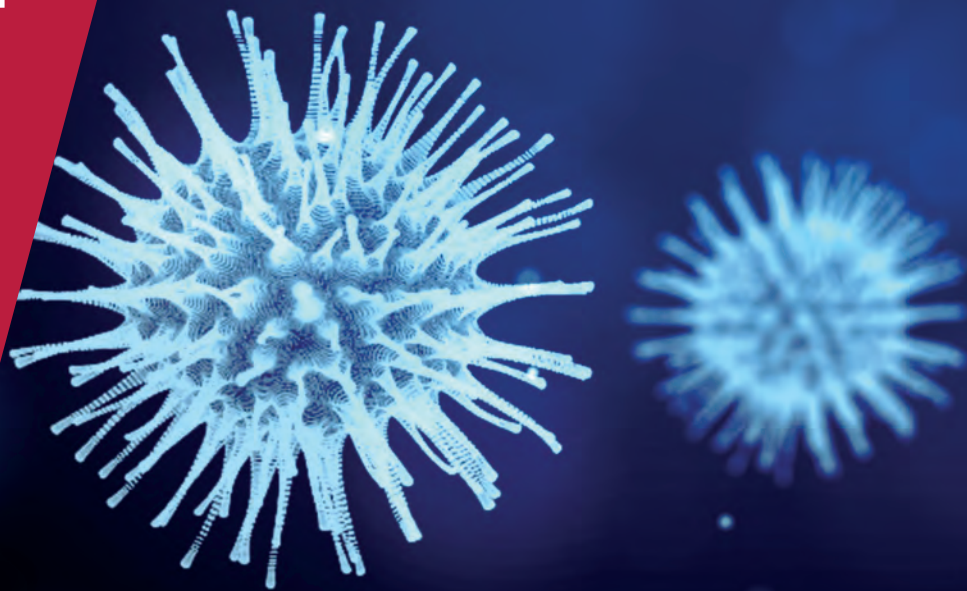


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COVID ECONOMICS
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DISTANCING**

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and Luca Guerrieri

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THE FINANCIAL CRISIS AND COVID

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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.

<i>American Economic Journal, Applied Economics</i>	<i>Journal of Economic Theory</i>
<i>American Economic Journal, Economic Policy</i>	<i>Journal of the European Economic Association*</i>
<i>American Economic Journal, Macroeconomics</i>	<i>Journal of Finance</i>
<i>American Economic Journal, Microeconomics</i>	<i>Journal of Financial Economics</i>
<i>American Economic Review</i>	<i>Journal of Health Economics</i>
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<i>American Journal of Health Economics</i>	<i>Journal of Labor Economics*</i>
<i>Canadian Journal of Economics</i>	<i>Journal of Monetary Economics</i>
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<i>Journal of Economic Growth</i>	<i>Review of Economics and Statistics</i>
	<i>Review of Economic Studies*</i>
	<i>Review of Financial Studies</i>

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

Covid Economics

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Economic and epidemiological effects of mandated and spontaneous social distancing¹

Martin Bodenstein,² Giancarlo Corsetti³ and Luca Guerrieri⁴

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Based on a standard epidemiological model, we derive and apply empirical tests of the hypothesis that contacts, as proxied by mobility data, have an effect on the spread of the coronavirus epidemic, as summarized by the reproduction rates, and on economic activity, as captured by subsequent initial claims to unemployment benefits. We show that changes in mobility through the first quarters of 2020, be it spontaneous or mandated, had significant effects on both the spread of the coronavirus and the economy. Strikingly, we find that spontaneous social distancing was no less costly than mandated social distancing. Our results suggest that the rebound in economic activity when stay-at-home orders were lifted was primarily driven by the improvement in epidemiological parameters. In other words, without the reduction in the reproduction rate of the coronavirus, we could have expected a doubling down on spontaneous social distancing.

1 This paper is a section of "Social Distancing and Supply Disruptions in a Pandemic", a paper we wrote in the spring of 2020 and recently revised bringing the model to bear on the evolution of the COVID-19 pandemic in the first quarters of the year (see Bodenstein, Corsetti and Guerrieri 2020). The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or of any other person associated with the Federal Reserve System. Giancarlo Corsetti gratefully acknowledges support from Cambridge-INET.

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1 Introduction

By the end of March 2020, nearly four months after the first detection of significant coronavirus infections in China, most advanced economies adopted measures restricting people's movements and activity on their territory, introduced tough controls at their borders, and mandated norms implementing social distancing. If only with some delay, governments converged on the idea that some restrictions were required to reduce the human cost of the disease—strongly influenced by early scenario analyses in which an uncontrolled and rapid spread of the disease would have overwhelmed national health systems and caused a sharp rise in mortality rates.¹ At the same time, mobility fell precipitously (although not uniformly across locations) as individuals took precautions. During the subsequent months, contagion and death rates, while high, turned out to be much lower than indicated by these early scenario analysis, as social distancing, whether mandated or spontaneous, became widespread practice.

A key question in academic and policy debates concerns the extent to which social distancing is effective in reducing contagion and mortality, and, most crucially, whether, for given epidemiological effects, the economic costs of social distancing can be expected to be lower when driven by individual decisions, as opposed to policy measures. These questions are obviously complex, as the evolution of the disease over time responds to a number of factors, including environmental factors (e.g., extreme hot or cold weather may bring people to spend more time indoors), mutation in the virus (at the end of 2020, a new surge associated with more infectious variants of the virus motivated once again the widespread adoption of strict lockdown policies) as well as the adoption and efficacy of precautions (such as wearing masks or washing hands) in social contacts. With these considerations in mind, we exploit cross-sectional epidemiological, institutional and mobility data for the U.S. states, to derive a test of the epidemiological and economic effects of social distancing—distinguishing the latter depending on its spontaneous or mandated origin.

We show that changes in mobility through the first quarters of 2020 slowed down both the spread of the coronavirus and economic activity, regardless of whether these changes stemmed

¹ Among the leading papers that have formalized this view early on, see [Eichenbaum, Rebelo, and Trabandt \(2020\)](#), [Jones, Philippon, and Venkateswaran \(2020\)](#) and [Alvarez, Argente, and Lippi \(2020\)](#). The literature on the economic effects of the COVID-19 pandemic has grown very fast, see [Atkeson \(2020\)](#), [Alfaro, Chari, Greenland, and Schott \(2020\)](#), [Baker, Bloom, Davis, Kost, Sammon, and Viratyosin \(2020\)](#), [Guerrieri, Lorenzoni, Straub, and Werning \(2020\)](#), and [Koren and Petó \(2020\)](#) among many others.

from individual or policy decisions. Strikingly, our evidence suggests that spontaneous social distancing was no less costly than stay-at-home orders.

We derive our empirical framework from the standard epidemiological model. We test the null hypotheses is that contacts, as proxied by mobility data, have an effect on the spread of the epidemic, as summarized by the reproduction rates, and economic activity, as captured by initial claims to unemployment benefits. Our sample consists of state-level data for the United States from March through September 2020. We proxy contacts using Google mobility data, and instrument mobility with either the stay-at-home orders issued by individual U.S. states, or political leanings as captured by the share of the vote for the Republican presidential candidate in the 2016 elections by state. Specifically, in a first test, we run a panel regression model instrumenting changes in mobility with stay-at-home orders, taking advantage of the different timing of these orders across states. In a second, cross-sectional, test, we investigate the evolution of contagion in the two-week period in March 2020 that preceded any mandatory measures at the state level. This sample choice implies that all observed variation in mobility stems from spontaneous decisions. Google data suggest that, while much of the reduction in mobility had already occurred by the time the first stay-at-home order was imposed, this initial mobility reduction was far from homogeneous across states. We instrument mobility with political leanings, drawing on the results by [Gollwitzer et al. \(2020\)](#), who document a correlation between these leanings and the spread of COVID-19. Given our focus on the first part of March, before the introduction of mandatory measures, we collapse the time dimension of our initial panel regression and rely only on the cross-sectional variation at the state level. As epidemiological outcome, we use, alternatively, the reproduction rates estimated by [Fernández-Villaverde and Jones \(2020\)](#) and the rates estimated by [Systrom, Vladek, and Krieger \(2020\)](#).

Our main results are as follows. Concerning mandatory social distancing, based on our panel analysis, we find that, at the first stage of our regression model, stay-at-home orders push up the residential mobility index 1.85 percent (capturing an increase in time spent at home). At the second stage, a 1 percent increase in the instrumented residential mobility reduces the running reproduction rate about 3.5 percent, all else equal. Putting these two estimates together, on average, the stay-at-home orders led to a decline in the reproduction rate of about $1.85 \times 3.5 \approx 6.5$ percent. In other words, starting from a basic reproduction rate of 2, the stay-a-home order would reduce it to about 1.9. Correspondingly, our regression results point to an increase in

the unemployment rate of roughly 0.3 percentage point for every week that the stay-at-home orders were in force. With a median duration of 6 weeks and the orders applying to much of the country, this could account for about a 2 percentage points rise in unemployment.

