column 1). Similarly, focusing on countries with past SARS experience is also significantly associated with lower Covid-19 death rates (column 5). Using either instrument, lower Covid-19 deaths (instrumented by past experience) is associated with higher GDP growth in 2020 (columns 2 and 6), independent of whether or not this involved larger fiscal support.

The Role of Covid-19 Containment measures

The analysis above shows that higher success in containing Covid-19 through smart containment strategies was associated with better growth outcomes. Smart containment enabled some countries to successfully contain Covid-19 early, and allowed them to reduce containment measures later on in 2020. By contrast, other less successful countries in many cases had strong containment measures in place for longer in order to curb the spread of Covid-19. Stringency measures, while important to flatten the infection curve, also reduce economic growth by restricting people's movements and activities.

To study the relation between economic performance and containment measures taken by governments to slow the spread of Covid-19, we estimate:

$$Y_i = \beta_0 + \beta_1 C_i + \beta_2 X_i + u_i \tag{3}$$

where Y_i denotes country i's outcome variable of interest in 2020 (GDP growth, primary balance, or fiscal support measures), and C_i denotes the containment measures implemented on average throughout the year. The set of control variables X_i includes log GDP per capita in U.S. dollar PPP terms and WEO country income

[20]Results are also robust to additional tests e.g. controlling for oil and commodity exporter dummies, which may help explain economic performance and fiscal revenues. Results are available from the authors upon request.

groups, while β_0 and u_i are the constant and error term, respectively.

Table A.8 shows that stronger average Covid-19 containment measures were associated with lower economic growth, and this was driven by stringency measures whereas health policies are insignificant. This could plausibly be due to larger outbreaks in those countries slowing down economic activity. Table A.9 shows that accounting for death rates is part of the story. After controlling for deaths, weaker evidence still suggests that higher average stringency may have mattered in slowing economic activity. Higher deaths, controlling for stringency measures, are also associated with lower activity, possibly due to voluntary social distancing (people consuming and/or producing less because of being scared of catching Covid-19). This is in line with recent evidence showing that what matters the most is the voluntary decision of people to social distance and take precautions, rather than de-jure non-pharmaceutical interventions (Chen et al., 2020). Interaction effects are also found to matter: the marginal effect of the Covid-19 death rate is lower (negative and significant) for economic growth when this comes at the cost of higher average stringency measures (Figure A.13). Moreover, controlling for mobility fully explains any effects captured by stringency measures. Results are largely robust to measuring economic activity in terms of GDP growth rather than GDP per capita growth (Tables A.10 and A.11).

Table A.12 (columns 3 and 6) shows that countries with stronger average Covid-19 measures (explained by stronger stringency measures) saw larger downward revisions in their primary balances. This result is robust to controlling for the severity of the pandemic (Covid-19 deaths) and reduced mobility (Table A.13). This is, however, not explained by larger fiscal support in 2020 (Table A.14 column 3 and Table A.15), except for in combination with controlling for Covid-19 deaths (Table A.14 column 6). In general, we do not find evidence that fiscal support packages depended on containment measures (average stringency) or on the severity of the pandemic (Covid-19 death rates) or on the extent to which mobility was reduced (Table A.16). The exception is for advanced economies, where fiscal support was larger in 2020 in countries that applied more stringent containment measures (Table A.15, column 4). Fiscal space is likely to have constrained fiscal support in many countries, and especially those with lower income. As a result, more stringent containment measures imposed by country governments were not, on average, accompanied by more fiscal support to cushion the impact on the economy.

Covid Economics 74, 30 March 2021: 94-141

CEPR PRESS

5 Concluding Remarks

Countries have taken a variety of approaches to 'flatten the curve' of Covid-19 infections. Our results show that countries that imposed stronger containment measures on average experienced higher output losses, whereas countries that were able to contain the spread of Covid-19 through smart containment measures fared better in terms of economic growth. Lessons can be learned from these examples. Some of the more successful cases, including countries with experience in containing past epidemics, relied on an effective combination of early restrictions (including travel controls) and smart containment strategies based on large-scale testing, contact tracing, and public information campaigns. Authorities should prepare themselves to adopt smart strategies to fight possible new waves of infections and remember these lessons for future pandemics.

Covid Economics 74, 30 March 2021: 94-141

References

Acemoglu, D., V. Chernozhukov, I. Werning, and M. D. Whinston (2020). Optimal targeted lockdowns in a multi-group sir model. Technical report, Working Paper 27102, National Bureau of Economic Research May.

Andrabi, T., M. Andrews, A. Cheema, J. Das, A. Q. Khan, A. I. Khwaja, F. Majid, A. A. Malik, A. Malkani, T. McCormick, S. Omer, and M. Syed (2020). Smart containment with active learning (scale): A proposal for a data-responsive and graded response to covid-19 working draft. Technical report, mimeo.

Baldwin, R. (2020). Covid-19 testing for testing times: Fostering economic recovery and preparing for the second wave. *VOX CEPR Policy Portal, 26th March*.

Baldwin, R. and B. W. di Mauro (2020). Mitigating the covid economic crisis: Act fast and do whatever it takes. *VoxEU. org eBook*.

Berger, D. W., K. F. Herkenhoff, and S. Mongey (2020). An seir infectious disease model with testing and conditional quarantine. *Covid Economics 13*, 1–30.

Brotherhood, L., P. Kircher, C. Santos, and M. Tertilt (2020). An economic model of the covid-19 epidemic: The importance of testing and age-specific policies.

Chen, S., I. Deniz, N. Pierri, and A. Presbitero (2020). Tracking the economic impact of covid-19 and mitigation policies in europe and the united states. *Covid Economics 36*, 1–24.

Chinazzi, M., J. T. Davis, M. Ajelli, C. Gioannini, M. Litvinova, S. Merler, A. P. y Piontti, K. Mu, L. Rossi, K. Sun, et al. (2020). The effect of travel restrictions on the spread of the 2019 novel coronavirus (covid-19) outbreak. *Science 368*(6489), 395–400.

Coibion, O., Y. Gorodnichenko, and M. Weber (2020). The cost of the covid-19 crisis: Lockdowns, macroeconomic expectations, and consumer spending. *Covid Economics 20*, 1–51.

Cowling, B. J., S. T. Ali, T. W. Ng, T. K. Tsang, J. C. Li, M. W. Fong, Q. Liao, M. Y. Kwan, S. L. Lee, S. S. Chiu, et al. (2020). Impact assessment of non-pharmaceutical interventions against coronavirus disease 2019 and influenza in hong kong: an observational study. *The Lancet Public Health*.

Deb, P., D. Furceri, J. Ostry, and N. Tawk (2020a). The economic effects of covid-19 containment measures. *Covid Economics 24*, 32–75.

Deb, P., D. Furceri, J. Ostry, and N. Tawk (2020b). The effect of containment measures on covid-19 pandemic. *Covid Economics 19*, 53–86.

Dewatripont, M., M. Goldman, E. Muraille, and J.-P. Platteau (2020). Rapidly identifying workers who are immune to covid-19 and virus-free is a priority for restarting the economy. *VOX CEPR Policy Portal 23*.

Eichenbaum, M. S., S. Rebelo, and M. Trabandt (2020). The macroeconomics of epidemics. Technical report, National Bureau of Economic Research.

Favero, C. A., A. Ichino, and A. Rustichini (2020). Restarting the economy while saving lives under covid-19.

Forslid, R. and M. Herzing (2020). Assessing the consequences of quarantines during a pandemic. *Covid Economics 15*, 159–183.

Gourinchas, P.-O. (2020). Flattening the pandemic and recession curves. *Mitigating the COVID Economic Crisis: Act Fast and Do Whatever it Takes 31*.

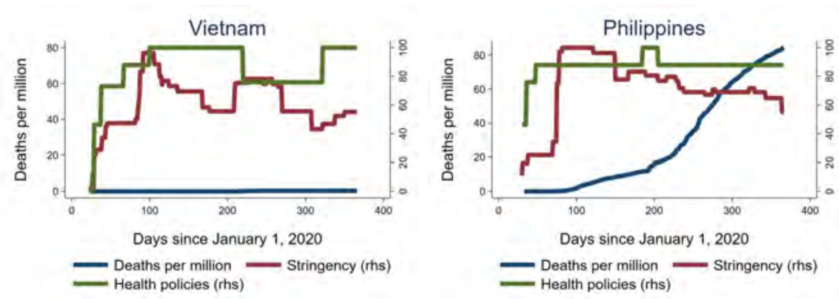
Kaplan, G., B. Moll, and G. L. Violante (2020). The Great Lockdown and the Big Stimulus: Tracing the Pandemic Possibility Frontier for the U.S. Technical report.

Covid Economics 74, 30 March 2021: 94-141

A Appendix

Figure A.1: Apple Mobility Trends: Walking and Driving Behavior

Figure A.2: Vietnam (Early Stringency) vs. Philippines (Delayed Stringency)

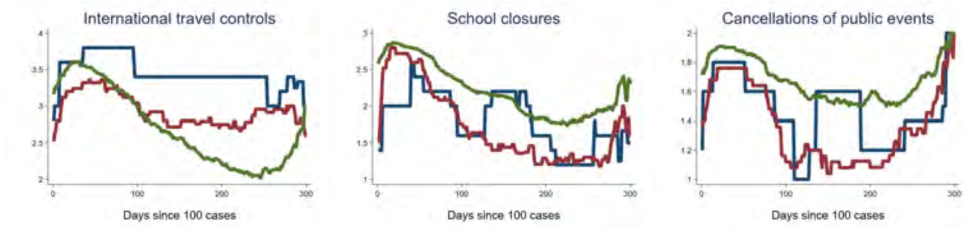


Covid Economics 74, 30 March 2021: 94-141

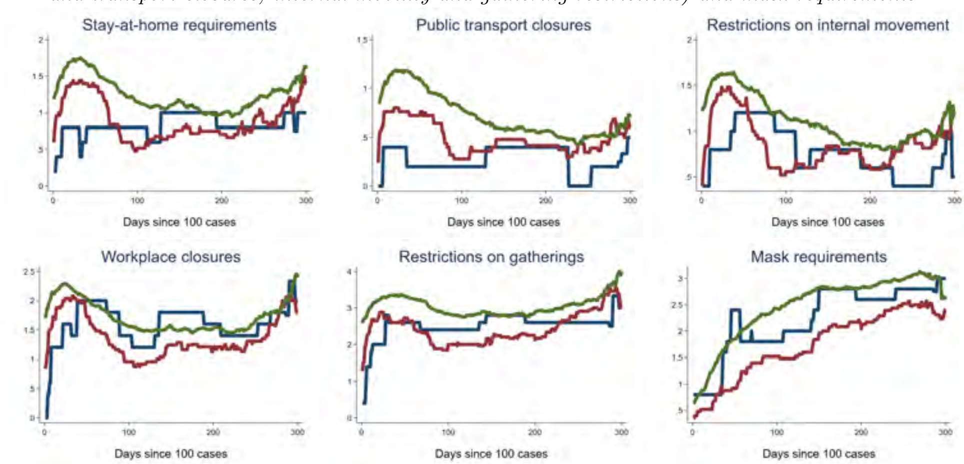
Figure A.3: Containment Measures Since 100 Cases: Countries with Past SARS Experience

At the time of 100 positive cases, countries with past SARS experience already had stronger health policies (public information campaigns, testing, and contact tracing) …

… but not tighter restrictive measures such as international travel controls, school closures, and public event cancellations …



… nor stronger policies limiting mobility and gatherings of people (e.g. stay-at-home orders, workplace and transport closures, internal mobility and gathering restrictions) and mask requirements.

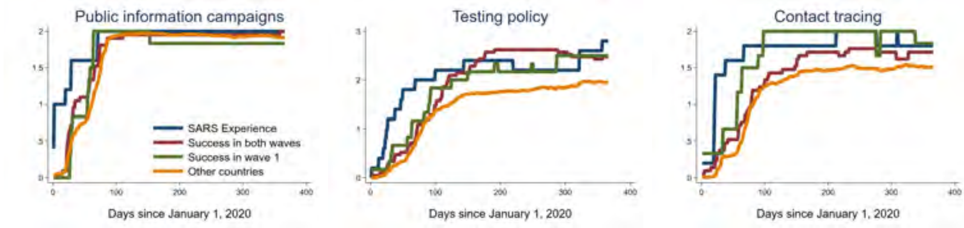


Source: OxCGRT Database and authors' calculations.

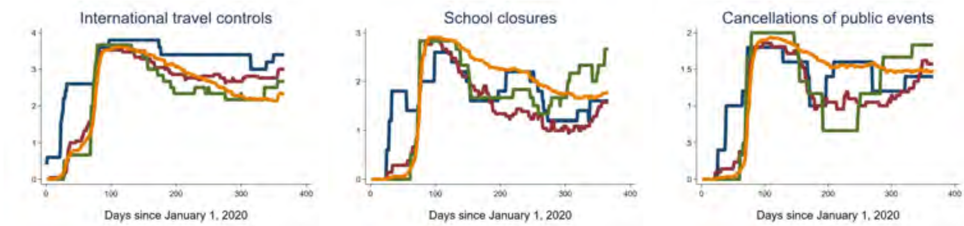
Covid Economics 74, 30 March 2021: 94-141

Figure A.4: Timeline of Containment Measures, by 1st Wave Containment Success Groups

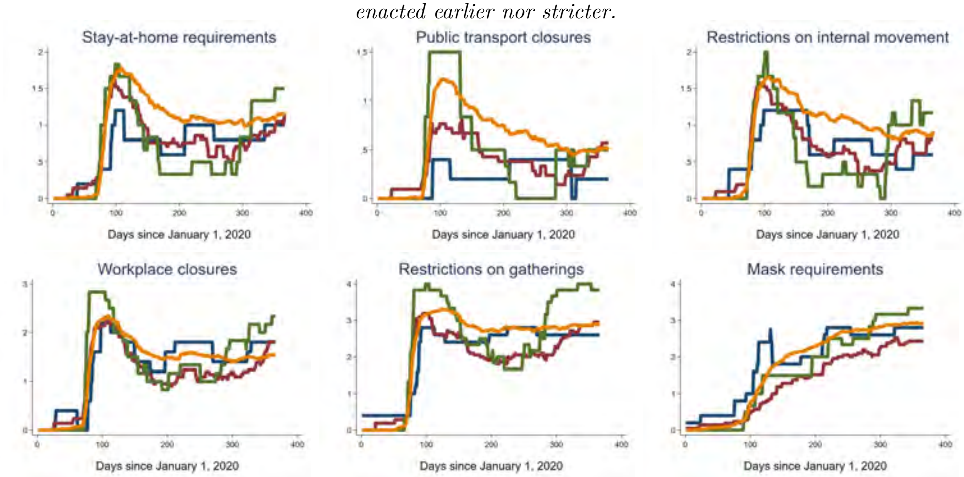
Countries with past SARS experience enacted earlier and stronger health policies (public information campaigns, testing, and contact tracing) ...



... and earlier restrictive measures such as international travel controls, school closures, and public event cancellations.



Yet, policies limiting mobility and gatherings of people (e.g. stay-at-home orders, workplace and transport closures, internal mobility and gathering restrictions) and mask requirements were not enacted earlier nor stricter.



Source: OxCGRT Database and authors' calculations.

Covid Economics 74, 30 March 2021: 94-141

Figure A.5: Containment Measures by Income Group

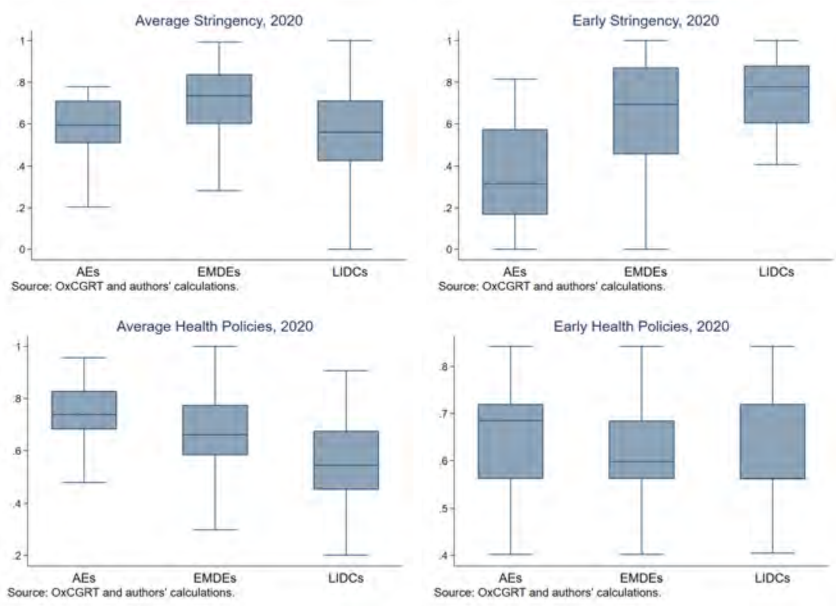


Figure A.6: WEO Growth Revisions by Income Group

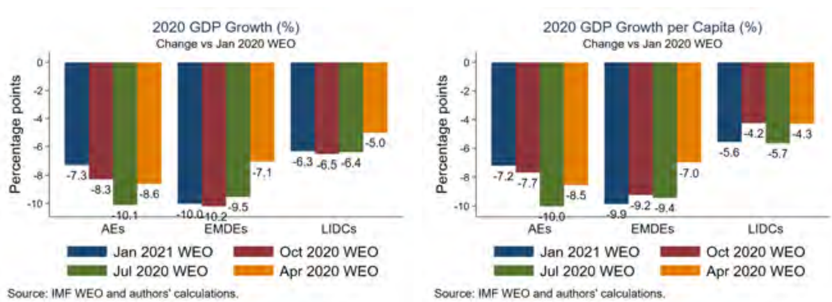
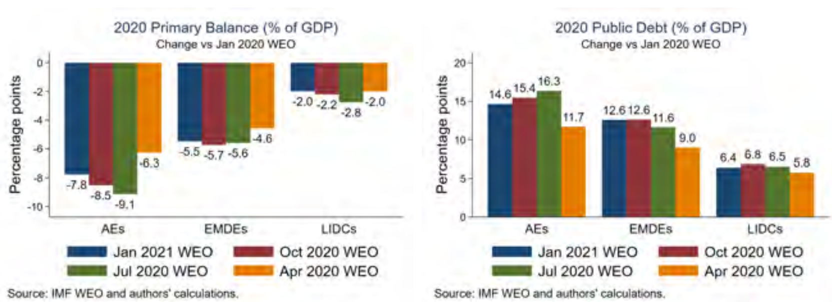


Figure A.7: WEO Fiscal Position Revisions by Income Group



Covid Economics 74, 30 March 2021: 94-141

Figure A.8: Covid-19 Fiscal Support Measures by Income Group

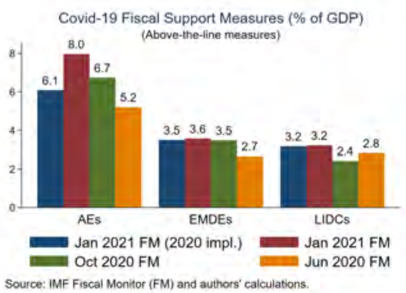


Table A.1: Covid-19 Containment Success

	(1)	(2)	(3)	(4)	(5)
		Covid-19 success ranking			
	Deaths	Success	Success	Success	Success
Containment success rank	-6.07***				
	(0.36)				
Containment (average)		-77.43***			
		(25.01)			
Stringency (average)			-86.60***	-96.55***	-83.90***
			(21.28)	(20.51)	(20.67)
Health policies (average)			70.22*		62.87**
			(36.95)		(27.15)
Travel controls (average)				27.92***	
				(7.23)	
Early containment (at 100 cases)		10.77			
		(17.85)			
Stringency (at 100 cases)			1.78	-2.63	
			(16.52)	(15.70)	
Health policies (at 100 cases)			0.24	27.80	
			(28.46)	(19.76)	
Early containment (PHRT)					-0.11
					(0.11)
Log GDP per capita	-2.10	0.25	-7.37	-5.16	-8.04
	(27.31)	(6.21)	(6.37)	(5.94)	(6.43)
EMDEs	-330.84***	-21.21*	-16.38	-17.72*	-18.14
	(48.71)	(11.23)	(10.99)	(10.58)	(11.14)
LIDCs	-495.83***	-5.12	-6.62	-6.34	-9.76
	(87.84)	(19.90)	(19.40)	(18.66)	(19.46)
Constant	138.29	-24.04	-42.44	-77.82***	-42.87
	(109.49)	(27.11)	(27.61)	(28.65)	(27.73)
Observations	153	150	150	150	143
R-squared	0.75	0.15	0.21	0.26	0.21

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Covid Economics 74, 30 March 2021: 94-141

Table A.2: Effect of Containment Measures for Covid Performance Index

	(1) Score	(2) Score	(3) Score	(4) Score	(5) Score
Containment (2020 average)	-62.750***				
	(13.046)				
Containment (at 100 cases)	31.924***				28.356***
	(8.574)				(7.900)
Stringency (2020 average)		-57.148***		-64.327***	-64.588***
		(10.500)		(10.170)	(10.084)
Health policies (2020 average)		44.950***		30.789	37.669***
		(13.252)		(18.691)	(12.620)
Stringency (at 100 cases)			10.555	21.541***	
			(8.747)	(7.650)	
Health policies (at 100 cases)			22.866**	13.488	
			(10.906)	(13.669)	
Log GDP per capita	6.980**	-1.337	2.376	1.386	1.621
	(3.112)	(3.136)	(3.609)	(3.088)	(3.060)
EMDE dummy	-15.389***	-11.100**	-19.295***	-13.751***	-14.333***
	(4.766)	(4.534)	(5.146)	(4.400)	(4.356)
LIDC dummy	8.052	5.711	0.207	1.898	1.583
	(9.591)	(9.312)	(10.717)	(8.954)	(8.827)
Constant	60.540***	63.177***	30.688**	52.069***	52.573***
	(13.933)	(13.683)	(14.499)	(13.930)	(13.195)
Observations	96	96	96	96	96
R-squared	0.425	0.453	0.296	0.520	0.522

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.3: GDP Growth Revisions for 2020 - Relation with Deaths

	(1)	(2)	(3)	(4)	(5)	(6)
	2020 GDP Growth (%)					
	Difference vs. Jan 2020 WEO Forecast				vs. 2019	Actual
WEO Edition	Apr 2020	Jul 2020	Oct 2020	Jan 2021	Jan 2021	Jan 2021
Cumulated Covid-19 deaths	-2.653*	-5.270***	-3.711***	-2.118**	-2.538***	-2.872***
	(1.376)	(1.585)	(1.278)	(0.876)	(0.867)	(0.949)
Log GDP per capita	0.379	0.093	0.599	0.722	0.566	0.662
	(0.308)	(0.418)	(0.501)	(0.522)	(0.516)	(0.565)
EMDEs	1.963***	0.273	-1.118	-1.827**	-1.041	-1.232
	(0.545)	(0.745)	(0.868)	(0.924)	(0.915)	(1.002)
LIDCs	4.262***	2.879**	2.718*	2.109	2.133	4.015**
	(0.985)	(1.361)	(1.618)	(1.729)	(1.711)	(1.874)
Constant	-9.710***	-9.456***	-9.540***	-8.788***	-8.128***	-6.094***
	(1.215)	(1.653)	(1.990)	(2.102)	(2.080)	(2.278)
Observations	139	147	153	155	155	155
R-squared	0.325	0.257	0.200	0.176	0.161	0.275

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Covid Economics 74, 30 March 2021: 94-141

Table A.4: 2020 GDP Growth - Relation with Covid-19 Containment Success

	(1)	(2)	(3)	(4)	(5)	(6)
	2020 GDP Per Capita Growth (%)			2020 GDP Growth (%)		
	Actual 2020	Change vs. 2019	Revision vs. Jan 2020	Actual 2020	Change vs. 2019	Revision vs. Jan 2020
Containment success rank	0.019***	0.015**	0.013*	0.017**	0.015**	0.014**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Log GDP per capita	1.006*	0.720	0.877	0.679	0.578	0.739
	(0.563)	(0.528)	(0.530)	(0.570)	(0.523)	(0.524)
EMDEs	-0.344	-0.104	-0.928	-0.406	-0.289	-1.194
	(1.005)	(0.942)	(0.945)	(1.016)	(0.933)	(0.935)
LIDCs	4.746***	3.756**	3.631**	5.399***	3.360**	3.133*
	(1.812)	(1.699)	(1.704)	(1.833)	(1.682)	(1.687)
Constant	-8.086***	-8.843***	-9.476***	-6.457***	-8.483***	-8.993***
	(2.259)	(2.118)	(2.124)	(2.285)	(2.096)	(2.103)
Observations	153	153	153	153	153	153
R-squared	0.195	0.143	0.168	0.263	0.144	0.173

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.5: 2020 Fiscal Policy - Relation with Covid-19 Containment Success

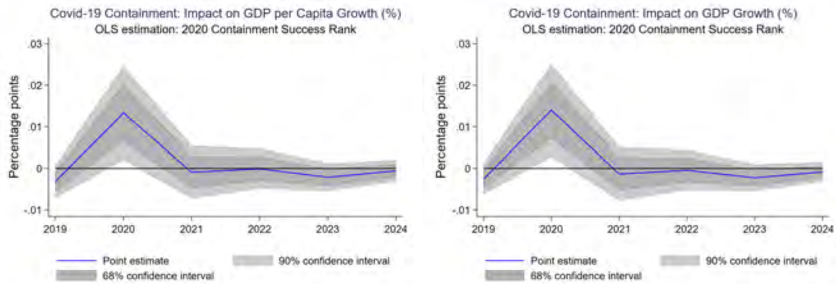
	(1)	(2)	(3)	(4)	(5)	(6)
	2020 Primary Balance (% of GDP)			Covid-19 Fiscal Support (% of GDP)		
	Actual	Change	Revision	Announced fiscal packages		
	2020	vs. 2019	vs. Jan 2020	Impl. 2020	FM Jan 2021	FM Oct 2020
Containment success rank	0.012	0.009	0.006	0.001	0.004	0.002
	(0.007)	(0.006)	(0.006)	(0.005)	(0.007)	(0.005)
Log GDP per capita	-1.356**	-1.155**	-0.576	0.087	-0.159	0.286
	(0.555)	(0.481)	(0.432)	(0.377)	(0.513)	(0.381)
EMDEs	-0.016	1.689*	1.925**	-2.834***	-4.717***	-3.502***
	(0.988)	(0.855)	(0.769)	(0.669)	(0.913)	(0.677)
LIDCs	0.049	2.427	3.972***	-3.131**	-5.318***	-3.673***
	(1.778)	(1.539)	(1.384)	(1.200)	(1.636)	(1.213)
Constant	-1.495	-3.086	-5.257***	5.709***	8.756***	5.874***
	(2.217)	(1.919)	(1.726)	(1.510)	(2.059)	(1.527)
Observations	151	151	151	146	146	145
R-squared	0.188	0.320	0.347	0.219	0.256	0.325

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

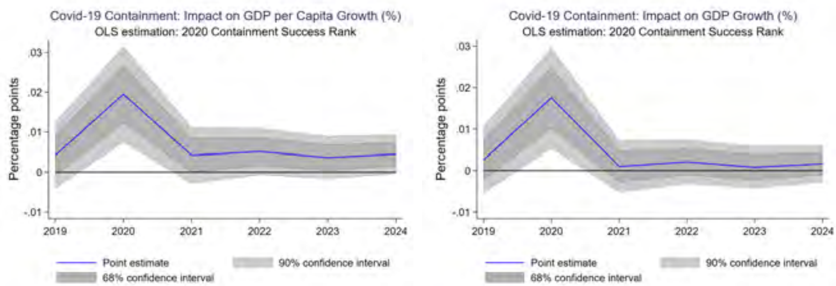
Covid Economics 74, 30 March 2021: 94-141

Figure A.9: OLS: Effect of Success Ranking on Medium-Term WEO Growth Projections

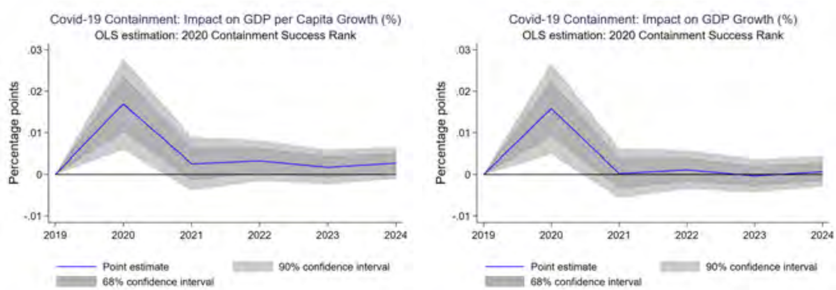
(a) Effect on WEO Projection Revisions vs Jan 2020 WEO



(b) Effect on WEO Projections, without controlling for 2019



(c) Effect on WEO Projections, controlling for 2019

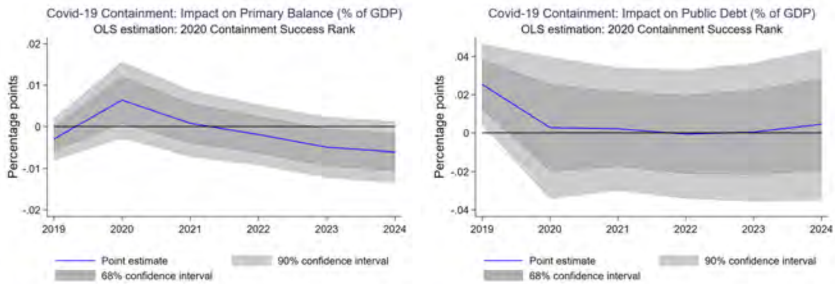


Note: This plots regression coefficients (and 68% and 90% confidence intervals) of an OLS regression of medium-term WEO revisions on countries' Covid-19 success ranking (of age-adjusted Covid-19 deaths per capita), controlling for log GDP per capita and WEO income group dummies.