Our estimates imply that most of the fall in mobility was linked to spontaneous social distancing—a point stressed early on by [Goolsbee and Syverson \(2021\)](#). To study the effect of spontaneous distancing, we take advantage of the fact that no mandatory measures were enacted in the 14-day period through March 17 2020, two days before the first stay-at-home order went into effect in California. Remarkably, for the initial claims to unemployment benefits, the elasticity estimated in this exercise for spontaneous social distancing is close to the corresponding elasticity estimated from mandated distancing (our point estimates are, respectively, 0.15 and 0.17). At the margin, social distancing, whether spontaneous or not, has analogous economic effects. However, the elasticity of the reproduction rate to spontaneous mobility reductions is lower (our point estimates for spontaneous and mandated social distancing are, respectively, 2.3 and 3.5). In other words, for the same economic impact, a decline in spontaneous mobility leads to a smaller decline in the reproduction rate. Or, to put it in another way, the economic costs of containing the reproduction rate are no lower for spontaneous than for mandated reductions in mobility.

These findings suggest that, while economic activity rebounded as stay-at-home orders were lifted, this rebound was possible in large part because of the improvement in the epidemiological parameters—that is, without the observed reduction in the reproduction rate of the coronavirus, we could have expected a doubling down on spontaneous social distancing. Our analysis cannot rule out nonlinearities such that the marginal costs of reducing the spread of the disease rises progressively with the reduction in mobility. However, one may note that, since spontaneous social distancing preceded the imposition of stay-at-home orders, such non-linearities would not undermine our main conclusions.

Several other papers have sized empirically the economic effects of mandated social distancing, including [Allcott et al. \(2020\)](#) and [Coibion, Gorodnichenko, and Weber \(2020\)](#). Our approach is closest to [Gupta et al. \(2020\)](#), who also use a difference in difference approach to size the effects on the labor market. Our framework helps us distinguish between the direct effects of the structured policies through reduction in mobility and outcomes related to spontaneous social distances predating the policies. [Goolsbee and Syverson \(2021\)](#) also rely on a difference

in difference estimation method but use more capillary data at the local level. Nonetheless, their results on the economic effects of mandated social distancing are broadly in line with ours. Alternative approaches to estimating the effects of mandated social distancing measures are offered by [Chernozhukov, Kasahara, and Schrimpf \(2021\)](#) and [Huang \(2020\)](#). They focus on epidemiological effects, whereas we are also interested in a comparison of the epidemiological benefits and of the economic consequences of mandated and spontaneous social distancing.

The rest of the paper is structured as follows. Section 2 sets the stage for our analysis by providing and discussing evidence on the dynamic of the COVID-19 pandemic in the United States in the first three quarters of 2020, and the effects of social distancing on the spread of the disease and unemployment across U.S. states. Throughout our analysis, we will make extensive use of mobility data to approximate social distancing and trace its effect on the economy. Section 2 describes a one-group SIRD model—capturing how a disease spreads by direct person-to-person contact in a population. Section 3 reviews stylized facts on the diffusion of the disease over time and across states in the United States, including data on mobility and health measures adopted at state level. Drawing on the SIRD model, Section 4 specifies a simple econometric framework and provides evidence on the effects of social distancing on the dynamic of the pandemic and employment.

2 A Baseline One-Group SIRD Model

The one-group SIRD model in this section follows [Fernández-Villaverde and Jones \(2020\)](#) — broader introductions to epidemiological modeling are given in [Hethcote \(1989\)](#), [Allen \(1994\)](#), and [Brauer, Driessche, and Wu \(2008\)](#). Time is discrete and measured in days. At every instant in time, the total population N is divided into the classes of:

1. susceptible S_t consisting of individuals who can incur the disease but are not yet infected;
2. infective I_t consisting of individuals who are infected and can transmit the disease;
3. resolving R_t consisting of sick individuals who are no longer infective;
4. recovered (or, equivalently, cured) C_t consisting of individuals who have recovered from the disease;
5. dead D_t consisting of individuals who died from the disease.

This model differs from the standard SIRD model by distinguishing between the infective and the resolving class. [Fernández-Villaverde and Jones \(2020\)](#) found this distinction necessary to obtain a good model fit in their empirical application to U.S. data.

An important assumption of standard SIRD models is that “law of mass action” applies: The rate at which infective and susceptible individuals meet is proportional to their spatial density $S_t I_t$. The effective contact rate per period β_t is the average number of adequate contacts per infective period. An adequate contact of an infective individual is an interaction that results in infection of the other individual if that person is susceptible. Thus, β_t can be expressed as the product of the average of all contacts q_t and the probability of infection (transmission risk) given contact between an infective and a susceptible individual, μ_t .

It is important to note that the effective contact rate is not constant but can vary over time for a number of reasons. First, an individual’s number of contacts, q_t , can drop in a pandemic because of mandated social restrictions (e.g., school closures, closures of shops and restaurants, stay-at-home orders) or voluntary adjustments of behavior (e.g., online shopping instead of in-person shopping, refraining from attending larger gatherings). As both mandated and spontaneous contact restrictions may take place simultaneously, it may be challenging to disentangle their effects on β_t . We may note, however, that from the perspective of our study restrictions have an impact on the economy regardless of whether they are mandated or spontaneous in nature. Second, the probability of infection given contact between an infectious and a susceptible individual μ_t can vary over time. In the case of COVID-19, this probability is influenced both by human behavior (e.g., masks, keeping sufficient physical distance) and by the characteristics of the virus (e.g., transmission in closed versus open spaces, sensitivity to temperature and seasonality, aggressiveness of the virus strains).

In detail, we write the discrete time SIRD model as:

$$S_{t+1} = S_t - \beta_t S_t I_t / N, \quad (1)$$

$$I_{t+1} = I_t + \beta_t S_t I_t / N - \gamma I_t, \quad (2)$$

$$R_{t+1} = R_t + \gamma I_t - \vartheta R_t, \quad (3)$$

$$C_{t+1} = C_t + (1 - \varpi) \vartheta R_t, \quad (4)$$

$$D_{t+1} = D_t + \varpi \vartheta R_t, \quad (5)$$

$$N = S_t + I_t + R_t + C_t + D_t, \quad (6)$$

with the initial conditions $S_0 > 0$ and $I_0 > 0$. In addition, $S_t \geq 0$, $I_t \geq 0$, and $S_t + I_t \leq 1$. Total new infections at time t are given by $\beta_t S_t I_t / N$. Infectiousness resolves at the Poisson rate γ . A person in the resolving class (R_t) either recovers (C_t) with probability $1 - \varpi$ or dies (D_t) with probability ϖ . The recovery rate is denoted by ϑ . In principle, the recovery rate and the death rate could also be time-varying to reflect advancements in medical treatment as the pandemic progresses.

The basic reproduction number $R_{0,t} = \frac{\beta_t}{\gamma}$ determines whether the infectious disease becomes an pandemic, i.e., the disease goes through the population in a relatively short period of time. This is the case for $\frac{\beta_t}{\gamma} > 1$; otherwise, the number of infective individuals decreases to zero as time passes. If $R_{0,t} \leq 1$, there is no pandemic, and the number of infective individuals converges monotonically to zero.

3 The Dynamic of the COVID-19 Spread in the United States

Conditional on keeping the effective contact rate β , with an empirically relevant reproduction rate equal to 2, almost the entire population is infected in a matter of months. According to leading scenarios debated in March 2020, for instance, it could not be ruled out that between 15 and 20 percent of the U.S. population could have simultaneously developed symptoms, and that, over a short time frame, 20 percent of these symptomatic individuals would have required hospitalization.² These developments would have put devastating pressure on the health care system.

Scenarios conditional on a constant β played a crucial role in motivating stark health measures in many countries—for this reason, we will study this type of scenario as a benchmark reference below. Remarkably, however, these grim developments did not come to pass. Figure 1 superimposes data for the spread of COVID-19 in the United States, death rates and confirmed cases, and data on the timing of stay-at-home orders and changes in residential mobility—culled from cellphones, as captured in Google’s mobility reports, and reflecting both trips towards

² For instance, see [Ferguson et al. \(2020\)](#).

residential addresses and time spent at those addresses.³

Tracking the spread of COVID-19 is no easy feat. Even the best available data are subject to important drawbacks. As Figure 1 shows, confirmed new cases surged in March 2020, reached a first peak in early April, a second peak in mid-July and climbed back up through the fall. Using confirmed new cases to measure the intensity of the pandemic is challenging as severe rationing of testing at the beginning of the pandemic kept the data artificially low. Data on death rates do not suffer from that problem and confirm at least three cycles for the spread of the disease, with death rates climbing again through October, albeit with a delay relative to the number of confirmed cases. However, the relationship between the spread of the disease and death rates can also vary as new treatment protocols are developed or the age composition of infected individuals evolve, given that older individuals experience greater mortality rates. The middle panel of the figure shows the reproduction rate for the model in Equations (1)-(6) estimated by Fernández-Villaverde and Jones (2020) based on data on death rates. The solid black line shows the overall estimate for the United States. Two cycles are clearly visible in the estimates of the reproduction rate. The state-level estimates show much greater variation, as indicated by the point-wise maximum and minimum dashed red lines for these estimates.

Figure 1 also shows that stay-at-home orders were put in place at different points in time across states, roughly within a three week window from mid-March to early April.⁴ These orders had a median duration of six weeks, but the duration also varied considerably by state. Twelve states did not impose stay-at-home orders. In the states that did, the shortest orders lasted three weeks and the longest, for California, is still standing in parts of the state at the time of writing.

The figure suggests that social distancing contributed significantly to slowing down the spread of the disease. It also shows that mobility capturing time spent at home ramped up even before the imposition of stay-at-home orders at the regional level. We will take advantage of the timing of these events to gain some insight on the relative role of spontaneous vs. mandated social distancing in driving the evolution of the disease.

³ The data for death rates and confirmed cases are from JHU CSSE (2020), also see Dong, Du, and Gardner (2020). The data on stay-at-home orders are from Raifman et al. (2020). The mobility data are from Google LLC (2020).

⁴ The earliest stay-at-home order started in California on March 19.

4 The Effects of Social Distancing

In this section we provide evidence that social distancing, be it spontaneous or mandatory, has comparable epidemiological and economic effects. Specifically, based on the epidemiological model, we derive and apply two empirical tests of the hypothesis that contacts, as proxied by mobility data, have an effect on the reproduction rate and the initial jobless claims. First, we will focus on changes in mobility in response to stay-at-home orders, using a difference-in-difference approach. Then we will investigate the dynamic evolution of contagion in the two-week period in March that preceded any mandatory measure, based on cross-sectional evidence.

For both tests below, we derive our regression framework from the SIRD model described in Section 2. In the SIRD framework, the status of the pandemic is summarized by the reproduction rate

$$R_{0,t} = \frac{1}{\gamma} \beta_t. \quad (7)$$

where the effective contact rate β_t is the product of contacts q_t , normalized to 1, and the probability of transmission, μ_t . We can therefore express the reproduction rate as

$$\ln(R_{0,t}) = -\ln(\gamma) + \ln(\mu_t) + \ln(q_t - r_t) \quad (8)$$

where the term r_t represents policy restrictions that can reduce the level of contacts. We will use this equation to derive a panel regression and a cross-sectional test. [Atkeson, Kopecky, and Zha \(2021\)](#) provide framework consistent with ours to decompose the reproduction rate but allow for a feedback mechanism between the reproduction and infection rates.

4.1 Mandated Social Distancing: A Panel Regression Approach

The relationship between the reproduction rate and contacts in Equation 8 can be mapped into the following panel regression equation:

$$\ln(R_{0,s,t}) = FE_m + bm_{s,t} + FE_s + e_{s,t}. \quad (9)$$

where the subscript s denotes the geographical region and the term $R_{0,s,t}$ is the regional counterpart to the aggregate $R_{0,t}$ in Equation 8. The dependent variable in our baseline, consistent

with the model in Section 2, is the reproduction rate estimated by Fernández-Villaverde and Jones (2020). We average the daily estimates by these authors to the weekly frequency and use readings for the 48 U.S. states in their dataset and the District of Columbia.⁵ We use monthly fixed effects, FE_m , to capture the time-varying probability of transmission μ_t , which might depend on taking precautions such as frequent hand-washing and mask-wearing that have become more prevalent with the spread of the virus.⁶ We proxy contacts $q_t - r_t$ at the regional level with the term $m_{s,t}$, the Google index for residential mobility in percent deviation from its value at the beginning of 2020, also averaged to the weekly frequency. The term FE_s denotes regional-level fixed effects, which allow for regional characteristics to influence the relationship between contacts and mobility. Finally, $e_{s,t}$ is a stochastic term in the relationship between contacts and mobility. Our main interest is the regression coefficient b . An important restriction imposed by our regression framework is that this coefficient does not vary across regions.

We estimate Equation 9 by two-stage least squares, using a dummy for the stay-at-home orders as an instrument for residential mobility. To lessen endogeneity concerns we lag the dummy for the stay-at-home orders by one week. At the first stage, we also allow for monthly and regional fixed effects. The estimation sample has starting points that vary by region, in line with regional variation in the spread of the disease. The earliest estimates of the reproduction rate are for the state of Washington, starting on March 12, 2020. By contrast estimates of the reproduction rate for Hawaii only start on August 7, 2020. The end point for our sample is September 28, 2020, across all regions. Overall, the sample includes 1204 observations.

Our estimates of Equation 9, first and second stage, are shown in Table 1. In the table, Column 1 indicates that stay-at-home orders push up the mobility index 1.85 percent. Returning to the table, Column 2 shows that a 1 percent increase in residential mobility reduces the reproduction rate by about 3.5 percent, all else equal. Putting the two estimates in columns 1 and 2 together, on average, the stay-at-home orders led to a decline in the reproduction rate of about $1.85 \times 3.5 \approx 6.5$ percent. In other words, starting from a basic reproduction rate of 2, the stay-a-home order would reduce it to about 1.9. One may note that, at its peak, the index of residential mobility increased by about 20 percent (reflecting an increase in time spent at home). Even if all states had enacted stay-at-home orders, our estimates would attribute only

⁵ The dataset of Fernández-Villaverde and Jones (2020) excludes Wyoming and Montana.

⁶ The framework of Atkeson, Kopecky, and Zha (2021) captures these effects as a time-varying wedge.

1.85 percentage points of this increase to those orders. Accordingly the great majority of the 20 percent increase was linked to spontaneous social distancing.

To gauge the effects of the stay-at-home orders on initial unemployment claims, we use a regression framework analogous to that of Equation 9. We consider

$$U_{0,s,t+1} = FE_m + b_u m_{s,t} + FE_s + e_{s,t+1}, \quad (10)$$

where the term $U_{0,s,t}$ represents initial jobless claims as a share of the working age population in region s at time t . For the sake of comparison, we select an estimation sample with exactly the same span of the sample for the regression of the reproduction rate. We also estimate Equation 10 by two-stage least squares, using a dummy for the stay-at-home orders as an instrument for residential mobility. Once again, using standard Durbin and Wu-Hausman tests, we fail to reject the null hypothesis that the instrument is exogenous. This time, probability values for the tests are of 0.13 and 0.14, respectively. Connecting the estimates in columns (1) and (3) of Table 1, the regression results point to an increase in the unemployment rate of roughly 0.3 ($1.85 \times 0.153 \approx 0.3$) percentage point for every week that the stay-at-home orders were in force. With a median duration of 6 weeks and the orders applying to much of the country, they could have accounted for an increase in the unemployment rate of about 2 percentage points.

4.2 Spontaneous Social Distancing: A Cross-Sectional Approach

To study the effect of spontaneous social distancing, we consider a two-week period before the imposition of any stay-at-home order—the 14-day period through March 17, which is two days before the first stay-at-home order went into effect in California. The evidence reviewed above suggests that much of the reduction in mobility had already occurred by the time mandatory rules started to be imposed. Yet, this initial mobility reduction was far from homogeneous across states.

A useful observation for our purpose is by [Gollwitzer et al. \(2020\)](#), who note that individual political leanings influence social distancing practices, and through these practices also influence health outcomes. We design a second test of our hypothesis building on this observation. Namely, we instrument mobility with political leanings by U.S. state, as captured in the share of the vote for the Republican candidate in the 2016 presidential election. Given our focus on the first part

of March, before the introduction of mandatory measures, we collapse the time dimension of our initial panel regression and rely only on the cross-sectional variation at the state level.

Starting from the regression framework in Equation 9, we now difference the specification between two points in time on the same month. Focusing on the regression for reproduction rate, this differencing yields

$$\ln(R_{0,t,s}) - \ln(R_{0,t-h,s}) = b(m_{s,t} - m_{s,t-h}) + e_{s,t} - e_{s,t-h}. \quad (11)$$

We proceed analogously for equation 10, which focuses on initial jobless claims.

We again estimate the elasticity coefficient b by two-stage least squares. In the first stage we use political leanings to instrument the change in mobility between two points in time. In the second stage, we regress our dependent variable—either the reproduction rate or the initial claims—on the fitted change in residential mobility. In this exercise, we cannot use the estimates of the reproduction rate in Fernández-Villaverde and Jones (2020), since these start in the second half of March for most regions. We rely instead on the estimates from System, Vladek, and Krieger (2020), which start earlier and are based on an adaptation of the estimation method of Bettencourt and Ribeiro (2008). The middle and bottom panels of Figure 1 offer a comparison of these alternative estimates of the reproduction rate when aggregated at the national level.