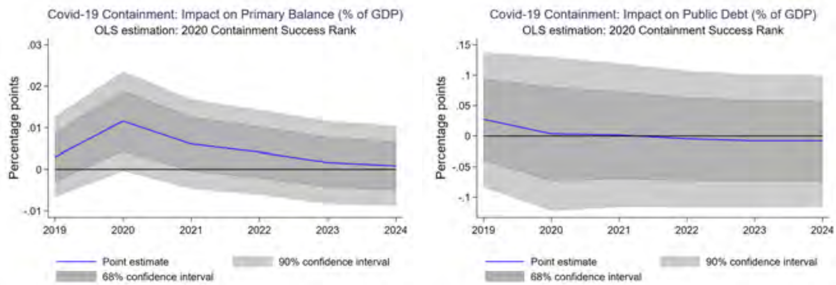
Covid Economics 74, 30 March 2021: 94-141

Figure A.10: OLS: Effect of Success Ranking on Medium-Term WEO Fiscal Projections

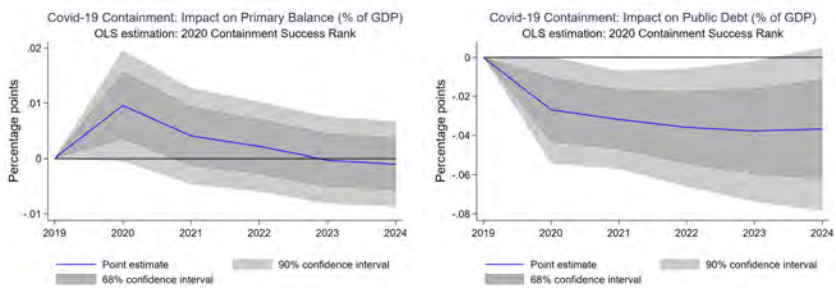
(a) Effect on WEO Projection Revisions vs Jan 2020 WEO



(b) Effect on WEO Projections, without controlling for 2019



(c) Effect on WEO Projections, controlling for 2019



Note: This plots regression coefficients (and 68% and 90% confidence intervals) of an OLS regression of medium-term WEO revisions on countries' Covid-19 success ranking (of age-adjusted Covid-19 deaths per capita), controlling for log GDP per capita and WEO income group dummies.

Covid Economics 74, 30 March 2021: 94-141

Table A.6: 2SLS Regression: Robustness Tests

	(1)	(2)	(3)	(4)	(5)	(6)
	1st stage	2nd stage		1st stage	2nd stage	
	Deaths	GDP growth	Prim. bal.	Deaths	GDP growth	Prim. bal.
Coronavirus experience	-0.43***			-0.42***		
	(0.11)			(0.12)		
Covid-19 deaths		-6.81**	9.37*		-6.04*	7.69
		(3.47)	(5.10)		(3.48)	(4.70)
Median age	0.02***	0.08	-0.17			
	(0.01)	(0.11)	(0.14)			
Fiscal support in 2020				0.01	-0.07	-0.53***
				(0.01)	(0.12)	(0.16)
Log GDP per capita	-0.04	0.38	-0.96	0.06	0.60	-1.59**
	(0.05)	(0.70)	(0.84)	(0.05)	(0.56)	(0.67)
EMDEs	-0.01	-1.31	0.39	-0.12	-1.65	-0.22
	(0.08)	(1.12)	(1.35)	(0.09)	(1.15)	(1.38)
LIDCs	-0.16	3.07	2.58	-0.33**	2.24	2.01
	(0.15)	(2.16)	(2.68)	(0.16)	(2.35)	(2.84)
Constant	-0.25	-6.46**	-1.94	0.29	-3.91	-2.81
	(0.22)	(3.04)	(3.64)	(0.20)	(2.76)	(3.27)
Observations	155	155	153	148	148	147
R-squared	0.40	0.18	-0.34	0.32	0.21	-0.12
F-stat	19.6			13.2		

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

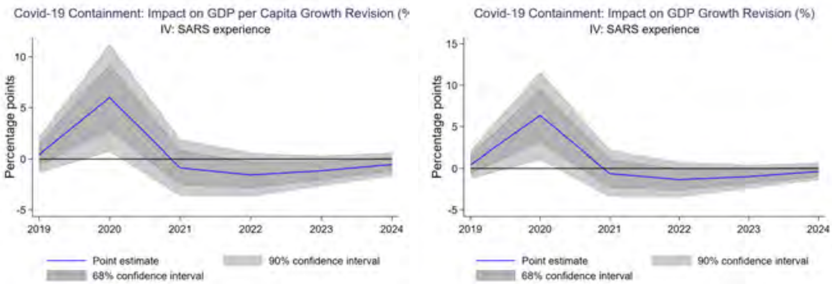
Table A.7: 2SLS Regression: Instrument Robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1st stage	2nd stage			1st stage	2nd stage		
	Covid-19 deaths	GDP growth	Primary balance	Fiscal support	Covid-19 deaths	GDP growth	Primary balance	Fiscal support
Epidemic experience	-0.29***							
	(0.10)							
SARS experience					-0.41***			
					(0.14)			
Covid-19 deaths		-7.04*	9.60	-5.34		-7.44*	18.08	-14.24**
		(4.15)	(6.72)	(3.74)		(4.33)	(11.72)	(7.07)
Log GDP per capita	0.03	0.72	-1.68**	0.22	0.04	0.73	-1.91*	0.38
	(0.05)	(0.60)	(0.75)	(0.47)	(0.05)	(0.60)	(1.08)	(0.80)
EMDEs	-0.20**	-1.94	1.71	-3.83***	-0.21**	-2.02	3.47	-5.32***
	(0.08)	(1.28)	(1.87)	(1.02)	(0.08)	(1.31)	(3.02)	(1.81)
LIDCs	-0.45***	2.09	4.53	-5.60**	-0.45***	1.90	8.54	-9.60**
	(0.15)	(2.72)	(3.93)	(2.23)	(0.15)	(2.80)	(6.46)	(4.05)
Constant	0.50***	-4.04	-6.86	8.25***	0.47**	-3.84	-11.02	12.48***
	(0.19)	(3.11)	(4.35)	(2.54)	(0.19)	(3.19)	(7.04)	(4.58)
Observations	156	156	154	148	156	156	154	148
R-squared	0.30	0.17	-0.42	-0.17	0.30	0.15	-1.90	-2.41
F-stat	16.2				16.0			

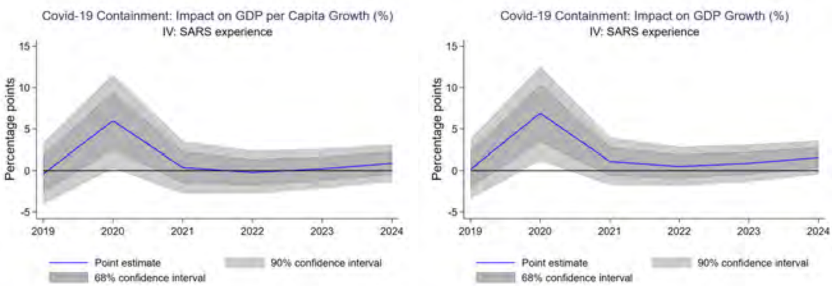
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure A.11: 2SLS: Effect of Lower Deaths on Medium-Term WEO Growth Projections

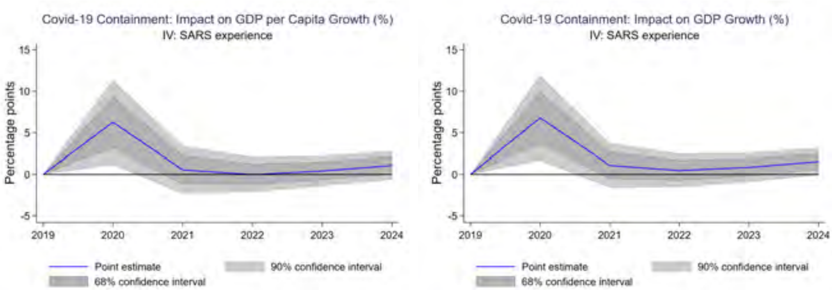
(a) Effect on WEO Projection Revisions vs Jan 2020 WEO



(b) Effect on WEO Projections, without controlling for 2019



(c) Effect on WEO Projections, controlling for 2019

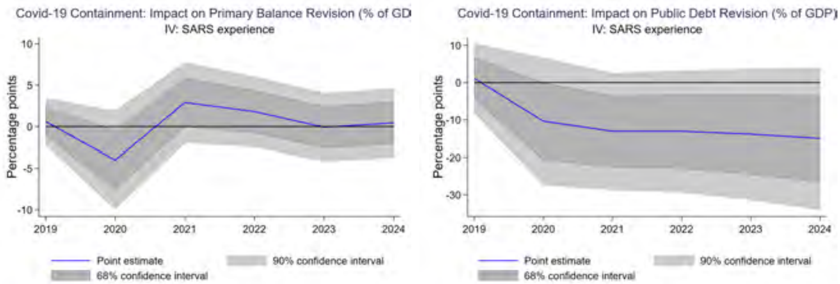


Note: This plots regression coefficients (and 68% and 90% confidence intervals) of a 2SLS regression of medium-term WEO revisions on Covid-19 deaths per capita instrumented by past SARS experience, controlling for log GDP per capita and WEO income group dummies.

Covid Economics 74, 30 March 2021: 94-141

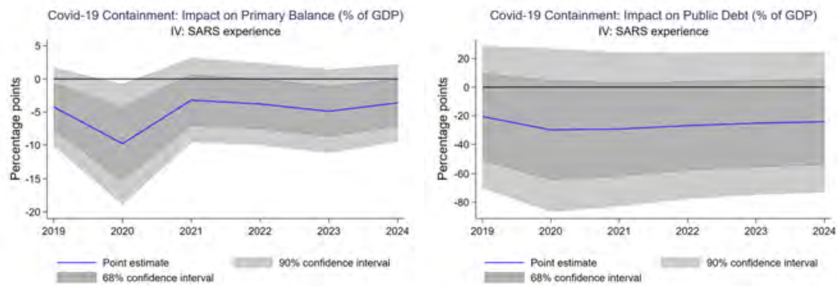
Figure A.12: 2SLS: Effect of Lower Deaths on Medium-Term WEO Fiscal Projections

(a) Effect on WEO Projection Revisions vs Jan 2020 WEO

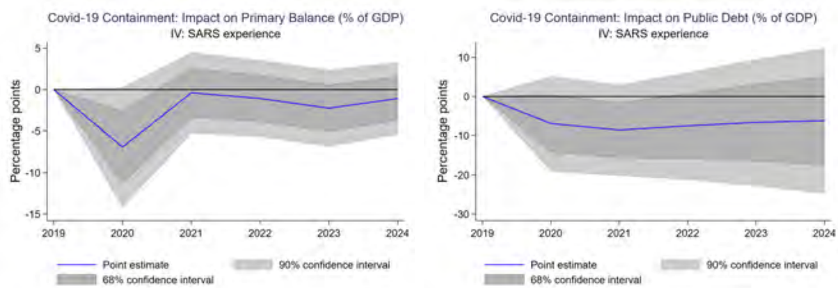


(b)

Effect on WEO Projections, without controlling for 2019



(c) Effect on WEO Projections, controlling for 2019



Note: This plots regression coefficients (and 68% and 90% confidence intervals) of a 2SLS regression of medium-term WEO revisions on Covid-19 deaths per capita instrumented by past SARS experience, controlling for log GDP per capita and WEO income group dummies.

CEPR PRESS

Table A.8: GDP Per Capita Growth Revisions for 2020 - Relation with Stringency

	(1)	(2)	(3)	(4)	(5)	(6)
	2020 GDP Growth Per Capita (%)					
	Actual 2020	Change vs. 2019	Revision vs. Jan 2020	Actual 2020	Change vs. 2019	Revision vs. Jan 2020
Containment (average)	-2.32	-3.80*	-4.31**			
	(2.15)	(2.05)	(2.06)			
Stringency (average)				-3.81*	-2.50	-3.94**
				(2.03)	(1.96)	(1.96)
Health policies (average)				3.86	-2.11	0.06
				(2.63)	(2.54)	(2.54)
Log GDP per capita	1.23**	1.00*	1.13*	0.86	1.06*	1.00
	(0.60)	(0.58)	(0.58)	(0.63)	(0.61)	(0.61)
EMDEs	-0.11	0.04	-0.64	0.11	-0.07	-0.62
	(1.12)	(1.07)	(1.07)	(1.12)	(1.08)	(1.08)
LIDCs	5.94***	4.80***	4.58**	5.75***	4.73**	4.43**
	(1.92)	(1.84)	(1.84)	(1.91)	(1.85)	(1.85)
Constant	-9.00***	-8.63***	-8.69***	-9.72***	-8.20***	-8.68***
	(2.57)	(2.46)	(2.46)	(2.69)	(2.60)	(2.61)
Observations	166	166	166	165	165	165
R-squared	0.17	0.14	0.17	0.18	0.14	0.17

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.9: GDP Per Capita Growth Revisions for 2020 - Relation with Mobility

	(1)	(2)	(3)	(4)	(5)	(6)
	2020 GDP Growth Per Capita (%)					
	Actual 2020	Change vs. 2019	Revision vs. Jan 2020	Actual 2020	Change vs. 2019	Revision vs. Jan 2020
Stringency (average)	-1.63	-2.46	-3.17*	-0.18	-1.72	-1.92
	(1.86)	(1.70)	(1.71)	(2.40)	(2.13)	(2.24)
Covid-19 deaths	-2.14**	-2.36***	-1.85**			
	(0.97)	(0.89)	(0.89)			
Google mobility (average)				1.13***	0.67*	0.80**
				(0.42)	(0.37)	(0.40)
Log GDP per capita	0.97*	0.71	0.87*	1.26*	1.09*	1.34**
	(0.57)	(0.52)	(0.52)	(0.66)	(0.59)	(0.62)
EMDEs	-0.84	-0.49	-1.06	-0.16	-0.05	-0.45
	(1.05)	(0.96)	(0.96)	(1.10)	(0.98)	(1.03)
LIDCs	3.72*	2.60	2.76	4.67**	3.49*	3.76**
	(1.90)	(1.73)	(1.74)	(1.99)	(1.77)	(1.87)
Constant	-7.27***	-7.20***	-7.55***	-10.41***	-10.27***	-11.02***
	(2.50)	(2.28)	(2.29)	(3.05)	(2.71)	(2.86)
Observations	154	154	154	126	126	126
R-squared	0.18	0.17	0.19	0.23	0.18	0.22

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Covid Economics 74, 30 March 2021: 94-141