The estimates of the reproduction rate from System, Vladek, and Krieger (2020) cover all 50 U.S. states and the District of Columbia. The starting date for these estimates varies by state, in line with the differential spread of the disease. The earliest estimates are for February 19, 2020 for the state of Washington, whereas, at the other end of the spectrum, estimates for Alaska, Idaho, and West Virginia only start on March 8, 2020.⁷

The message from our new exercise is loud and clear. As shown in Table 2, Column 1, there is a strong correlation between political leanings and the change in mobility. In columns 2 and 3, the null hypothesis that the coefficient on the instrumented mobility is 0 can be rejected at standard significance levels, despite the fact that we only have 51 observations. The elasticity of initial jobless claims with respect to mobility in column 3 of this table, at about 0.17, is remarkably close to the analogous elasticity in column 3 of Table 1, which is approximately 0.15. This finding indicates that the economic costs of changes in mobility are comparable, regardless

⁷ Given the later start of estimates for the reproduction rate, for Alaska, Idaho, and West Virginia we use a shorter window of nine days when computing the changes in Equation 11.

of whether the changes are driven by mandated or spontaneous measures. However, it could still be the case that for comparable costs, the spontaneous measures could have induced a bigger decline in the reproduction rate. Moving back to Table 1 for the panel regression instrumented with stay-at-home orders, Column 2 shows an elasticity of the reproduction rate with respect to mobility of about -3.5. By contrast the analogous estimate in Column 2 of Table 2 is about -2.3, which implies a lower effectiveness of spontaneous measures in reducing the reproduction rate relative to mandated measures.⁸ In other words, for the same economic impact, a decline in spontaneous mobility leads to a smaller decline in the reproduction rate.

5 Conclusions

We investigated empirically the epidemiological benefits and economic costs of social distancing at the onset of the pandemic. We derived our empirical framework from the standard model, proxying contacts using Google mobility data, and instrumenting mobility with either the stay-at-home orders issued by individual U.S. states, or political leanings by state. Our results suggest that, at the margin, changes in mobility through the first quarters of 2020 in the United States had significant effects on both reproduction rates and initial jobless claims. Strikingly, the magnitude of the economic effects is comparable whether social distancing is spontaneous or mandated—the epidemiological effects are however stronger when social distancing is mandated.

In light of these results, it is plausible that when economic activity rebounded as stay-at-home orders were lifted, this rebound was made possible by the observed improvement in the epidemiological conditions. Counterfactually, if the reproduction rate of the coronavirus had remained high or had matched the initially pessimistic scenario, the lifting of the health measured could have been offset by a new hike in spontaneous social distancing.

⁸ For our comparison we used estimates based on different datasets for the mandated and spontaneous measures, the datasets of Fernández-Villaverde and Jones (2020) and of Systrom, Vladek, and Krieger (2020), respectively. We can also estimate the elasticity of the reproduction rate with respect to mobility for mandated measures using the dataset of Systrom, Vladek, and Krieger (2020) and find an even more sizable elasticity of about -5.1.

References

- Alfaro, L., A. Chari, A. N. Greenland, and P. K. Schott (2020). Aggregate and firm-level stock returns during pandemics, in real time. *Covid Economics, Vetted and Real Time Papers* (4), 2–24.
- Allcott, H., L. Boxell, J. C. Conway, B. A. Ferguson, M. Gentzkow, and B. Goldman (2020, October). What Explains Temporal and Geographic Variation in the Early US Coronavirus Pandemic? NBER Working Papers 27965, National Bureau of Economic Research, Inc.
- Allen, L. (1994). Some discrete-time SI, SIR, and SIS epidemic models. *Mathematical Bioscience* 124(1), 83–105.
- Alvarez, F., D. Argente, and F. Lippi (2020). A Simple Planning Problem for COVID-19 Lockdown. *Covid Economics, Vetted and Real Time Papers* (14), 1–32.
- Atkeson, A. (2020). What Will be the Economic Impact of COVID-19 in the US? Rough Estimates of Disease Scenarios. Staff Report 595, Federal Reserve Bank of Minneapolis.
- Atkeson, A., K. A. Kopecky, and T. Zha (2021, February). Behavior and the Transmission of COVID-19. Staff Report 618, Federal Reserve Bank of Minneapolis.
- Baker, S. R., N. Bloom, S. J. Davis, K. J. Kost, M. C. Sammon, and T. Viratyosin (2020). The unprecedented stock market impact of covid-19. *Covid Economics, Vetted and Real Time Papers* (1), 33–42.
- Bettencourt, L. and R. Ribeiro (2008). Real time bayesian estimation of the epidemic potential of emerging infectious diseases. *PLoS ONE*.
- Bodenstein, M., G. Corsetti, and L. Guerrieri (2020). Social Distancing and Supply Disruptions in a Pandemic. *Covid Economics, Vetted and Real Time Papers* (19), 1–52.
- Brauer, F., P. Driessche, and J. Wu (2008). *Mathematical Epidemiology*. Number 1945 in Lecture Notes in Mathematics, Springer, Berlin, Heidelberg.
- Chernozhukov, V., H. Kasahara, and P. Schrimpf (2021). Causal impact of masks, policies, behavior on early covid-19 pandemic in the u.s. *Journal of Econometrics* 220(1), 2362.
- Coibion, O., Y. Gorodnichenko, and M. Weber (2020). The Cost of the Covid-19 Crisis: Lockdowns, Macroeconomic Expectations, and Consumer Spending. *Covid Economics, Vetted and Real Time Papers* (20), 1–51.
- Dong, E., H. Du, and L. Gardner (2020). An interactive web-based dashboard to track covid-19 in real time. *The Lancet Infectious Diseases* 20(5), 533 – 534.
- Eichenbaum, M. S., S. Rebelo, and M. Trabandt (2020). The Macroeconomics of Epidemics. NBER Working Papers 26882, National Bureau of Economic Research, Inc.
- Ferguson, N. M., D. Laydon, G. Nedjati-Gilani, N. Imai, K. Ainslie, M. Baguelin, S. Bhatia, A. Boonyasiri, Z. Cucunub, G. Cuomo-Dannenburg, A. Dighe, I. Dorigatti, H. Fu, K. Gaythorpe, W. Green, A. Hamlet, W. Hinsley, L. C. Okell, S. van Elsland, H. Thompson, R. Verity, E. Volz, H. Wang, Y. Wang, P. G. Walker, C. Walters, P. Winskill, C. Whitaker, C. A. Donnelly, S. Riley, and A. C. Ghani (2020). Impact of non-pharmaceutical interventions (npis) to reduce covid-19 mortality and healthcare demand. Report 9, Imperial College, COVID-19 Response Team.
- Fernández-Villaverde, J. and C. I. Jones (2020, October). Macroeconomic Outcomes and COVID-19: A Progress Report. NBER Working Papers 28004, National Bureau of Economic Research, Inc.

- Gollwitzer, A., C. Martel, W. J. Brady, P. Prnamets, I. G. Freedman, E. D. Knowles, and J. J. Van Bavel (2020). Partisan differences in physical distancing are linked to health outcomes during the covid-19 pandemic. *Nature Human Behaviour* 4(11), 1186–1197.
- Google LLC (2020). Google covid-19 community mobility reports. <https://www.google.com/covid19/mobility/> accessed on October 29.
- Goolsbee, A. and C. Syverson (2021). Fear, lockdown, and diversion: Comparing drivers of pandemic economic decline 2020. *Journal of Public Economics* 193, 104311.
- Guerrieri, V., G. Lorenzoni, L. Straub, and I. Werning (2020). Macroeconomic implications of covid-19: Can negative supply shocks cause demand shortages? Technical report, NBER Working Paper No. 26918.
- Gupta, S., L. Montenegro, T. D. Nguyen, F. L. Rojas, I. M. Schmutte, K. I. Simon, B. A. Weinberg, and C. Wing (2020, May). Effects of Social Distancing Policy on Labor Market Outcomes. NBER Working Papers 27280, National Bureau of Economic Research, Inc.
- Hethcote, H. (1989). Three Basic Epidemiological Models. In S. Levin, T. Hallam, and L. G. (eds) (Eds.), *Applied Mathematical Ecology. Biomathematics*. Springer, Berlin, Heidelberg.
- Huang, D. (2020). How effective is social distancing? *Covid Economics, Vetted and Real-Time Papers* (59), 118–148.
- JHU CSSE (2020). Covid-19 data. [urlhttps://github.com/CSSEGISandData/COVID-19](https://github.com/CSSEGISandData/COVID-19) accessed on October 29.
- Jones, C., T. Philippon, and V. Venkateswaran (2020). Optimal Mitigation Policies in a Pandemic: Social Distancing and Working from Home . Technical report, NBER working paper 26984.
- Koren, M. and R. Petó (2020). Business disruptions from social distancing. *Covid Economics, Vetted and Real Time Papers* (2), 13–31.
- Raifman, J., K. Nocka, D. Jones, J. Bor, S. Lipson, J. Jay, and P. Chan (2020). Covid-19 us state policy database. <https://github.com/USCOVIDpolicy/COVID-19-US-State-Policy-Database> accessed on October 29.
- Systrom, K., T. Vladek, and M. Krieger (2020). r_t covid-19. <https://github.com/rtcovidlive/covid-model>.

Table 1: The Effects of Stay-at-Home Orders

	(1) Res. Mobility 2sls 1 st step	(2a) Reproduction Rate 2sls 2 nd step J.-F.V. dataset	(2b) Reproduction Rate 2sls 2 nd step Rt.Live dataset	(3) Init. Unemp Claims 2sls 2 nd step
Stay-at-home orders	1.850** (0.000)			
Residential mobility index		-3.502* (0.010)	-5.059** (0.000)	0.153** (0.000)
r ²	0.918	0.153	0.402	0.610
N	1204	1204	1204	1204

p-values in parentheses

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

All the regressions are run with data at the weekly frequency and include state and month fixed effects. A state-by-state dummy that takes a value of 1 if a stay-at-home order is in force and zero otherwise is the instrument for the Google residential mobility index in the 2-stage-least-squares regressions in columns (2a), (2b), and (3). The results in column (2a) are based on the reproduction rate from the dataset of [Fernández-Villaverde and Jones \(2020\)](#). The results in column (2b) are based on the reproduction rate from the Rt.Live dataset of [Systrom, Vladek, and Krieger \(2020\)](#).

Table 2: The Effects of Spontaneous Social Distancing

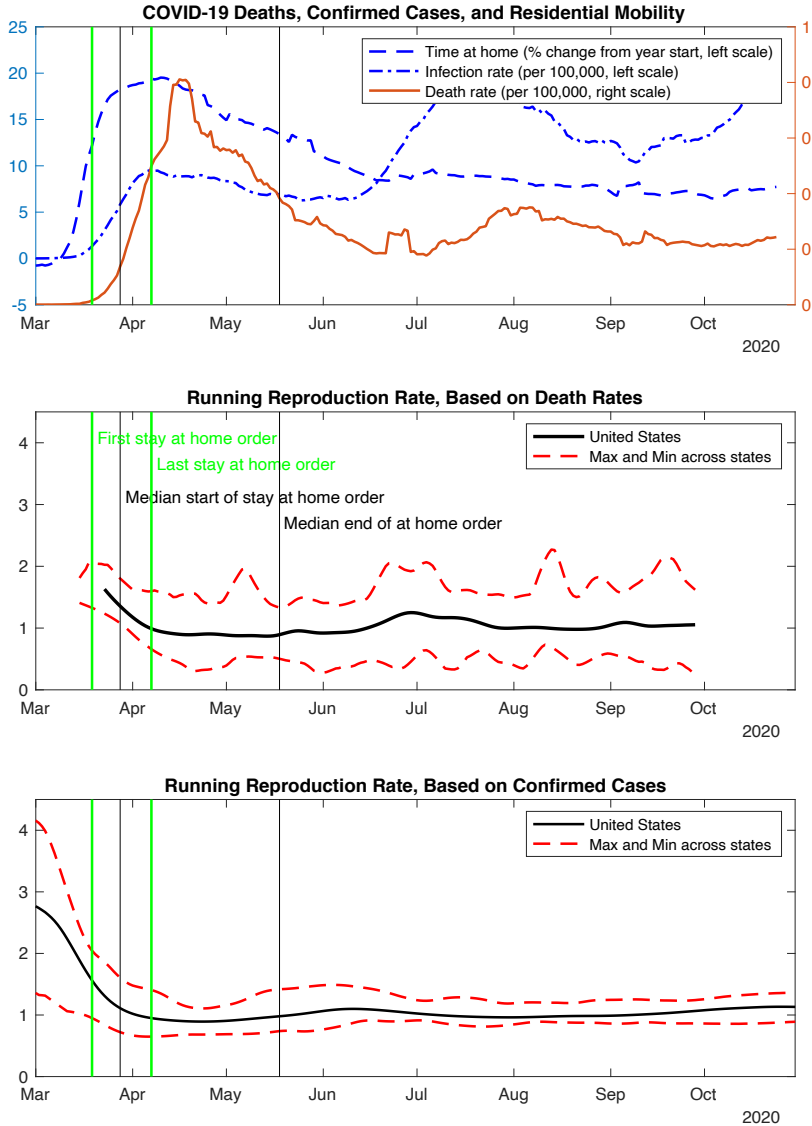
	(1) % Change Res. Mobility 2sls 1 st step	(2) % Change R 2sls 2 nd step Rt.Live dataset	(3) PPt. Change Init. Claims 2sls 2 nd step
% Republican Votes in 2016	-0.189** (0.000)		
PPt. Change Res. Mobility		-2.268 ⁺ (0.099)	0.168** (0.003)
r ²	0.607	0.0439	0.140
N	51	51	51

p-values in parentheses

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

Political leanings, as measured by the share of votes for the Republican presidential candidate in the 2016 election are the instrument for the Google residential mobility index in the 2-stage-least-squares regressions in columns (2) and (3). The results in column (2) are based on the reproduction rate from the Rt.Live dataset of [Systrom, Vladek, and Krieger \(2020\)](#).

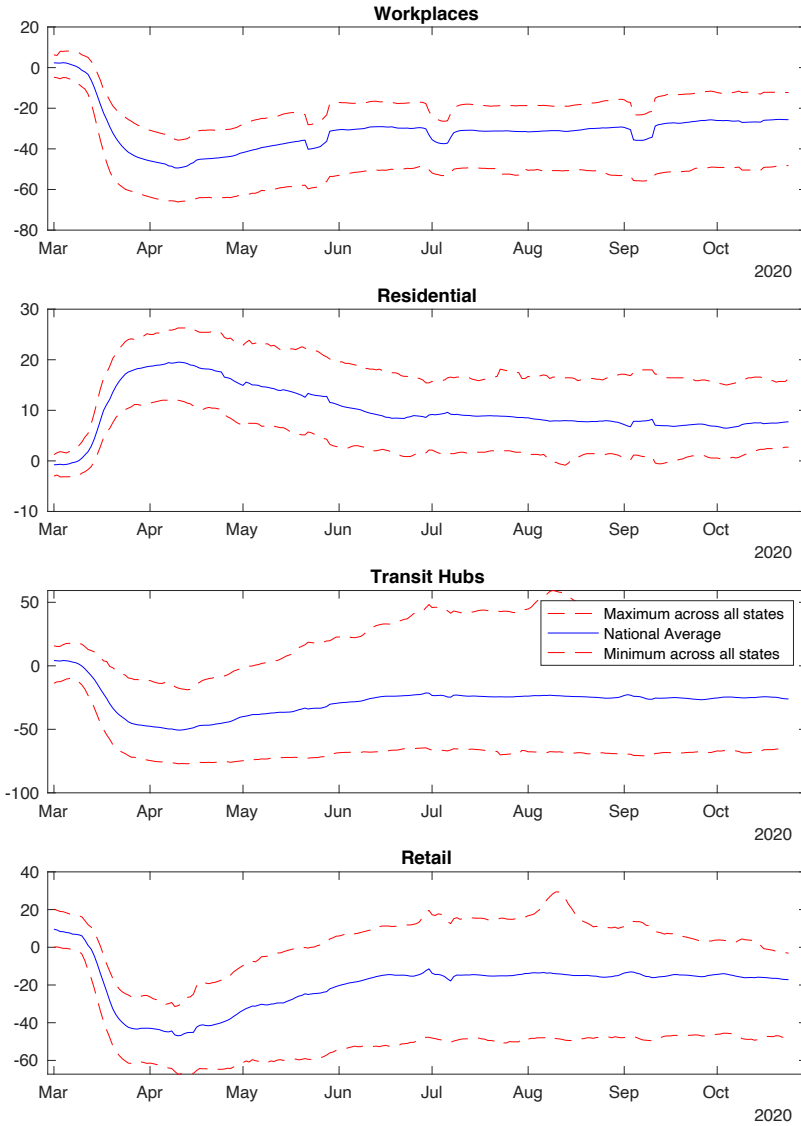
Figure 1: Stay-at-Home Orders, Mobility, COVID19 Death and Infection Rates — 7-Day Moving Average



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Note: The vertical lines denoting key dates are repeated in each panel. Sources: The data for death rates and confirmed cases are from [JHU CSSE \(2020\)](#). The data on stay-at-home orders are from [Raifman et al. \(2020\)](#). The residential mobility data are from [Google LLC \(2020\)](#). The estimates of the running reproduction rate based on deaths are from [Fernández-Villaverde and Jones \(2020\)](#). The estimates of the running reproduction rate based on confirmed cases are from [Systrom, Vladek, and Krieger \(2020\)](#).

Figure 2: Workplace and Residential Mobility—7-Day Moving Average



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Note: The dips in workplace mobility at the end of May, beginning of July and end of September correspond to national holidays. Their effects are prolonged by the moving average.
Source: Google LLC (2020).

The K-shaped recovery: Examining the diverging fortunes of workers in the recovery from the COVID-19 pandemic using business and household survey microdata¹

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This paper examines employment patterns by wage group over the course of the coronavirus pandemic in the United States using microdata from two well-known data sources from the Bureau of Labor Statistics: the Current Employment Statistics and the Current Population Survey. We find that both establishments paying the lowest average wages and the lowest wage workers had the steepest decline in employment and are still the furthest from recovery as of the most recent data for workers in December 2020 and establishments in January 2021. We disentangle the extent to which the effect observed for low wage workers is due to these workers being concentrated within a few low wage sectors of the economy versus the pandemic affecting low wage workers in a number of sectors across the economy. Our results indicate that the experience of low wage workers is not entirely due to these workers being concentrated in low wage sectors – for many sectors, the lowest wage quintile in that sector also has had the worst employment outcomes. For each month from March 2020 to January 2021, at least 20% of the decline in employment among the lowest wage establishments was due to within-industry changes. Another important finding is that even for those who remain employed during the pandemic, the probability of becoming part-time for economic reasons increased, especially for low-wage workers.