Table A.10: GDP Growth Revisions for 2020 - Relation with Stringency

	(1)	(2)	(3)	(4)	(5)	(6)
	2020 GDP Growth (%)					
	Actual 2020	Change vs. 2019	Revision vs. Jan 2020	Actual 2020	Change vs. 2019	Revision vs. Jan 2020
Containment (average)	-0.96	-2.72	-3.54**			
	(1.95)	(1.81)	(1.77)			
Stringency (average)				-1.58	-0.37	-1.90
				(1.85)	(1.71)	(1.68)
Health policies (average)				1.71	-4.40**	-2.62
				(2.40)	(2.21)	(2.18)
Log GDP per capita	0.54	0.54	0.63	0.38	0.82	0.74
	(0.55)	(0.51)	(0.50)	(0.58)	(0.53)	(0.53)
EMDEs	-0.62	-0.55	-1.32	-0.53	-0.80	-1.47
	(1.02)	(0.94)	(0.92)	(1.02)	(0.94)	(0.93)
LIDCs	5.06***	3.02*	2.51	4.98***	3.05*	2.46
	(1.74)	(1.62)	(1.58)	(1.75)	(1.61)	(1.59)
Constant	-6.74***	-7.71***	-7.39***	-7.09***	-6.96***	-6.98***
	(2.33)	(2.16)	(2.12)	(2.46)	(2.27)	(2.24)
Observations	166	166	166	165	165	165
R-squared	0.23	0.12	0.16	0.23	0.13	0.15

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.11: GDP Growth Revisions for 2020 - Relation with Mobility

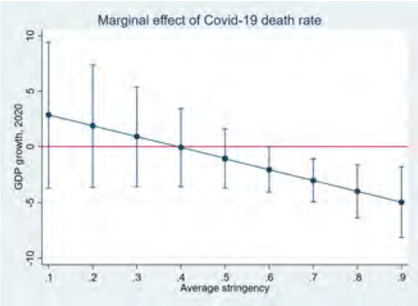
	(1)	(2)	(3)	(4)	(5)	(6)
	2020 GDP Growth (%)					
	Actual 2020	Change vs. 2019	Revision vs. Jan 2020	Actual 2020	Change vs. 2019	Revision vs. Jan 2020
Stringency (average)	-1.16	-2.32	-3.34**	0.12	-1.54	-1.99
	(1.85)	(1.68)	(1.69)	(2.43)	(2.10)	(2.20)
Covid-19 deaths	-2.77***	-2.32***	-1.81**			
	(0.97)	(0.88)	(0.88)			
Google mobility (average)				1.09**	0.77**	0.87**
				(0.43)	(0.37)	(0.39)
Log GDP per capita	0.66	0.57	0.73	0.90	1.07*	1.15*
	(0.57)	(0.52)	(0.52)	(0.68)	(0.58)	(0.61)
EMDEs	-1.05	-0.68	-1.30	-0.24	-0.05	-0.72
	(1.05)	(0.95)	(0.96)	(1.12)	(0.97)	(1.01)
LIDCs	4.08**	2.22	2.27	5.21**	3.37*	3.12*
	(1.89)	(1.71)	(1.72)	(2.03)	(1.75)	(1.83)
Constant	-5.48**	-6.92***	-7.03***	-8.74***	-10.46***	-10.40***
	(2.49)	(2.26)	(2.27)	(3.10)	(2.68)	(2.80)
Observations	154	154	154	126	126	126
R-squared	0.27	0.17	0.20	0.27	0.19	0.23

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Covid Economics 74, 30 March 2021: 94-141

Figure A.13: Marginal Effect of Death Rates, Conditional on Average Stringency

(a) GDP growth in 2020



(b) GDP growth in 2020 vs. Jan 2020 WEO

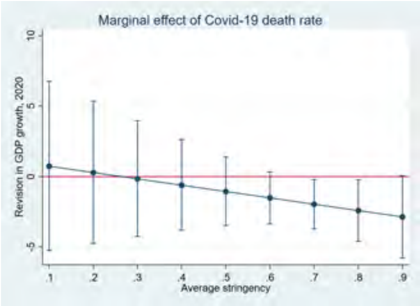


Table A.12: Primary Balance Revisions for 2020 - Relation with Stringency

	(1)	(2)	(3)	(4)	(5)	(6)
	2020 Primary Balance (% of GDP)					
	Actual 2020	Change vs. 2019	Revision vs. Jan 2020	Actual 2020	Change vs. 2019	Revision vs. Jan 2020
Containment (average)	-1.40	-0.18	-4.65***			
	(2.01)	(2.12)	(1.68)			
Stringency (average)				-0.96	-3.40*	-3.27**
				(1.88)	(1.77)	(1.61)
Health policies (average)				-3.27	0.59	-2.08
				(2.46)	(2.32)	(2.11)
Log GDP per capita	-1.53***	-0.77	-0.62	-1.36**	-0.94*	-0.58
	(0.56)	(0.59)	(0.47)	(0.58)	(0.54)	(0.49)
EMDEs	-0.18	1.71	2.09**	-0.25	1.92**	1.99**
	(1.04)	(1.10)	(0.87)	(1.02)	(0.96)	(0.87)
LIDCs	-0.83	3.17*	3.81**	-0.74	3.21*	3.71**
	(1.76)	(1.87)	(1.48)	(1.73)	(1.63)	(1.49)
Constant	-0.81	-4.90*	-2.48	0.66	-2.76	-2.08
	(2.37)	(2.51)	(1.98)	(2.45)	(2.30)	(2.10)
Observations	163	163	163	162	162	162
R-squared	0.14	0.18	0.33	0.17	0.28	0.32

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.13: Primary Balance Revisions for 2020 - Relation with Mobility

	(1)	(2)	(3)	(4)	(5)	(6)
	2020 Primary Balance (% of GDP)					
	Actual 2020	Change vs. 2019	Revision vs. Jan 2020	Actual 2020	Change vs. 2019	Revision vs. Jan 2020
Stringency (average)	-2.29	-2.86*	-2.81*	-3.35	-4.03*	-3.72*
	(1.84)	(1.59)	(1.44)	(2.44)	(2.08)	(1.89)
Covid-19 deaths	-0.20	-0.32	-0.12			
	(0.96)	(0.84)	(0.76)			
Google mobility (average)				0.21	-0.34	-0.16
				(0.43)	(0.36)	(0.33)
Log GDP per capita	-1.36**	-1.13**	-0.54	-1.60**	-1.11*	-0.66
	(0.56)	(0.49)	(0.44)	(0.67)	(0.57)	(0.52)
EMDEs	-0.15	1.57*	1.89**	0.67	1.88**	2.04**
	(1.03)	(0.90)	(0.81)	(1.11)	(0.94)	(0.86)
LIDCs	-0.18	2.10	3.74**	-0.67	2.50	3.80**
	(1.85)	(1.61)	(1.45)	(2.01)	(1.71)	(1.56)
Constant	-0.68	-1.69	-3.85**	0.25	-1.47	-3.21
	(2.45)	(2.13)	(1.92)	(3.08)	(2.62)	(2.39)
Observations	152	152	152	124	124	124
R-squared	0.18	0.31	0.34	0.17	0.30	0.34

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.14: Primary Balance Revisions for 2020 - Relation with Fiscal Packages

	(1)	(2)	(3)	(4)	(5)	(6)
	2020 Primary Balance (% of GDP)					
	Actual 2020	Change vs. 2019	Revision vs. Jan 2020	Actual 2020	Change vs. 2019	Revision vs. Jan 2020
Stringency (average)	-1.27	-1.16	-3.61**	-1.94	-2.71	-1.89
	(1.80)	(2.05)	(1.62)	(1.93)	(1.71)	(1.46)
Covid-19 fiscal support in 2020	-0.57***	-0.31**	-0.17	-0.43***	-0.27**	-0.43***
	(0.11)	(0.13)	(0.10)	(0.13)	(0.11)	(0.10)
Covid-19 deaths				-0.12	-0.67	-0.20
				(0.97)	(0.86)	(0.74)
Log GDP per capita	-1.61***	-0.79	-0.83*	-1.34**	-1.16**	-0.63
	(0.53)	(0.60)	(0.48)	(0.55)	(0.49)	(0.42)
EMDEs	-1.59	1.20	1.73*	-1.02	0.99	0.85
	(1.04)	(1.18)	(0.93)	(1.07)	(0.95)	(0.81)
LIDCs	-2.44	2.46	3.17**	-1.04	1.28	2.44*
	(1.73)	(1.96)	(1.56)	(1.84)	(1.63)	(1.40)
Constant	2.57	-2.64	-1.70	1.22	-0.11	-1.87
	(2.43)	(2.75)	(2.19)	(2.52)	(2.23)	(1.91)
Observations	155	155	155	146	146	146
R-squared	0.27	0.22	0.35	0.25	0.36	0.44

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Covid Economics 74, 30 March 2021: 94-141

Table A.15: Covid-19 Fiscal Support Packages - Relation with Stringency

	(1)	(2)	(3)	(4)	(5)	(6)
	Covid-19 Above-the-line Fiscal Support (% of GDP)					
	Support in 2020	Total support		Support in 2020	Total support	
FM Edition	Jan 2021	Jan 2021	Oct 2020	Jan 2021	Jan 2021	Oct 2020
Stringency (average)	-1.11	-0.10	-1.06	-1.91	-0.95	-1.03
	(1.34)	(1.65)	(1.25)	(1.41)	(1.74)	(1.33)
Stringency (average) x AE dummy				7.37*	7.91	-0.24
				(4.27)	(5.30)	(4.03)
Log GDP per capita	0.05	-0.18	0.14	0.07	-0.16	0.14
	(0.40)	(0.49)	(0.37)	(0.39)	(0.49)	(0.37)
EMDEs	-2.85***	-4.87***	-3.43***	1.70	0.02	-3.58
	(0.74)	(0.92)	(0.69)	(2.74)	(3.40)	(2.58)
LIDCs	-3.10**	-5.22***	-3.93***	1.36	-0.44	-4.08
	(1.26)	(1.57)	(1.18)	(2.87)	(3.56)	(2.71)
Constant	6.62***	8.69***	6.83***	2.60	4.36	6.97**
	(1.72)	(2.12)	(1.60)	(2.89)	(3.59)	(2.72)
Observations	157	157	156	157	157	156
R-squared	0.18	0.24	0.29	0.19	0.25	0.29

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.16: Covid-19 Fiscal Support Packages - Relation with Mobility

	(1)	(2)	(3)	(4)	(5)	(6)
	Covid-19 Above-the-line Fiscal Support (% of GDP)					
	Support in 2020	Total support		Support in 2020	Total support	
FM Edition	Jan 2021	Jan 2021	Oct 2020	Jan 2021	Jan 2021	Oct 2020
Stringency (average)	0.25	1.00	-0.02	0.16	0.06	-0.03
	(1.33)	(1.80)	(1.35)	(1.62)	(2.09)	(1.77)
Covid-19 deaths (average)	0.52	0.21	0.14			
	(0.67)	(0.91)	(0.68)			
Google mobility (average)				-0.20	-0.24	-0.06
				(0.27)	(0.35)	(0.29)
Log GDP per capita	0.07	-0.19	0.28	0.23	0.04	-0.01
	(0.38)	(0.52)	(0.38)	(0.43)	(0.55)	(0.46)
EMDEs	-2.75***	-4.89***	-3.49***	-2.97***	-4.90***	-3.87***
	(0.70)	(0.96)	(0.71)	(0.71)	(0.92)	(0.77)
LIDCs	-2.91**	-5.25***	-3.62***	-3.52***	-5.68***	-4.80***
	(1.24)	(1.70)	(1.26)	(1.27)	(1.64)	(1.39)
Constant	5.28***	7.84***	5.68***	5.31***	7.99***	6.93***
	(1.67)	(2.27)	(1.69)	(1.99)	(2.56)	(2.17)
Observations	146	146	145	120	121	120
R-squared	0.22	0.25	0.32	0.32	0.37	0.35

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Covid Economics 74, 30 March 2021: 94-141

CEPR PRESS

Working from home: Its effects on productivity and mental health[1]

Ritsu Kitagawa,[2] Sachiko Kuroda,[3] Hiroko Okudaira[4] and Hideo Owan[5]

Date submitted: 25 March 2021; Date accepted: 26 March 2021

Covid Economics 74, 30 March 2021: 142-171

The coronavirus disease 2019 (COVID-19) pandemic has impacted the world economy in various ways. In particular, the drastic shift to telework has dramatically changed how people work. Whether the new style of working from home (WFH) will remain in our society highly depends on its effects on workers' productivity. However, to the best of our knowledge, the effects of WFH on productivity are still unclear. By leveraging unique surveys conducted at four manufacturing firms in Japan, we identify the possible factors of productivity changes due to WFH. Our main findings are as follows. First, after ruling out the time-invariant component of individual productivity and separate trends specific to employee attributes, we find that workers who worked from home experienced productivity declines more than those who did not. Second, our analysis shows that poor WFH setups and communication difficulties are the major reasons for productivity losses. Third, we find that the mental health of workers who work from home is significantly better than that of workers who are unable to work from home. Our result suggests that if appropriate investments in upgrading WFH setups and facilitating communication can be made, WFH may improve productivity by improving employees' health and well-being.

1 This study was conducted as joint research under the "Research on Working-style Reform, Health and Productivity Management" (Kuroda) and "Productivity Effect of HRM Policies and Changing Employment Systems" (Owan) projects undertaken at the Research Institute of Economy, Trade and Industry (RIETI). The authors are grateful for helpful comments and suggestions given from Arata Ito, Masayuki Morikawa, Kotaro Tsuru, Makoto Yano, and participants at the RIETI discussion paper seminar.

2 Graduate Student, Graduate School of Economics, Waseda University.
3 Professor, Waseda University; Faculty Fellow, the Research Institute of Economy, Trade and Industry.
4 Associate Professor, Doshisha University.
5 Professor, Waseda University; Faculty Fellow, the Research Institute of Economy, Trade and Industry.

1. Introduction

The coronavirus disease 2019 (COVID-19) pandemic has impacted the world economy in various ways. As one of the major changes, teleworking or working from home (WFH) has become widespread across countries. For example, Brynjolfsson et al. [1] suggest that in May 2020, approximately half of the workforce in the U.S. was WFH. Felstead and Rueschke [2] reported that in April 2020, the WFH percentage in the U.K. reached 43.1% and, in June 2020, remained high, 36.5%. Additionally, Eurofound [3] showed that in July 2020, nearly half of all employees in EU countries worked from home. For Japan, the Cabinet Office [4] reported that the WFH percentage was 34.5% at the end of May 2020, and Morikawa [5] reported that it was approximately 32% in June 2020 (see also Okubo [6], who reported a smaller figure: 17% in June 2020). Regarding other countries, see Pouliakas [7] for Greece and Delaporte and Pena [8] for 23 Latin American and Caribbean countries; both studies reported smaller figures. While the WFH percentages vary across countries, two common features are observed: (1) many people reported that during the crisis, it was their first time WFH (for example, see [2], [3] and [6]), and (2) the majority of workers WFH wished to continue the new working style if there were no COVID-19 restrictions ([2], [3] and [4]). This new global experience indicates that WFH may increase the welfare of workers, at least for those who are able to pursue their job at home (see Kroll and Nuesch [9], Bellmann and Hubler [10], and [11]). Although WFH may not be applicable to all occupations (see [12], [13], [14] and [11]), the experience of WFH during the crisis may lead to growth in teleworking even after the crisis abates ([3]).

This pandemic-driven WFH has dramatically changed people's way of work, and it is crucial to sustain production during this ongoing crisis. Whether the new style will remain in our society highly depends on its effects on workers' productivity. However, the effects of WFH on productivity are still unclear (OECD [15]). For example, based on a field experiment conducted in the call center of a Chinese firm, Bloom et al. [16] found that WFH had a positive effect on workers' productivity and reduced turnovers. While the paper ([16]) reporting evidence based on data collected before the COVID-19 pandemic, Emanuel and Harrington [17] also found a positive effect on the productivity of call center workers during the COVID-19 crisis. Analyzing not only specific workers but also broader occupations in the U.K., Felstead and Rueschke [2] indicated mixed results under COVID-19. Their paper showed that two-fifths of workers reported that they were able to complete as much work in June 2020 as they were able to complete six months earlier;

Covid Economics 74, 30 March 2021: 142-171

additionally, over a quarter of workers said that they accomplished more, while 30.2% said that their productivity had fallen. Additionally, Ipsen et al. [18] showed that among WFH workers in Denmark, 55% complete the same amount of work or more when WFH than when physically working at a workplace. They also reported that the majority of WFH workers indicated that they worked fewer hours, which suggests that WFH is more efficient and productive on a per-hour basis. On the other hand, Morikawa [5] showed that the mean WFH productivity relative to working at the usual workplace was approximately 60% to 70% in Japan, and 82% of workers reported a decline in productivity in a WFH environment during the COVID-19 crisis.

Several studies have also reported both positive and negative effects of WFH on productivity, depending on skills, education, tasks or industry. For example, Etheridge et al. [19] reported that in the U.K., while workers who have increased their intensity of WFH reported substantial productivity increases, those who previously always worked from home, women and those in low-paying jobs suffered the worst average declines in productivity (see also [20], [21], [22]). The paper ([19]) also reported that declines in productivity are strongly associated with declines in mental well-being. Using firm surveys, Bartik et al. [23] reported that employers think that there have been less productivity losses from remote working in better educated and higher-paying industries. Dutcher [24] indicated that WFH may have positive effects on productivity in creative tasks but negative effects on productivity in dull tasks. In summary, although there has been a rapid accumulation of studies on WFH and productivity, the reported evidence is mixed, and we believe that additional evidence on when WFH is productivity-enhancing is needed.

In this study, we try to contribute additional evidence on the effects of WFH by using data from our original employee-level survey conducted in cooperation with four large listed manufacturing companies in Japan from April to June 2020. On April 7, 2020, the Japanese government declared a countrywide state of emergency. Although the state of emergency ended on May 25, the request for self-restraint on movement between prefectures was extended until June 19. In the meantime, the government asked firms to let workers work from home as much as possible.[1] According to the panel survey conducted by the Japan Institute for Labour Policy and Training (JILPT) (2020), the number of WFH workers rapidly increased from early April and peaked in the second week of May 2020. It then started to decline after the state of emergency was

[1] Prime Minister Shinzo Abe (at that time) asked firms to allow at least 70% of employees to work from home during a press conference on April 7.

Covid Economics 74, 30 March 2021: 142-171

lifted at the end of May and dropped significantly by the end of July. Notably, although the government declared a state of emergency, it was only *on a request basis* and was not mandatory; therefore, the final decision on whether to introduce WFH was made completely at the discretion of employers. Moreover, many Japanese firms allowed each workplace to individually decide whether to use WFH. Therefore, even in the same firm, while workers in some units worked entirely from home, workers in other units had to commute to the office even though both groups of workers performed similar tasks. The variations in WFH within the same company enable us to investigate whether there are productivity losses or gains due to WFH. However, because companies and division managers had the discretion to comply with or to defy the official request, the decision to opt for WFH may be endogenous if workers with specific unobserved traits or roles in the workplace tended to be chosen for WFH. We overcome this concern over endogeneity in two ways, which we explain as part of the empirical strategy in Section 3.

The survey we use includes questions on subjective productivity and the perceived factors of productivity losses, allowing us to investigate the possible determinants of deteriorations in productivity. It also contains questions on mental health and the perceived advantages of WFH, making it possible to examine the relationship between WFH and workers' mental health.

Our major contributions are threefold. First, using employee survey data with high response rates, we exploit the heterogeneities among workers within the same companies. Specifically, we identify the effects of WFH on productivity within the same company and within the same occupation, which vary depending on the number of days spent WFH. Focusing on specific companies also allows us to exclude the differences in productivity among firms. For example, using firm panel data, Bloom et al. [25] reported evidence that productivity widely varies between firms and that the least productive firms have been disproportionately affected by COVID-19. Based on our analysis, workers who worked from home experienced a productivity decline compared with those who did not. Second, owing to the rich information available in our original surveys, we could identify the potential factors that determine deteriorations in productivity due to WFH. We find that poor WFH setups and communication difficulties are the major reasons for productivity losses. In addition, although the reasons above are common features of all occupations, we find that the major reasons that reduce productivity the most differ by occupation. Our findings provide managerial implications that are useful for designing desirable investments to improve the productivity of employees while WFH. Third, we complement our

Covid Economics 74, 30 March 2021: 142-171

findings by analyzing the impact of WFH on mental health. Since a lack of time series information on mental health prevents us from ruling out a time-invariant component of employees' mental status, the findings here should be handled with reservation, we find that the mental health of WFH workers is significantly better than that of workers who are unable to work from home. In addition, our results imply that better concentration, less fatigue, and a shorter commute time may contribute to better mental health. Our result suggests that if appropriate WFH investments can be made, WFH may also improve productivity by improving employees' health and well-being.

The remainder of this paper is organized as follows. Section 2 describes our data, and Section 3 presents our quantitative methods. Section 4 explains the results, and Section 5 concludes.

2. Data

We use data retrieved from our original survey on WFH productivity during the COVID-19 pandemic, which was conducted in cooperation with four listed manufacturing companies in Japan (Companies A, B, C, and D) from April to June 2020. Companies A, B, and D are chemical manufacturing companies, while Company C is an automobile manufacturing company. Companies A, B, and D have approximately 8,000, 7,000, and 27,000 employees, respectively, while Company C has more than 30,000 employees on a consolidated basis.

The survey was administered to both white- and blue-collar employees (Companies A, B, and D) or white-collar employees (Company C).[2] The employees of Companies B and D also included those of subsidiary companies. All employees of the four companies were asked to complete the survey. The survey included questions on topics such as the number of days spent WFH per week, productivity (presenteeism; details will be explained in Section 2.1.1.) before and after the state of emergency, the perceived causes of productivity losses, the respondents' mental health status (details will be explained in Section 2.1.2.), the perceived advantages of WFH, and the respondents' occupation, job grade, division, and basic individual characteristics. The response rates were high across the companies, ranging from 72% to 91%. The total sample size was 24,175, which fell to 22,815 after excluding invalid responses. Because the survey asked about the

---

[2] Hence, the Company C sample does not include production line workers, who regularly worked at the factory during the survey period, resulting in the smaller proportion of "no WFH" responses compared to the other companies.

Covid Economics 74, 30 March 2021: 142-171

respondents' productivity level both before and after the state of emergency, our analyses could rule out the time-invariant component of individual productivity.

Table 1. The proportion of workers working from home

	Company A	Company B	Company C	Company D
Sample	All employees	All employees (incl. subsidiaries)	All employees (excl. production line workers)	All employees (incl. subsidiaries)
Reference period	From April 1 to the date of reponse	From May 11 to the date of reponse	From May 11 to the date of reponse	From April 8 to the date of reponse
Survey period	May 20-26	May 20-June 3	June 17-26	April 23-May 7
Days spend WFH per week (%)				
5 days	8.1	22.5	18.4	21.2
3-4 days	14.9	9.9	31.4	17.0
1-2 days	25.0	19.6	41.0	18.7
None	52.0	48.0	9.2	43.1
Number of Observations	2877	3458	3989	12941
% of those who worked from home in early March	NA	35.2	20.1	10.7

The survey included a question on the number of days spent WFH per week during the reference period. We consolidated the answers into four categories based on the number of days spent WFH: none, once or twice, three or four times, and five times a week (i.e., exclusively WFH). Table 1 shows the percentage of employees who worked from home by the number of days worked from home per week on a company-by-company basis. It shows that among employees within the same company, there is variation in the number of days spent WFH. Moreover, the percentage of workers who completely worked from home, i.e., those who worked from home five days a week, ranged from approximately 8% to 22% across the four companies. On the other hand, the figures show that approximately 40% to 50% of employees of Companies A, B, and D and 10% of employees of Company C worked entirely at the office. Note that this share of employees not WFH is low for Company C because it asked only white-collar employees to complete the survey.

Covid Economics 74, 30 March 2021: 142-171

2.1. Outcome variables

2.1.1. Productivity

In our survey, productivity was measured based on answers to the questions that are modified version of the Health and Work Performance Questionnaire (HPQ), which is developed by the World Health Organization (WHO) and used to measure subjective productivity (presenteeism). Our productivity measurement was conducted based on two-stage questions following the WHO-HPQ. The first item asked respondents the following retrospective question: "(*o*)*n a scale from 0 to 10 where 0 is the worst job performance anyone could have at your job, 5 is the performance of average workers, and 10 is the performance of a top worker, how would you rate your usual job performance (in the one-year period) before the declaration of the state of emergency?*"[3] This item aimed to determine the average level of productivity of individual employees in the pre-COVID-19 period. The second question asked respondents to also apply a "0 to 10" scale to grade their overall job performance since a specific reference date, which varied by company. Taking the difference between the answers to these two questions, we calculated the changes in productivity before and after the state of emergency.[4] Regarding Company D, the simplified University of Tokyo version of the one-item presenteeism scale (Presenteeism-UT), which aimed to reduce the number of questions based on the HPQ, was used. For Company D, the employee survey was conducted twice, first in early March 2020 before the state of emergency was declared and again in April 2020. Therefore, unlike the other companies for which presenteeism before the state of emergency was evaluated in a retrospective manner, for Company D, presenteeism was measured at two time points—before and after the state of emergency.[5]

We use this presenteeism measure as one of our main outcome variables. Higher values indicate less presenteeism (i.e., higher productivity).

[3] In the questionnaire used for Company A, the phrase "*in the one-year period"* in the parentheses was not included.
[4] We shall note that while some previous literature evaluate productivity when working from home, we measure total productivity before and after the declaration of the state of emergency regardless of the number of days working from home.
[5] Specifically, the Presenteeism-UT asked employees to "*Suppose that 100% is your work performance when you are neither sick nor injured. Please evaluate your current work performance*." For the April survey, the question was changed to "*Suppose that 100% is your work performance when you are neither sick nor injured before the state of emergency. Please evaluate your current work performance after April 8*." We standardized the responses to a 0-10 scale by dividing by 10.

2.1.2. Mental health index

Another main outcome variable of this paper is employees' mental health. In the survey, we asked respondents to "(p)lease answer the following questions concerning your health since [the start date of the reference period]" along with the following three questions about workers' mental health: "I have been depressed," "I have felt weary or listless, " and "I have felt worried or insecure." The respondents were asked to choose from four options: "almost always," "often," "sometimes," and "almost never." We coded these responses on a 1 to 4 scale and reduced the total scores from the three questions into one dimension by using correspondence analysis; this one dimension was used as the mental health index. Correspondence analysis reduces the dimension of scales among a set of qualitatively similar categorical variables (see, for instance, [26]). Higher values indicate better mental health. Note that this variable is not available for Company A.

2.2. Covariates of interest

2.2.1. Perceived factors of deteriorations in productivity

The survey also asked respondents who worked from home during the reference period to choose potential factors that caused declines in their productivity. Specifically, the respondents were asked the following multiple-choice question: "what factors, if any, do you think lower productivity when working from home?" The choices were "*the inability to retrieve data from outside of the office because of security,*" *"the inability to use exclusive equipment that is available only at the office," "poor WFH setups (e.g., do not have own office space)," "lack of articulate orders and/or poor support from superiors," "poor workplace communication," "poor communication with clients," "fatigue from an excessive workload," "not feeling well physically (stiff shoulders, back pain, etc.)," "feeling mentally under the weather," and "having distractions or responsibilities to deal with (such as kids who want attention, nursing care for parents, and other family responsibilities)."*

In the survey, we also asked WFH employees another multiple-choice question about workers' perceived advantages of WFH. Specifically, we asked, "*While working from home, did you find any advantages of WFH, if any?*" The choices were "*no distractions and a quiet environment that facilitates a greater focus on work,*" "*can avoid frequent and/or unnecessary conversations with coworkers,*" *"free from stress caused by annoying relationships with coworkers and bosses," "improvement in IT skills," "zero commuting and saving time on getting*

Covid Economics 74, 30 March 2021: 142-171

ready for work," "being able to wear casual clothes," "less fatigue and having a healthier condition," "eating healthier meals," "spending more time exercising," "reducing alcohol consumption," "having extra time for sleep and rest," "less smoking," "having extra time with family and friends," "the ability to fit in household chores, parental care, and extra time with kids," "better family relationships," and "finding new hobbies due to the constraints on going out."

2.2.2. Functional roles

Using the occupational classification of each employee, we categorized the employees into four functional roles: *corporate*, *sales*, *R&D*, and *production*. Production included not only blue-collar employees who engage in the production process but also white-collar employees who manage production and quality control. In the following, we divide our observations into subsamples by these four categories to investigate whether the possible causes that reduce WFH productivity may differ across functional roles.

The descriptive statistics of each company are presented in Appendix Table 1.

3. Empirical strategy

3.1. Main model

We are interested in identifying the impact of the individual's WFH status on the outcome variable (y_{ijt}) for individual *i* at division *j* at time *t*. We start with a simple linear model:

$$y_{ijt} = z_{ijt}\beta + X_{ijt}\gamma + \epsilon_{ijt} \tag{1}$$

where z_{ijt} is the number of days spent WFH per week or a vector of dummies (*wfh2d*, *wfh4d*, *wfh5d*); X_{ijt} is a vector of individual and division-specific characteristics; and ϵ_{ijt} is an error term. $wfh2d_i$, $wfh4d_i$, and $wfh5d_i$ indicate the number of days spent WFH per week, i.e., "once or twice," "three or four times," and "five times (exclusively)," respectively. The reference is none

Covid Economics 74, 30 March 2021: 142-171

(zero WFH days). A vector of dummies (*wfh2d*, *wfh4d*, *wfh5d*) is used when we suspect a nonlinear relationship between the frequency of WFH and the outcome.

This study used different identification strategies for the presenteeism and mental health variables. For presenteeism, our survey asked for a subjective assessment of productivity in March (i.e., prior to the declaration of the state of emergency) and in April or May (i.e., after the declaration), and we had one observation point for mental health. We first explain our approach to the former in this section and to the latter in the next section.