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Introduction

The coronavirus (COVID-19) pandemic plunged the U.S. economy into recession in early 2020 and has fundamentally affected the labor market. As of February 2021, COVID-19 was responsible for more than 450,000 deaths in the United States. The unemployment rate rose from 3.5 percent in February 2020 to 14.7 percent in April before falling to 6.3 percent in January 2021.

At the start of the pandemic, there were strong indications that the lowest-paid workers would be disproportionately affected. Analyzing the Bureau of Labor Statistics' (BLS) Quarterly Census of Employment and Wages and Occupational Employment Statistics data, Dey and Loewenstein (2020) showed that low-paid occupations were heavily represented and high-paid occupations lightly represented in the industry sectors most susceptible to employment losses during the pandemic. Using data from BLS's Current Population Survey (CPS), Dey, Loewenstein, Piccone, and Polivka (2020) found that in 2019, the median hourly wage of workers in highly exposed sectors was \$15.00, compared to \$21.50 for workers in other sectors. Furthermore, a larger share of workers in highly exposed sectors worked part-time hours in 2019.

Analysis of private data from various sources appears to bear out that low wage workers have borne the brunt of the pandemic induced recession. Using data from ADP, a large payroll processor, to analyze labor market trends through June 2020, Cajner et al. (2020) found employment losses to be largest among workers in the lowest quintile, where quintiles are defined on the basis of workers' hourly wage in February data. In their data, by mid-April workers in the lowest quintile had experienced a decline in employment of about 35 percent relative to mid-February levels; as of late June, employment had recovered but was still 20 percent lower than

mid-February. Bartik, Bertrand, Lin, Rothstein, and Unrath's (2020) findings using Homebase work records provide further evidence that low wage workers have fared poorly during the early part of the recession. Their sample, which is skewed toward lower wage workers in the hospitality/restaurant sector, shows that as of mid-April the number of hours worked by workers with a wage below \$15 an hour was about 75% below the level in late January while the hours of workers with wage above \$15 was about 60% below the January level. By June, the hours of all workers in their sample had recovered to about 50% to 60% of the January level.

Chetty, Friedman, Hendren, Stepner, and the Opportunity Insights Team (2020) combined payroll processing information from Paychex and Intuit and financial management data from Earnin to analyze employment declines through August 2020 for workers grouped into three wage classes. The Opportunity Insights Economic Tracker indicated that employment bottomed out in the third week of April, at which time the employment level for workers with annual earnings below \$27,000 was 37.4% below the level in January. For workers earning between \$27,000 and \$60,000, this figure was 23.3%, and it was 13.7% for workers earning more than \$60,000. By the third week in August, the employment level of workers in the lowest earnings group was still 17.5% below the January level. In contrast, the employment of workers in the middle earnings group was 5.4% below the January level and the employment of high wage workers had nearly recovered completely, as it was only 1% below its level in January.

This paper provides a further look at employment patterns by wage group over the course of the pandemic using microdata from two BLS data sources: the Current Employment Statistics (CES) and the Current Population Survey (CPS). In contrast to the datasets described above, the CES

survey offers a large, representative sample of employers and the CPS offers a large, representative sample of workers. We also present additional evidence from the Business Response Survey to the Coronavirus Pandemic, a special BLS survey that collected establishments' responses to a series of questions related to business experiences during the pandemic.

An important aspect of our work is an exploration of workers within industry sectors. This will allow us to disentangle the extent to which the effect observed for low wage workers is due to these workers being concentrated within low wage sectors of the economy as opposed to the pandemic affecting low wage workers in a number of sectors across the economy. A within industry exploration also will allow us to examine whether there were some industries in which the effects of the pandemic were more uniformly distributed across workers with different levels of earnings than other industrial sectors. The within and across industry analysis has important implications for the effect of the pandemic on evolving earnings inequality and attempts to address the potential widening of earnings disparities in the U.S. economy. If the effects on low wage workers are concentrated in specific industries this may call for more targeted support of specific industries. If instead, low wage workers suffer disproportionately across all industries the pursuit of more economy-wide actions may be warranted.

We present two key findings. First, both establishments paying the lowest average wages and the lowest wage workers had the steepest decline in employment and are still the furthest from recovery as of the most recent data for establishments in January 2021 and workers in December 2020. These results are consistent across two large and representative BLS surveys, one based on

establishments (the CES survey) and one based on households (the CPS). The second key finding is that these effects are not entirely explained by industry effects – for many sectors, the lowest wage quintile in that sector also has had the worst employment outcomes. Additional evidence for these findings is provided by the Business Response Survey to the Coronavirus Pandemic (BRS). Corroborating results from the BRS show that even within industry lower wage establishments were less likely to pay employees told not to work, less likely to pay part of health insurance premiums for employees told not to work, and less likely to offer telework for employees before or during the pandemic.

While previous research has shown the long-run consequences of an unemployment spell to a worker during a recession, such as significant lifetime earnings displacement (Davis and Von Wachter 2011) and higher risk of mortality (Sullivan and Von Wachter 2009), many of these negative outcomes may be even worse for low-wage workers whose inequalities in mortality outcomes have already been documented (Chetty et al. 2016). Given the slow jobless recovery seen in recent recessions for the lowest wage workers (Yagan 2019), the potential for significant increases in inequality resulting from the pandemic recession is clear. Heathcote, Perri, and Violante (2020) found that hours and earnings fall the most during recessions and do not fully recover during expansions, hitting low-skilled men extra hard.

Another important finding in this paper is that even for those who remain employed during the pandemic, there is a higher probability of becoming part-time for economic reasons, in particular for low-wage workers. This is additional evidence showing the multiple pathways through which low-wage workers are struggling over the course of the pandemic.

Using the CES and CPS to Track Employment

To examine employment from an establishment perspective, we use microdata from the Current Employment Statistics survey (CES). The CES is one of the longest running and most relied-upon sources of current data on the U.S. labor market. The CES is a monthly survey that collects data from 145,000 businesses and government agencies representing 697,000 worksites. The survey asks about employment, hours, and earnings in the pay period that includes the 12th of the month. Preliminary estimates at the national level by industry are usually published on the first Friday of the following month, with revisions published in the 2 succeeding months. We track employment changes using monthly data for private-sector establishments starting in March 2020 and going through January 2021. In doing so, we utilize a longitudinal component to the CES that we take advantage of by conditioning the analytical sample on establishments that responded to the survey in both February 2020 and the reference month observed in the figures and tables. Additionally, we use information from the 2019 Quarterly Census of Employment and Wages (QCEW) to get wage information for the establishments interviewed in the CES.¹

For an examination from the workers' perspective, we use microdata from the Current Population Survey (CPS). Conducted by the U.S. Census Bureau for BLS, the CPS is a monthly survey of 60,000 households that collects information about demographics, labor force status, wage information, hours worked, and occupation and industry of jobs. Similar to the CES, the reference period includes the 12th of the month. As with the CES, we track employment changes using

¹ The QCEW provides the sampling frame for the CES and other BLS establishment surveys. The QCEW program also publishes estimates of employment and wages. QCEW data are collected from the full universe of employers covered by Unemployment Insurance programs in the United States.

monthly data starting in March 2020 and going through December 2020.² We again rely on the longitudinal aspect of the data: we are able to observe wage information for surveyed individuals that were interviewed between January 2019 and February 2020 along with other important employment information for an individual prior to the pandemic. We then observe their labor force status and hours worked in 2020 during the pandemic.

CES Analysis

Each establishment is grouped into a wage class, defined as an establishment's average wage per worker in 2019: the establishment's total annual wages in 2019 in the QCEW divided by the establishment's average monthly employment across all 12 months of 2019 in the QCEW. Table 1 shows the proportion of establishments and employment in each category.

Table 1. Establishment and Employment Distribution, by Average Wages in the Establishment

Average wage per worker	Proportion of Establishments, as of 2019	Proportion of Employment, as of 2019
<20k	0.28	0.14
20k-40k	0.29	0.27
40k-60k	0.18	0.24
60k-80k	0.09	0.15
80k+	0.17	0.20

² As a result of the sampling patterns used in the CPS, it is not possible to use the same methodology on data after December 2020 because the sample size and composition would change. For that reason, the CPS results end in December 2020.

The key results constructed for this section are based on the methodology described in Dalton, Handwerker, and Loewenstein (2020). In that paper, estimates for changes in employment by size class are constructed for each month relative to an establishment's reported employment in February 2020, exploiting the panel-sample structure of the CES. An analogous strategy is used here, except instead of dividing establishments by size class, establishments are grouped by wage class.

The total change in employment for each wage class is the sum of two separate components:

- 1) The employment change in establishments continuing with positive employment, which is assumed to be the same for both respondents and nonrespondents.
- 2) Employment decline due to closures. Closures for respondents are based on reported zero employment in the data. Closures for nonrespondents are imputed based on historical data showing an increased likelihood for nonrespondents to be closed.

Closures will only have a negative impact on employment, whereas the component for continuing establishments may be positive or negative.

The employment for establishment i in month M , wage class j , and sector k is designated by E_{iMjk} . Letting R_M denote the set of sampled establishments in month M that responded in February 2020, which is the union of $R_M^{Continuing}$ (the set of responding establishments that continue to be open in month M), R_M^{Closed} (the set of responding establishments that report zero employment in month M), and R'_M (the set of establishments that responded in February 2020 but were nonrespondents in month M). The percentage employment change for continuing

establishments (those with positive employment in month M) who respond in month M , wage class j , and sector k is depicted as

$$\% \Delta E_{RMjk}^{Continuing} = \frac{\sum_{i \in R_M^{Continuing}} E_{iMjk} - E_{iFebjk}}{\sum_{i \in R_M^{Continuing}} E_{iFebjk}} \tag{1}$$

The level of employment change, $\Delta E_{Mjk}^{Continuing}$, for all continuing establishments (including nonrespondents) in month M , wage class j , and sector k is then given by

$$\Delta E_{Mjk}^{Continuing} = \% \Delta E_{RMjk}^{Continuing} \left[\sum_{i \in R_M^{Continuing}} [E_{iFebjk}] + (1 - \widehat{c_{Mjk}}) * \sum_{i \in R'_M} [E_{iFebjk}] \right] \tag{2}$$

The first summation is for continuing respondents with a valid response in month M , and the second summation over R'_M , all nonresponding establishments, is the imputed employment for nonrespondents that are estimated to be continuing establishments in month M . For the imputed employment, continuing establishments are assumed to have the same percentage change in employment as responding continuing establishments. $\widehat{c_{Mjk}}$ is the estimated probability of closure for nonresponding establishments.³

The estimate of the percentage change in employment due to establishments that continue to be open can then be expressed as

³ Details of how this is calculated are explained in Dalton, Handwerker, and Loewenstein (2020). It is the product of the percentage of responding employers that report zero employment in month M and an adjustment based on historical patterns of closures related to nonrespondents in the CES.

$$\% \Delta E_{Mj}^{Continuing} = \frac{\sum_k \Delta E_{Mjk}^{Continuing}}{\sum_k \sum_{i \in R_M} E_{iFebjk}} \tag{3}$$

where the denominator is the employment level at all responding establishments in February 2020 who were still in the sample as of month M .

The estimated change in the employment level for closed establishments is

$$\Delta E_{Mjk}^{Closed} = \left[\sum_{i \in R_M^{Closed}} [-E_{iFebjk}] - \widehat{c}_{Mjk} * \sum_{i \in R'_M} [E_{iFebjk}] \right] \tag{4}$$

and the percentage change is

$$\% \Delta E_{Mj}^{Closed} = \frac{\sum_k \Delta E_{Mjk}^{Closed}}{\sum_k \sum_{i \in R_M} E_{iFebjk}} \tag{5}$$

Finally, the percentage employment change for wage class j in month M (relative to February 2020) is

$$\% \Delta E_{Mj} = \% \Delta E_{Mj}^{Continuing} + \% \Delta E_{Mj}^{Closed} \tag{6}$$

The sample used for our analysis is conditioned on an establishment having a valid employment response in the CES in February 2020 and being in the sample in the displayed month. Figure 1

depicts the two components to the overall employment change each month for that wage class,

$$\% \Delta E_{Mj}^{Continuing} \text{ and } \% \Delta E_{Mj}^{Closed}.$$

The results in Figure 1 show that for all wage classes, employment loss in continuing establishments was the primary component of employment loss since April. The percentage of employment loss due to closures was fairly steady for all wage classes since July, though employment loss due to closures increased in December for all wage classes, the first time that had happened in 2020 since April. Employment loss for continuing establishments was substantial for all wage classes in April and especially large for low-wage employers. The employment loss for continuing establishments mostly declined each month in each wage class, with only a few exceptions of increases by no more than a quarter of a percentage point.

Summing the two components in Figure 1, the solid lines in Figure 2 depict the total percentage change in the employment of each wage class every month. The lowest-wage establishments have consistently had the largest employment decline each month since February. Although the lowest-paying establishments have had some bounce back from the 38% fall in their employment in April, their employment in January 2021 was still 12.2% below the level in February 2020. The percentage reduction in employment in January 2021 from the level in February was between 2.9% and 4.5% for the other four wage classes.

For all wage classes, the trough of employment occurred in April. The rate of employment growth for establishments in the lowest wage class was greatest between May and June (37% of lost employment recovered), but since then it has slowed considerably, having recovered in January 2021 only 26% of the employment loss as of July.

% Employment Change since February 2020 by Wage Class and Component of Change

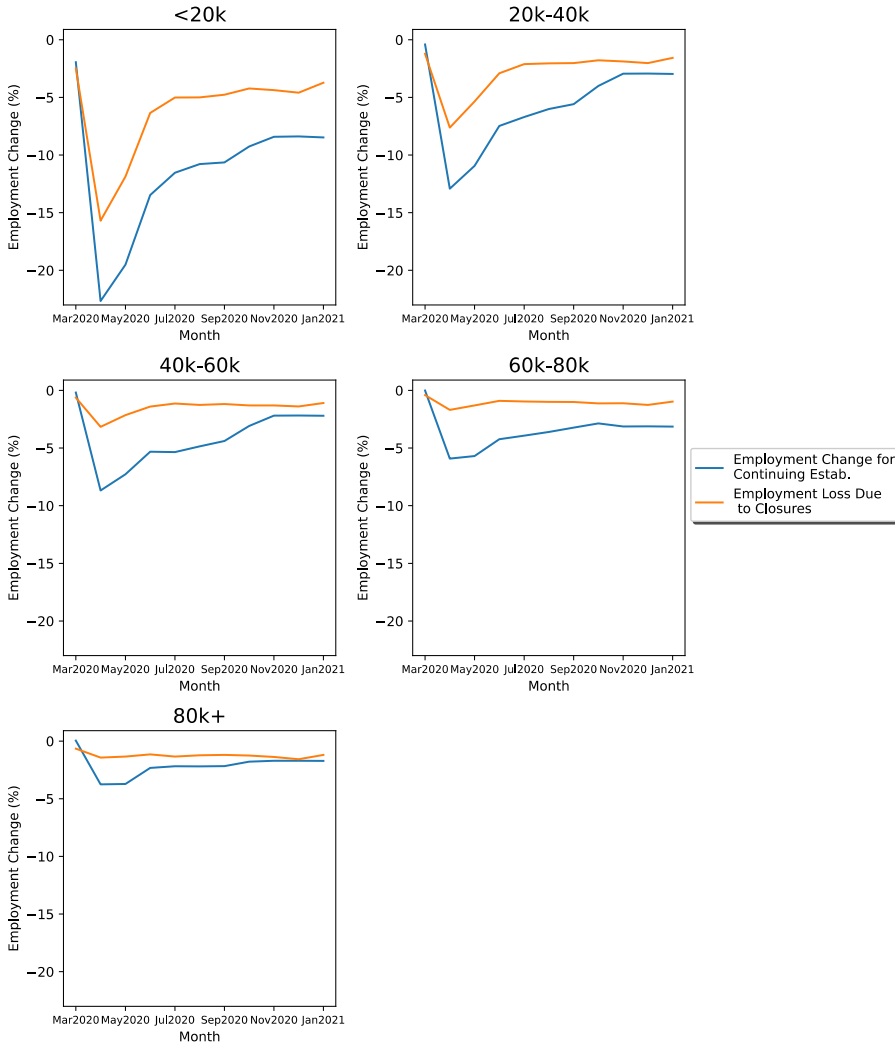


Figure 1. Percentage Employment Change since February 2020, by Wage Class. Results are based on microdata from the Current Employment Statistics survey.