We can identify β using ordinary least squares (OLS) if the WFH term is orthogonal to the error term, conditional on individual characteristics. This assumption is likely to be violated if workers with specific unobserved traits or roles in the workplace tend to be chosen for WFH. If companies are more likely to allow more productive workers to work from home, the estimated β will be overestimated. Likewise, if less productive workers volunteer to work from home disproportionately more often than more productive workers, then the estimate for β will be underestimated.

In our case, the shock to WFH adoption was mostly exogenous. Similar to the context of previous studies on the impact of WFH after the pandemic, the declaration of a state of emergency in Japan had a large and less expected impact on WFH adoption. According to Table 1, quite a large number of workers worked from home owing to the government's request in April. More than half of the employees in our sample worked from home at least once a week. Importantly, however, the government's WFH request was not mandatory. Because companies and division managers had the discretion to comply with or to defy the official request, the decision to opt for WFH may still be endogenous.

We overcome this concern over endogeneity in our subjective productivity measure in two ways. First, we take the first difference in equation (1) to rule out unobserved time-invariant individual and division-specific characteristics in the error term, which are correlated with factors affecting the WFH choice.

$$\Delta y_{ijt} = \Delta z_{ijt}\beta + \Delta X_{ijt}\gamma + \Delta\epsilon_{ijt} \tag{2}$$

where Δ is the first-difference operator.

As a result, our main sample is reduced to a cross-section of the first-differenced outcome variable. Δz_{ijt} is the difference in the number of days spent WFH during the period between the

Covid Economics 74, 30 March 2021: 142-171

two surveys. For Company A, information on the number of days spent WFH before April is lacking. We replace Δz_{ijt} with z_{ijt} under the assumption that a very small number of employees worked from home for a limited number of days before April.

As shown below, most covariates in X_{ijt} do not have much time series variation, which means that most values in ΔX_{ijt} are zero. Additionally, although time-invariant individual and division-specific characteristics are ruled out by taking the first difference, they might still contribute to selection bias because they are likely to be correlated with time-varying unobservables that affect both the WFH choice and the outcome. For these reasons, we replace ΔX_{ijt} with X_{ijt} in equation (2). Thus, our baseline model is as follows:

$$\Delta y_{ijt} = \Delta z_{ijt}\beta + X_{ijt}\gamma + \Delta\epsilon_{ijt} \tag{3}$$

In particular, we include the following terms as X_{ijt}: a female dummy, age category dummies, and dummies for job grades and divisions. Including dummies for job grades and divisions in equation (2) essentially allows us to control for separate trends across different job levels and divisions. Controlling for such trends is important in the analysis of WFH after the pandemic because a worker's occupation and functional and technical roles within the organization could correlate with her superior's WFH choice for her. In other words, by including dummies for job grades and divisions, the coefficient β is identified mainly based on the variation within the division and job level where the variation in WFH is primarily caused by the preference and management style of the worker's supervisor, which is less likely to be correlated with the worker's productivity.

To the extent that our estimation model controls for the selection bias arising from such endogenous adoption of WFH, the estimate of β represents the causal impact of WFH adoption. One cause for concern is that some employees were transferred across divisions during the reference period. However, their functional roles rarely changed after the transfer, and the effect of the division within the same functional role was not expected to differ substantially.

Another issue that we encounter is that the measurement of presenteeism is not necessarily consistent with the measurement of WFH. In the default questionnaire that we used, presenteeism was assessed for a one-year period before the declaration of the state of emergency, while the

Covid Economics 74, 30 March 2021: 142-171

frequency of WFH was assessed for a one-week period in early March. The measurement period for the two is consistent for the question asked for the post-declaration period. To mitigate the bias due to this time inconsistency, we add z_{ijt} as a control in some specifications. That is, we estimate the following:

$$\Delta y_{ijt} = \Delta z_{ijt}\beta_1 + z_{ijt}\beta_2 + X_{ijt}\gamma + \Delta\epsilon_{ijt} \tag{4}$$

3.2. Model for mental health

As discussed above, for our mental health variable, we have one observation point. Thus, taking the first difference is not feasible. We argue that for mental health, endogeneity bias is less of a concern for two reasons. First, it is unlikely that workers with a specific mental health condition tend to be chosen for WFH because a person's mental health condition is not known to her supervisor until it has deteriorated so much that her doctor's recommendation of sick leave or a job transfer is submitted. Even if the supervisor knows her subordinate's mental health condition before it becomes this bad, it is not a priori obvious whether choosing WFH will be good or bad for her health. Second, we have precise information about workers' workplace and job level, which can be used to account for the technical or operational reasons underlying the WFH choice. Including division dummies and job level dummies as controls also helps us to control for variations in mental health conditions across occupations and job levels, thus mitigating the endogeneity bias with regard to WFH.

For these two reasons, estimating equation (1) using OLS will allow us to make causal interpretations, although we still cannot rule out the possibility of some bias due to selection. Therefore, as a robustness check, we also estimate a model with sample selection bias.

3.3. Analysis using the WFH sample

Some survey questions, such as the item asking about the perceived factors of productivity declines, were asked only to workers who worked from home during the reference period. Furthermore, the answer to the question is likely to be correlated with the frequency of WFH. Therefore, the OLS estimates of equation (3) for presenteeism or equation (1) for mental health are biased if

Covid Economics 74, 30 March 2021: 142-171

$$E[\Delta\epsilon_{ijt}|X_{ijt}, \Delta z_{ijt}, d = 1] \neq 0$$

or

$$E[\epsilon_{ijt}|X_{ijt}, z_{ijt}, d = 1] \neq 0,$$

respectively, where d denotes a dummy for WFH at least one day a week.

Given our previous discussion, we predict that the OLS estimates of the first-difference equation for presenteeism might be biased due to selection if unobservable factors that separate trends of presenteeism are correlated with the decision to work from home. On the other hand, the OLS estimate of equation (1) for mental health is unlikely to be biased if the decision to work from home is uncorrelated with mental health, conditional on individual characteristics and divisions. To investigate our predictions, we have estimated both OLS and type II Tobit model (models with sample selection biases)

4. Results

4.1. Frequency of WFH and productivity

First, we estimate equation (2) without control variables to observe how the frequency of WFH affects productivity. The results are shown in Table 2. The coefficient estimates of the difference in the number of days spent WFH (the WFH dummies for Company A) are significantly negative for all companies. In summary, the results indicate that workers who worked from home experienced declines in productivity compared with those who did not. This adverse effect was considerably large for Company D, which may have resulted from the fact that the survey was conducted in late April, two weeks after the declaration of the state of emergency. At that time, many employees were forced to work from home without full preparation, which may have temporarily resulted in a large decline in productivity.

Covid Economics 74, 30 March 2021: 142-171

Covid Economics 74, 30 March 2021: 142-171

Table 2. Regression of productivity changes on WFH

	Company A	Company B	Company C	Company D
	prsnt_dif			
wfh_5d	-0.321***	-	-	-
	(0.104)	-	-	-
wfh_4d	-0.597***	-	-	-
	(0.0956)	-	-	-
wfh_2d	-0.400***	-	-	-
	(0.0653)	-	-	-
wfh_dif	-	-0.0811***	-0.0350***	-0.249***
	-	(0.0245)	(0.0100)	(0.0349)
Constant	-0.0304	0.0517	-0.711***	-0.413***
	(0.0380)	(0.0400)	(0.0472)	(0.141)
Divisions	No	No	No	No
Job grades	No	No	No	No
Observations	2,798	3,404	3,989	10,753
R-squared	0.037	0.005	0.003	0.044

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3 shows the full model including other explanatory variables (i.e., equation (4)). For Company B, the first difference of the WFH days becomes statistically insignificant. On the other hand, although the magnitude of the estimates decreases, the frequency of WFH still negatively affects productivity for Company D even after controlling for various individual and job characteristics. Note that the level of WFH dummies are negative for both Companies B and D. As for Company C, the magnitude of the first difference becomes even larger. However, the WFH dummy of 5 days is positive and statistically significant. We will reconsider this in the subsample analysis below.

Table 3. Regression of productivity changes on WFH with controls

	Company A	Company B	Company C	Company D
	prsnt_dif			
wfh_5d	-0.227*	-0.369***	0.437**	-0.963***
	(0.134)	(0.123)	(0.174)	(0.249)
wfh_4d	-0.457***	-0.396**	0.107	-1.152***
	(0.109)	(0.157)	(0.143)	(0.192)
wfh_2d	-0.337***	-0.169	-0.0453	-0.906***
	(0.0878)	(0.125)	(0.0980)	(0.149)
wfh_dif	-	-0.00550	-0.0861***	-0.0507**
	-	(0.0308)	(0.0183)	(0.0196)
female	0.0134	-0.0202	0.126	0.268***
	(0.0619)	(0.0842)	(0.0862)	(0.0694)
age30	-0.239**	-0.141	-0.325***	-0.241***
	(0.0926)	(0.123)	(0.0902)	(0.0635)
age40	-0.248***	0.0764	-0.193**	-0.404***
	(0.0791)	(0.122)	(0.0937)	(0.0774)
age50	-0.228**	0.0520	-0.118	-0.413***
	(0.0837)	(0.106)	(0.110)	(0.0871)
age60	-0.278	-0.144	0.0309	-0.629***
	(0.176)	(0.134)	(0.107)	(0.166)
Constant	-0.0691	-0.0560	-0.552***	3.428***
	(0.149)	(0.157)	(0.125)	(0.193)
Divisions	Yes	Yes	Yes	Yes
Job grades	Yes	Yes	Yes	Yes
Observations	2,798	2,827	3,720	10,690
R-squared	0.065	0.038	0.067	0.157

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The full model offers another causal parameter worth mentioning. The productivity losses are greater for employees in their 30s, 40s, and 50s in Companies A, C, and D. Young workers are not significantly affected by the shift to WFH presumably because (1) they are more familiar with online communication and recent information technology than their older counterparts and (2) they are assigned more specialized or solo tasks requiring less coordination; thus, their productivity is

Covid Economics 74, 30 March 2021: 142-171

less constrained by WFH. These results may provide evidence that, on average, employees experienced declines in productivity from WFH. Below, we investigate what factors caused such declines in productivity.

4.2. Causes of productivity losses

To identify the causes underlying the productivity losses, we add as explanatory variables the responses to the question of what factors the respondents perceived as causing their productivity to decline.[6] Here, the sample is restricted to those who worked from home at least one day per week after the state of emergency. Any factors that are strongly correlated with productivity losses should be the main mechanism underlying the drop in productivity. Table 4 reveals two important common channels. First, "*poor WFH setups*" have a significantly negative coefficients for all companies, and "*the inability to retrieve data from outside the office*" is also negatively correlated with changes in productivity for Companies A and B. These results indicate that the lack of sufficient infrastructure for WFH hinders employee performance. Second, *"poor workplace communication" and "poor communication with clients"* are significantly negative for almost all companies. This result implies that new communication applications such as social networking services (SNSs), chat apps and conference calls cannot easily replace traditional communication methods such as face-to-face communication or phones and their role in meeting spontaneous, simultaneous or urgent needs for communication. The significance of the coefficients of the other variables varies across companies. We shall also note that "having responsibilities (childcare and/or nursing care)" is also negative and statistically significant for Companies A and C. During the state of emergency in April to May, a number of children did not attend school because of closures. Also, many daycare centers for elders have closed in order to avoid cluster infection of COVID-19. Those closures have caused temporary loss of productivity for workers who needed to take care of their family members while working from home.

[6] For Company D, slightly different wording was used for some questions, but what was being asked was essentially the same. However, a few questions were not available. Accordingly, "*the inability to retrieve data*" and "*having responsibilities (childcare and/or nursing care)*" are missing for Company D.

Covid Economics 74, 30 March 2021: 142-171

Table 4. Regression of productivity changes on the perceived factors of productivity losses

	Company A	Company B	Company C	Company D
	prsnt_dif			
wfh_5d	0.150	-0.259	0.378***	0.0249
	(0.147)	(0.152)	(0.116)	(0.101)
wfh_4d	0.0819	-0.242	0.118	-0.170
	(0.0586)	(0.159)	(0.0758)	(0.103)
wfh_dif	-	0.0148	-0.0748***	-0.0597***
	-	(0.0315)	(0.0183)	(0.0202)
Inability to retrieve data	-0.459***	-0.341***	-0.0596	-
	(0.157)	(0.0694)	(0.0557)	-
Inability to use exclusive equipment	-0.589***	-0.0787	-0.168***	-
	(0.0975)	(0.116)	(0.0560)	-
Poor WFH setups	-0.536***	-0.506***	-0.415***	-0.641***
	(0.162)	(0.0585)	(0.0590)	(0.0767)
Lack of support and/or instruction from the supervisor	-0.144	-0.256	-0.0553	-
	(0.274)	(0.195)	(0.0660)	-
Poor workplace communication	-0.503***	-0.0906	-0.387***	-0.148**
	(0.136)	(0.0950)	(0.0504)	(0.0610)
Poor communication with clients	-1.028***	-0.382***	-0.114*	-0.517***
	(0.101)	(0.0964)	(0.0685)	(0.0961)
Fatigue from an excessive workload	-0.717	0.444***	0.0449	-
	(0.604)	(0.140)	(0.0992)	-
Not feeling well physically	-0.111	0.174*	-0.0480	0.334***
	(0.241)	(0.0965)	(0.0682)	(0.0530)
Feeling mentally under the weather	-0.306	-0.372***	-0.0949	0.276***
	(0.316)	(0.109)	(0.0937)	(0.102)
Having responsiblities (childcare and/or nursing care)	-0.985***	0.414	-0.284***	-
	(0.335)	(0.324)	(0.0906)	-
Miscellaneous	0.388	-0.570***	-0.402***	-
	(0.320)	(0.194)	(0.0918)	-
female	0.0278	-0.110	0.0833	0.129*
	(0.0672)	(0.127)	(0.0811)	(0.0703)
age30	-0.207*	-0.299***	-0.202**	-0.271**
	(0.116)	(0.0988)	(0.0931)	(0.105)
age40	-0.166	-0.187*	-0.0610	-0.528***
	(0.0990)	(0.107)	(0.0953)	(0.112)
age50	-0.243**	-0.305**	0.00719	-0.611***
	(0.0893)	(0.115)	(0.105)	(0.112)
age60	-0.248	-0.374**	0.147	-0.727***
	(0.184)	(0.169)	(0.116)	(0.146)
Constant	0.564***	0.339**	-0.212*	1.252***
	(0.167)	(0.153)	(0.112)	(0.160)
Divisions	Yes	Yes	Yes	Yes
Job grades	Yes	Yes	Yes	Yes
Observations	1,352	1,517	3,376	6,071
R-squared	0.354	0.090	0.122	0.120

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Covid Economics 74, 30 March 2021: 142-171

The first difference of WFH days and the WFH dummies become either statistically insignificant or at least their magnitude becomes small when we control for the causes. These results imply that WFH per se does not necessarily deteriorate workers' productivity and that declines in productivity while WFH can be ameliorated by addressing those undesirable factors. In particular, the infrastructure for WFH can be relatively easily improved by appropriate IT investment or by financial support provided by companies to their employees to establish a better work environment at home. In the long run, further technological development of IT security and communication devices and learning by doing among workers will help find efficient ways to communicate within and across companies.

To deal with sample selection bias, we also estimated type II Tobit models (the maximum likelihood estimator and Heckman's two-step estimator) to address potential selection into WFH as a robustness check. The estimation results did not provide evidence of selection bias and were qualitatively the same as the OLS estimation results.

4.3. Subsample analysis of causes

We now take a closer look at the causes of productivity losses by conducting subsample analysis. We divide the sample into four based on functional roles, i.e., corporate, sales, R&D, and production, and we estimate the model presented in Section 4.2. Tables 5-8 present the main results. Once again, the factor that is fairly common to all four functional roles is "*poor WFH setups*," the coefficient estimates are significantly negative for most cases. Apparently, it may be more important for corporate and R&D jobs since the estimates are all significant, except in the case of Company A, where the estimates are significant only at the 10% level.

Now, we turn to the specificity of each functional role. For corporate jobs and sales jobs, "*poor workplace communication*" and "*poor communication with clients*" have significantly negative effects on productivity across companies, which is consistent with the intuition that corporate jobs and sales jobs intensively involve engagement in coordination and organization both within and outside the company. This result is reasonable considering the nature of the tasks undertaken by employees who hold these roles. For sales jobs and R&D jobs, the coefficient estimate for "*the inability to retrieve data*" is significantly negative for Companies A and B, and the coefficient estimate for "*the inability to use exclusive equipment*" is significantly negative for Companies A and C. Once again, these results are reasonable since workers engaged in R&D tend to engage with confidential information such as patents. For production jobs, the estimate for "*poor workplace communication*" is significantly negative, except in the case of Company B, and this result is also fairly consistent with the duties and tasks of workers holding such jobs.

Table 5. Subsample analysis (corporate)

	Company A	Company B	Company C	Company D
	prsnt_dif			
Inability to retrieve data	0.211	-0.267	-0.144	-
	(0.203)	(0.198)	(0.157)	-
Inability to use exclusive equipment	-0.765***	-0.0780	0.0972	-
	(0.116)	(0.182)	(0.166)	-
Poor WFH setups	-0.686*	-0.412***	-0.378**	-0.776***
	(0.366)	(0.141)	(0.141)	(0.127)
Lack of support and/or instruction from the supervisor	0.306	-0.214	-0.147	-
	(0.411)	(0.208)	(0.219)	-
Poor workplace communication	-0.780***	-0.298	-0.314***	-0.364***
	(0.135)	(0.173)	(0.0992)	(0.133)
Poor communication with clients	-1.100***	-0.321*	-0.168	-0.493***
	(0.205)	(0.184)	(0.133)	(0.162)
Controls	Yes	Yes	Yes	Yes
Observations	402	579	522	1,621
R-squared	0.334	0.140	0.147	0.166

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
The controls include the difference of WFH, dummies for the WFH frequency after the state of emergency, other perceived factors, gender, age, job grades, divisions, and functional roles.

Across functional roles, there is a common factor of productivity losses, i.e., "*poor WFH setups*," which calls for comprehensive support for all occupations to improve the WFH conditions that employees face. In addition, our results indicate that the most important factor in improving WFH productivity differs by occupation, suggesting that employers should recognize that the optimal investment priorities may differ across occupations.

Covid Economics 74, 30 March 2021: 142-171

Covid Economics 74, 30 March 2021: 142-171

Table 6. Subsample analysis (sales)

	Company A	Company B	Company C	Company D
	prsnt_dif			
Inability to retrieve data	-0.590***	-0.478*	0.170	-
	(0.194)	(0.247)	(0.172)	-
Inability to use exclusive equipment	-0.588***	0.00242	-0.197	-
	(0.165)	(0.525)	(0.126)	-
Poor WFH setups	-0.399*	-0.474***	-0.290	-0.394***
	(0.206)	(0.105)	(0.198)	(0.118)
Lack of support and/or instruction from the supervisor	-0.556	-0.707**	0.127	-
	(0.621)	(0.258)	(0.118)	-
Poor workplace communication	-0.180	-0.159***	-0.422**	-0.0528
	(0.244)	(0.0445)	(0.159)	(0.134)
Poor communication with clients	-1.022***	-0.385	-0.301**	-0.482***
	(0.0979)	(0.233)	(0.119)	(0.136)
Controls	Yes	Yes	Yes	Yes
Observations	444	320	468	1,536
R-squared	0.456	0.207	0.103	0.187

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
The controls include the difference of WFH, dummies for the WFH frequency after the state of emergency, other perceived factors, gender, age, job grades, divisions, and functional roles.

Table 7. Subsample analysis (R&D)

	Company A	Company B	Company C	Company D
	prsnt_dif			
Inability to retrieve data	-0.925***	-0.516***	-0.108	-
	(0.153)	(0.123)	(0.0872)	-
Inability to use exclusive equipment	-0.501*	0.0137	-0.186**	-
	(0.265)	(0.205)	(0.0793)	-
Poor WFH setups	-0.645*	-0.589***	-0.524***	-0.638***
	(0.295)	(0.151)	(0.0935)	(0.186)
Lack of support and/or instruction from the supervisor	-0.575**	0.0617	-0.0519	-
	(0.235)	(0.433)	(0.126)	-
Poor workplace communication	-0.0500	0.0144	-0.353***	-0.230
	(0.292)	(0.178)	(0.0808)	(0.139)
Poor communication with clients	-1.676***	-0.541	-0.108	-0.0372
	(0.510)	(0.415)	(0.130)	(0.106)
Controls	Yes	Yes	Yes	Yes
Observations	387	342	1,427	1,186
R-squared	0.479	0.136	0.123	0.131

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
The controls include the difference of WFH, dummies for the WFH frequency after the state of emergency, other perceived factors, gender, age, job grades, divisions, and functional roles.

Table 8. Subsample analysis (production)

	Company A	Company B	Company C	Company D
	prsnt_dif			
Inability to retrieve data	-0.581***	-0.294	-0.0217	-
	(0.175)	(0.235)	(0.0849)	-
Inability to use exclusive equipment	-0.464	-0.149	-0.286***	-
	(0.641)	(0.164)	(0.0998)	-
Poor WFH setups	-1.617***	-0.579*	-0.325***	-0.822**
	(0.260)	(0.305)	(0.0835)	(0.404)
Lack of support and/or instruction from the supervisor	0.279	-0.205	-0.0777	-
	(0.721)	(0.481)	(0.0820)	-
Poor workplace communication	-1.082***	0.422	-0.438***	-1.106**
	(0.288)	(0.268)	(0.0901)	(0.529)
Poor communication with clients	-0.609	-0.190	-0.0428	0.167
	(0.420)	(0.353)	(0.120)	(0.589)
Controls	Yes	Yes	Yes	Yes
Observations	115	271	959	162
R-squared	0.523	0.150	0.114	0.437

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
The controls include the difference of WFH, dummies for the WFH frequency after the state of emergency, other perceived factors, gender, age, job grades, divisions, and functional roles.

4.4. Frequency of WFH and mental health

We next study the relationship between mental health and WFH by estimating equation (1). Table 9 shows the results obtained from the regression of $mental\_health_i$ on $wfh2d_i, wfh4d_i$, and $wfh5d_i$, controlling for individual and job characteristics. Overall, employees' mental health seems to have a positive association with the frequency of WFH.[7] As one caveat, unlike the estimates for presenteeism, which were based on two time points, the evidence may be too weak to establish a causal relationship since the dependent variable is simply cross-sectional. It may be the case that more specialized jobs allow more frequent WFH and job autonomy, which help to maintain good mental health, causing a spurious correlation between the two. Notably, however, even when we estimate sample selection models, we confirmed that the results are qualitatively

[7] Our mental health score calculated from correspondence analysis is highly correlated with the simple sum of the total Likert-based scales (the correlation coefficient is approximately 0.95 across firms). We also confirmed that even when we use the Likert-based scores, our regression results remain qualitatively the same.

Covid Economics 74, 30 March 2021: 142-171

the same, implying that selection is presumably innocuous after controlling for the respondents' job grades, divisions, and occupations.

Table 9. Regression of mental health on WFH frequency

	Company B	Company C	Company D
		mental_health	
wfh_5d	0.171*	0.196**	0.109***
	(0.0842)	(0.0748)	(0.0324)
wfh_4d	0.0950	0.125**	0.169***
	(0.0624)	(0.0615)	(0.0318)
wfh_2d	0.0669	0.0652	0.0877***
	(0.0412)	(0.0574)	(0.0267)
wfh_bf	0.0205	0.00883	-0.0933***
	(0.0473)	(0.0411)	(0.0265)
female	-0.0107	0.154***	-0.190***
	(0.0624)	(0.0583)	(0.0262)
age30	-0.189***	0.122*	0.100***
	(0.0681)	(0.0617)	(0.0300)
age40	-0.0580	0.0746	0.161***
	(0.0827)	(0.0552)	(0.0325)
age50	0.0454	0.225***	0.229***
	(0.0597)	(0.0661)	(0.0335)
age60	0.452***	0.425***	0.524***
	(0.0548)	(0.0812)	(0.0501)
Sales	-0.0417	0.237***	-0.102***
	(0.0523)	(0.0304)	(0.0319)
R&D	-0.0333	-0.177***	0.00342
	(0.0557)	(0.0247)	(0.0265)
Production	-0.112	0.106***	-0.208***
	(0.0816)	(0.0378)	(0.0420)
Constant	0.0891	0.0375	-0.0492
	(0.0782)	(0.0946)	(0.0383)
Section	Yes	Yes	Yes
Job Grade	Yes	Yes	Yes
Observations	2,789	3,720	12,380
R-squared	0.065	0.065	0.066

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Covid Economics 74, 30 March 2021: 142-171

4.5. Benefits of WFH

To identify what factors contribute to improvements in mental health, we estimate equation (1), adding as explanatory variables the responses to the question of what factors the respondents perceived as advantages of WFH and restricting the sample to those who worked from home after the state of emergency.[8] The factors that have a strong association with better mental health, conditional on individual and job characteristics, should be the main benefits of WFH. Two potential benefits emerge from the results shown in Table 10. First, the coefficient of "*facilitates a greater focus on work*" is significantly positive across companies. Second, "*less fatigue and having a healthier condition*" and "*zero commuting and saving time*" are significantly associated with better mental health for Companies C and D, although a similar pattern cannot be observed for Company B. Notably, "*having extra time for sleep and rest*" is significant for Company D. These results suggest that WFH eliminates the need to commute to work, which can be stressful for employees, and in this regard, time savings also enable employees to gain extra health benefits such as additional sleep and rest. Additionally, due to fewer interruptions that would normally occur at the workplace, WFH allows for a quieter environment that can facilitate a greater focus on work. Although undesirable aspects of WFH are oftentimes emphasized by business practitioners, WFH may improve productivity by improving employees' health and well-being.

This benefit due to the longer rest period enabled by WFH should have the same impact as shorter working hours. In fact, in the literature, there is some evidence of the benefits of shorter working hours. Using data on women working in manufacturing plants to produce artillery shells for the British military during the First World War, Pencavel [27] found that the hours-productivity profile exhibits a concave, nonmonotonic shape, implying that having a longer rest period could improve productivity when workers work excessive hours. Similarly, using single-company data on Japanese construction design projects, Shangguan et al. [28] showed that team productivity and the quality of work improved when working hours were reduced during the great recession.

[8] Notably, we estimated a sample selection model for mental health, but the evidence of selection bias was weak, and the estimates remained substantially identical.

Covid Economics 74, 30 March 2021: 142-171

Table 10. Regression of mental health on the perceived advantages of WFH

	Company B	Company C	Company D
		mental_health	
Facilitates a greater focus on work	0.135***	0.290***	0.240***
	(0.0366)	(0.0376)	(0.0309)
Can avoid unnecessary communication	-0.0721	-0.0160	0.0263
	(0.0606)	(0.0413)	(0.0319)
Free from annoying relationship	-0.260***	-0.206***	
	(0.0789)	(0.0437)	
Improvement in IT skills	-0.0860	0.0667	0.0436*
	(0.0588)	(0.0481)	(0.0261)
Zero commuting and saving time	0.0476	0.118**	0.106***
	(0.0473)	(0.0498)	(0.0286)
Being able to wear casual clothes	0.0442	0.0560*	-0.0317
	(0.0429)	(0.0323)	(0.0347)
Less fatigue and having a healthier condition	0.0529	0.323***	0.228***
	(0.0906)	(0.0430)	(0.0428)
Eating healthier meals	0.0837	-0.0179	0.0452
	(0.0716)	(0.0603)	(0.0328)
Spending more time exercising	0.137	0.125**	0.0538
	(0.116)	(0.0597)	(0.0547)
Reducing alcohol consumption	0.0763	-0.0286	0.0108
	(0.0645)	(0.0976)	(0.0442)
Having extra time for sleep and rest	0.0725	0.0507	0.0835***
	(0.0999)	(0.0430)	(0.0247)
Less smoking	-0.145	0.00788	0.0193
	(0.102)	(0.178)	(0.0766)
Having extra time with family and friends	-0.0107	0.0542	0.0297
	(0.0619)	(0.0368)	(0.0291)
Able to fit in household chores	0.0829	0.0446	0.0394
	(0.0560)	(0.0476)	(0.0397)
Better family relationship	0.233***	0.0433	0.0447
	(0.0794)	(0.0649)	(0.0430)
Finding new hobbies	-0.0349	0.0511	0.0180
	(0.0695)	(0.0532)	(0.0484)
Sales	-0.0532	0.212***	-0.0346
	(0.0443)	(0.0452)	(0.0367)
R&D	-0.0592	0.0116	-0.0126
	(0.0549)	(0.0342)	(0.0363)
Production	-0.285***	0.139***	-0.155
	(0.0709)	(0.0465)	(0.137)
Controls	Yes	Yes	Yes
Observations	1,535	3,376	4,612
R-squared	0.108	0.120	0.106

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
The controls include dummies for the WFH frequency after the state of emergency, a dummy for WFH experience in March, other perceived advantages, gender, age, job grades, and divisions.

Covid Economics 74, 30 March 2021: 142-171

5. Concluding remarks

Using unique data retrieved from our original survey conducted in cooperation with four manufacturing companies in Japan, we investigated the determinants of the quality of WFH under the COVID-19 pandemic. Specifically, we examined the effects of WFH on employees' productivity and mental health. Using employee survey data with high response rates, we identified the effects of WFH on productivity and mental health within the same company and within the same occupation. Focusing on specific companies also allowed us to exclude the differences in productivity among firms.

We present four findings. First, we confirmed that frequent WFH is associated with decreased productivity. In our interpretation, most workers experienced declines in productivity, probably due to their inadequate preparation for WFH under the sudden shock of the pandemic.

Second, to confirm our interpretation, we identified the possible factors of productivity losses during pandemic-driven WFH. Our estimation results suggest that the major contributors to deteriorations in productivity are poor WFH setups and poor communication at the workplace and with clients. These results imply that companies may enhance employees' productivity by investing in their WFH setups at home and communication tools.

Third, we also examined the heterogeneity across types of jobs. We categorized occupational categories into four functional roles, i.e., corporate, sales, R&D, and production. We have found that poor WFH setups are one of the major causes of productivity losses across the four occupation types. However, there are also several important causes that are specific to certain occupations. For corporate jobs and sales jobs, poor workplace communication and poor communication with clients seem to be the most crucial. For sales and R&D jobs, the lack of access to crucial information and exclusive equipment appear to contribute to productivity losses. Our findings provide managerial implications that are useful for designing desirable investments to improve employees' productivity while WFH.

Fourth, our results show that WFH is associated with better employee mental health. Our regression results suggest that workers benefit from a greater focus on work with a quieter environment, less fatigue, and additional time for sleep and rest as a result of the time saved by cutting commuting time. While more emphasis tends to be placed on the drawbacks of WFH, our result suggests that WFH may improve productivity by improving employees' health and well-being. To that end, let us introduce the answers to the question regarding WFH used in the

Company A surveys. The question asked, "*(a)fter the situation returns to normal, how often do you prefer to work from home?"* Among 1,381 employees who worked from home, only 7.2% answered "none," while 52.3% and 22.0% answered "1-2 days per week" and "3 days or more per week," respectively. These results suggest that these workers might have realized the advantages of WFH, and they are in line with the results of Eurofound's questionnaire survey ([3]) conducted with workers in EU member states. When asked for their WFH preference if there were no COVID-19 restrictions, 32% of all respondents expressed a wish to work from home a few days a week, 13% indicated that they would like to work from home every day, and only 22% of the respondents did not wish to work from home. The WFH style may take root around the world as a new working style.

Under these circumstances, companies should not dismiss remote working out of hand as a work arrangement option because of lower productivity compared with in-office work. Rather, they need to conduct a detailed analysis of the causes of the productivity gap, make the infrastructure improvements that are necessary for increasing WFH productivity, and send a clear message from top management that WFH can be a productivity booster.[9] Such changes will create opportunities for people who have been unable to work full-time or work as regular employees—that is, employees who are supposed to be willing to make business trips or accept workplace transfers—because of time constraints resulting from life circumstances, such as having to raise children or care for elderly individuals or individuals suffering from illness or a disability. In a way, WFH may be an option that can be used to take full advantage of the workforce's talents that could be wasted without such arrangement.

References

[1] E. Brynjolfsson, J. J. Horton, A. Ozimek, D. Rock, G. Sharma and H.-Y. TuYe, "COVID-19 and Remote Work: An Early Look at US Data," *NBER Working Paper No. 27344,* 2020, DOI 10.3386/w27344.

[9] For example, Fujitsu announced that it would allow their employees to freely choose where they work, and reduce the floor area of existing offices in Japan by 50% by 2023. The company instead provide a monthly payment of 5,000 yen as a subsidy for environment maintenance costs for working from home. This decision saves a large costs of office rents and commute expenses. If many firms follow such a move, the design of urban office spaces as well as the way workers work would change drastically.

[2] A. Felstead and D. Reuschke, "Homeworking in the UK: before and during the 2020 lockdown," *WISERD Report, Cardiff: Wales Institute of Social and Economic Research,* 2020, https://wiserd.ac.uk/publications/homeworking-uk-and-during-2020-lockdown.

[3] Eurofound, "Living, working and COVID-19," COVID-19 series, Publications Office of the European Union, Luxembourg, 2020, https://www.eurofound.europa.eu/publications/report/2020/living-working-and-covid-19.

[4] The Cabinet Office, "Survey on Changes in Attitudes and Behavior Under the Influence of the Novel Coronavirus (in Japanese)," The Government of Japan, 2020, https://www5.cao.go.jp/keizai2/manzoku/pdf/shiryo2.pdf.

[5] M. Morikawa, "Productivity of working from home during the COVID-19 pandemic: Evidence from an employee survey," *Covid Economics,* vol. 49, pp. 123-147, 2020, https://cepr.org/file/9658/download?token=dK8-3_E9.

[6] T. Okubo, "Spread of COVID-19 and telework: Evidence from Japan," *Covid Economics,* vol. 32, pp. 1-25, 2020, https://cepr.org/file/9252/download?token=UvHyo3s6.

[7] K. Pouliakas, "Working at Home in Greece: unexplored potential at times of social distancing?," *IZA DP No. 13408,* 2020, https://www.iza.org/publications/dp/13408/working-at-home-in-greece-unexplored-potential-at-times-of-social-distancing.

[8] I. Delaporte and W. Peña, "Working from home under covid-19: Who is affected? evidence from latin american and caribbean countries," *CEPR COVID Economics,* vol. 14, 2020.

[9] C. Kroll and S. Nuesch, "The effects of flexible work practices on employee attitudes: evidence from a large-scale panel study in Germany," *The Internati onal Journal of Human Resource Management,* vol. 30, no. 9, pp. 1505-1525, 2019, http://dx.doi.org/10.1080/09585192.2017.1289548.

[10] L. Bellmann and O. Hubler, "Job Satisfaction and Work-Life Balance: Differences between Homework and Work at the Workplace of the Company," *IZA DP No. 13504,* 2020, https://www.iza.org/publications/dp/13504/job-satisfaction-and-work-life-balance-differences-between-homework-and-work-at-the-workplace-of-the-company.

[11] J. M. Barrero, N. Bloom and S. J. Davis, "Why Working From Home Will Stick," *BFI WORKING PAPER,* 2020, https://bfi.uchicago.edu/wp-content/uploads/2020/12/BFI_WP_2020174.pdf.

[12] J.-V. Alipour, O. Falck and S. Schuller, "Germany's Capacities to Work from Home," *IZA DP No. 13152,* 2020, https://www.iza.org/publications/dp/13152/germanys-capacities-to-work-from-home.

[13] J. I. Dingel and B. Neiman, "How many jobs can be done at home?," *Journal of Public Economics,* vol. 189, pp. 1-8, 2020, https://doi.org/10.1016/j.jpubeco.2020.104235.

[14] M. Hatayama, M. Viollaz and H. Winkler, "Jobs' amenability to working from home: Evidence from skills surveys for 53 countries," *Covid Economics,* vol. 19, 2020, https://cepr.org/file/9088/download?token=c6oU20eH.

[15] OECD, "Productivity gains from teleworking in the post COVID-19 era: How can public policies make it happen?," OECD, Paris, 2020.

Covid Economics 74, 30 March 2021: 142-171

[16] N. Bloom, J. Liang, J. Roberts and Z. J. Ying, "Does Working from Home Work? Evidence from a Chinese Experiment," *The Quarterly Journal of Economics,* vol. 130, no. 1, p. 165–218, 2015, doi:10.1093/qje/qju032.

[17] N. Emanuel and E. Harrington, "“Working” Remotely? Selection, Treatment, and the Market Provision of Remote Work," 2020, https://scholar.harvard.edu/files/eharrington/files/remote_work.pdf.

[18] C. Ipsen and K. Kirchner, "Experiences of Working from Home in Times of COVID-19: International survey conducted the first months of the national lockdowns," 2020, DOI:10.11581/dtu:00000085.

[19] B. Etheridgey, T. Li and Y. Wang, "Worker Productivity during Lockdown and Working from Home: Evidence from Self-Reports," *ISER Working Paper Series No. 2020-12,* 2020, https://www.iser.essex.ac.uk/research/publications/working-papers/iser/2020-12.

[20] A. Adams-Prassl, T. Boneva, M. Golin and C. Rauh, "Inequality in the Impact of the Coronavirus: Shock: Evidence from Real Time Surveys," *Journal of Public Economics,* vol. 189, pp. 1-33, https://doi.org/10.1016/j.jpubeco.2020.104245, 2020.

[21] A. Adams-Prassl, T. Boneva, M. Golin and C. Rauh, "Work That Can Be Done from Home: Evidence on variation within and across occupations," 2020.

[22] T. Alon, M. Doepke, J. Olmstead-Rumsey and M. Tertiltc, "The Impact of COVID-19 on Gender Inequality," *Covid Economics,* vol. 4, pp. 62-85, 2020.

[23] A. W. Bartik, Z. B. Cullen, E. L. Glaeser, M. Luca and C. T. Stanton, "What jobs are being done at home during the COVID-19 crisis? Evidence from firm-level surveys," *NBER Working Paper No. w27422,* 2020, https://www.nber.org/papers/w27422.

[24] E. G. Dutcher, "The effects of telecommuting on productivity: An experimental examination. The role of dull and creative tasks," *Journal of Economic Behavior & Organization,* vol. 84, pp. 355-363, 2012, http://dx.doi.org/10.1016/j.jebo.2012.04.009.

[25] N. Bloom, P. Bunn, P. Mizen, P. Smietanka and G. Thwaites, "The Impact of Covid-19 on Productivity," *NBER Working Paper No. 28233,* 2020, https://www.nber.org/papers/w28233.

[26] S. Yamaguchi, Y. Asai and R. Kambayashi, "How does early childcare enrollment affect children, parents, and their interactions?," *Labour Economics,* vol. 55, pp. 56-71, 2018.

[27] J. H. Pencavel, "The Productivity of Working Hours," *Economic Journal,* vol. 125, no. 589, p. 2052–2076, 2015.

[28] R. Shangguan, J. DeVaro and H. Owan, "Enhancing Team Productivity through Shorter Working: Evidence from the Great Recession," *Working Paper,* 2020.

[29] Eurofound, "Living, working and COVID-19," Publications Office of the European Union, Luxembourg, 2020.

Covid Economics 74, 30 March 2021: 142-171

CEPR PRESS

Appendix Table 1. Descriptive statistics

	Company A		Company B		Company C		Company D	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
prsnt_dif (presenteeism change)	-0.241	1.240	0.012	1.863	-0.776	1.540	-0.812	2.539
mental_health (mental health)	-	-	-0.001	1.000	0.000	1.000	0.000	1.000
wfh_dif (WFH frequency change)	-	-	0.775	1.654	1.893	2.445	1.574	2.135
wfh_5d (5 WFH days per week)	0.081	0.272	0.225	0.418	0.184	0.388	0.212	0.409
wfh_4d (3-4 WFH days per week)	0.149	0.357	0.099	0.299	0.314	0.464	0.170	0.375
wfh_2d (1-2 WFH days per week)	0.250	0.433	0.196	0.397	0.410	0.492	0.187	0.390
wfh_bf (at least one WFH day in March)	-	-	0.352	0.478	0.201	0.401	0.107	0.310
Perceived factors of productivity loss								
Inability to retrieve data	0.190	0.393	0.331	0.471	0.307	0.461	-	-
Inability to use exclusive equipment	0.207	0.405	0.408	0.492	0.498	0.500	-	-
Poor WFH setups	0.080	0.272	0.276	0.447	0.364	0.481	0.381	0.486
Lack of support and/or instruction from the supervisor	0.019	0.136	0.117	0.321	0.203	0.402	-	-
Poor workplace communication	0.115	0.319	0.448	0.497	0.584	0.493	0.443	0.497
Poor communication with clients	0.140	0.348	0.292	0.455	0.248	0.432	0.351	0.477
Fatigue from an excessive workload	0.012	0.107	0.090	0.286	0.092	0.289	-	-
Not feeling well physically	0.029	0.168	0.281	0.450	0.216	0.412	0.496	0.500
Feeling mentally under the weather	0.020	0.139	0.103	0.304	0.113	0.317	0.106	0.307
Having responsiblities (childcare and/or nursing care)	0.030	0.172	0.109	0.311	0.107	0.310	-	-
Miscellaneous	0.031	0.174	0.198	0.399	0.111	0.315	-	-
Perceived advantages of WFH								
Facilitates a greater focus on work	-	-	0.327	0.469	0.302	0.459	0.247	0.431
Can avoid unnecessary communication	-	-	0.206	0.404	0.206	0.404	0.246	0.431
Free from annoying relationship	-	-	0.268	0.443	0.258	0.438	-	-
Improvement in IT skills	-	-	0.090	0.286	0.120	0.324	0.193	0.395

Covid Economics 74, 30 March 2021: 142-171

Zero commuting and saving time	-	-	0.806	0.395	0.841	0.366	0.775	0.417
Being able to wear casual clothes	-	-	0.581	0.493	0.560	0.496	0.561	0.496
Less fatigue and having a healthier condition	-	-	0.114	0.317	0.129	0.335	0.131	0.338
Eating healthier meals	-	-	0.128	0.334	0.094	0.291	0.150	0.357
Spending more time exercising	-	-	0.048	0.214	0.060	0.237	0.055	0.227
Reducing alcohol consumption	-	-	0.052	0.222	0.024	0.154	0.056	0.229
Having extra time for sleep and rest	-	-	0.245	0.430	0.351	0.477	0.275	0.447
Less smoking	-	-	0.013	0.114	0.011	0.105	0.023	0.149
Having extra time with family and friends	-	-	0.252	0.434	0.251	0.434	0.299	0.458
Able to fit in household chores	-	-	0.161	0.367	0.177	0.382	0.164	0.370
Better family relationship	-	-	0.105	0.307	0.091	0.288	0.099	0.299
Finding new hobbies	-	-	0.072	0.258	0.080	0.271	0.068	0.251
Functional roles								
corporate function	0.379	0.485	0.271	0.445	0.151	0.358	0.260	0.438
sales	0.220	0.414	0.116	0.320	0.132	0.338	0.265	0.441
R&D	0.186	0.389	0.246	0.431	0.408	0.492	0.166	0.372
production	0.214	0.411	0.366	0.482	0.310	0.462	0.099	0.299
Age dummies (The base category is those under 30)								
age30 (30-39 years old)	0.229	0.421	0.216	0.412	0.259	0.438	0.190	0.392
age40 (40-49 years old)	0.277	0.447	0.311	0.463	0.261	0.439	0.311	0.463
age50 (50-59 years old)	0.314	0.464	0.314	0.464	0.247	0.431	0.275	0.447
age60 (60+ years old)	0.070	0.254	0.046	0.209	0.066	0.249	0.056	0.231
female dummy	0.139	0.346	0.189	0.392	0.147	0.354	0.208	0.406

Note: The number of observations vary across sets of variables. For Company A, the number of observations is 2877 for presenteeism change, WFH frequency dummies, age, and gender, 1381 and 2868 for perceived factors of productivity loss and functional role dummies, respectively. For Company B, the number of observations is 3749 for presenteeism change, 3498 for mental health, 3453 for WFH frequency change, 3458 for WFH frequency dummies, 3558 for the WFH in March dummy, 1833 for perceived factors of productivity loss, 1813 for percieved advantages of WFH, 3117 for functional roles, 3132 for age, and 3133 for gender. For Company C, the number of observations is 4032 for functional roles, and age, 3989 for WFH frequency change and WFH frequency dummies, 3622 for preceived factors of productivity loss and perceived advatnages of WFH, 3980 for gender. For Company D, the number of observations is 11497 for presenteeism change, 13281 for mental health, functional roles, and age, 12426 for WFH frequency change, 12941 for WFH frequency dummies, 12572 for the WFH in March dummy, 7216 for perceived factors of productivity loss, 4782 for perceived advantages of WFH, 13189 for gender.

Covid Economics 74, 30 March 2021: 142-171