Overall Employment Change since Prior February by Wage Class

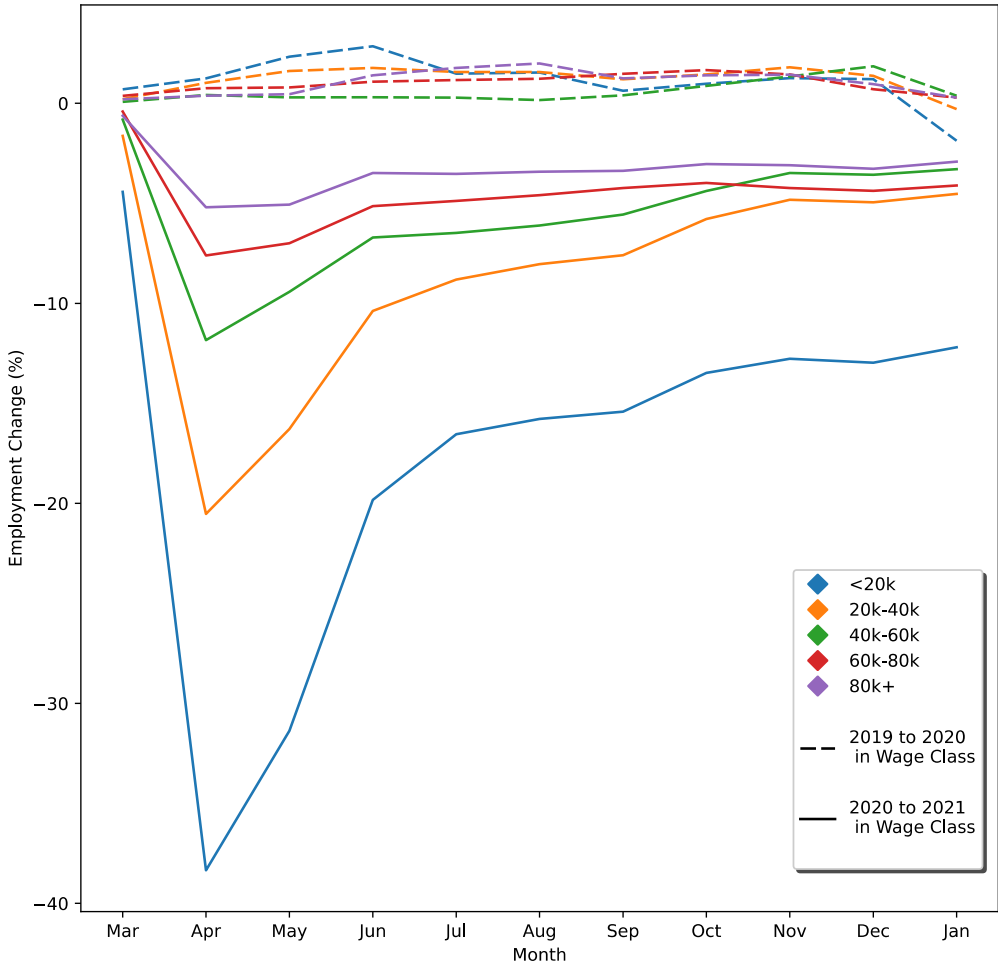


Figure 2. Overall Percentage Employment Change. Using microdata from the Current Employment Statistics survey.

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As a comparison to the pandemic-exposed employment pattern in 2020, the dashed lines in Figure 2 show analogous results for 2019. It is clear from the figure that the 2020 pattern is not explained by seasonality or systematic pre-pandemic differences between wage classes. The most apparent takeaway from Figure 2 is the magnitude of employment loss experienced in 2020. In 2019, all wage classes showed steady, slow, and positive growth through November 2019, the size of which pales in comparison to the employment loss in 2020. There is a small peak for the lowest-wage class in the summer that falls back towards the other wage classes by October. By January 2020, there is a small dip in employment for all wage classes. The patterns observed in 2019 do not offer much in terms of explaining the magnitude of the results observed during the pandemic.

A natural question is whether the relatively large employment declines at establishments paying lower wages simply reflect a drop in employment in low-wage industrial sectors such as other services and leisure and hospitality. We therefore now repeat our analysis for each of the sectors. Figure 3 shows employment changes within sector for establishments in each of the wage classes, using the same wage cutoffs across sectors.

Employment Change since February 2020 by Wage Class and Industry

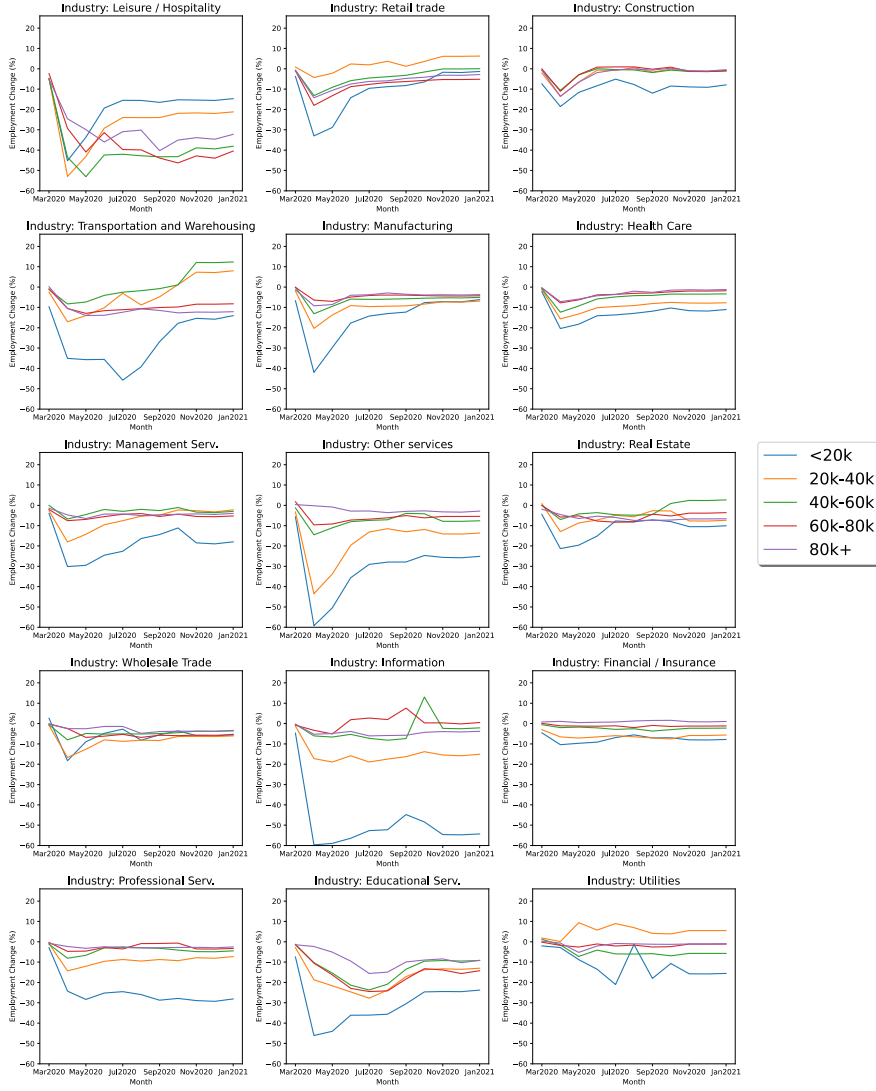


Figure 3. Employment Change since February 2020 by Wage Class and Industry.

Interestingly, the employment patterns within the various sectors are mostly similar to the overall pattern portrayed in Figure 2. Even within sectors, the lowest wage establishments disproportionately suffered the largest losses in employment. Specifically, in 10 of the 15 sectors, the lowest wage establishments within the sector have the biggest percentage declines in employment as of January 2021. Even within the typically low-wage sectors such as other services, establishments that paid the lowest wages had disproportionately larger declines in employment. Similarly within the higher wage sectors such as information, it was the establishments that paid the lowest wages that had the biggest declines in employment. The fact that low-wage establishments suffered the largest declines in employment across most of the sectors establishes that the aggregate results presented in Figure 2 are not simply due to low-wage industrial sectors of the economy being disproportionately affected by the pandemic.

Decomposition of Employment Change in the CES

In order to quantify how much of the employment loss is due to employment declines at the industry level and how much is due to changing proportions of employment in each wage class within major industry sector, we construct a decomposition of employment change into these two components.

Let E_{kjt} denote employment in wage class j and sector k in month t , W_{jt} denote the total employment in wage class j in month t , and N_{kt} denote the total employment in sector k in month t . Also, let E_{kj0} denote employment in wage class j and sector k in February 2020, W_{j0} denote the

total employment in wage class j in February 2020, and N_{k0} denote the total employment in sector k in February 2020.⁴ Then

$$\begin{aligned}
 \Delta W_{jt} &= W_{jt} - W_{j0} \\
 &= \sum_k E_{kjt} - \sum_k E_{kj0} \\
 &= \sum_k \left[\frac{E_{kjt}}{N_{kt}} N_{kt} - \frac{E_{kj0}}{N_{k0}} N_{kt} + \frac{E_{kj0}}{N_{k0}} N_{kt} \right] - \sum_k \left[\frac{E_{kj0}}{N_{k0}} N_{k0} \right] \\
 &= \sum_k \left[\left(\frac{E_{kjt}}{N_{kt}} - \frac{E_{kj0}}{N_{k0}} \right) N_{kt} \right] + \sum_k \left[\frac{E_{kj0}}{N_{k0}} (N_{kt} - N_{k0}) \right] \\
 &= \sum_k [(s_{kjt} - s_{kj0}) N_{kt}] + \sum_k [s_{kj0} (N_{kt} - N_{k0})]
 \end{aligned} \tag{7}$$

where $s_{kjt} = \frac{E_{kjt}}{N_{kt}}$ is the share of employment in sector k composed of wage class j and $s_{kj0} = \frac{E_{kj0}}{N_{k0}}$ is the share of employment in sector k composed of wage class j in February 2020. Letting $t = 0$ represent February and dividing both sides of Equation (7) by W_{j0} allows us to express the percentage change in employment for wage class j since February as the sum of two components:

$$\% \Delta W_{jt} = \frac{\overbrace{\sum_k [(s_{kjt} - s_{kj0}) N_{kt}]}^{\text{Shifting Share of Wage Class}}}{W_{j0}} + \frac{\overbrace{\sum_k [s_{kj0} (N_{kt} - N_{k0})]}^{\text{Change in Sectoral Employment}}}{W_{j0}} \tag{8}$$

⁴ Note that all totals for both month t and month 0 are establishments in the month t sample that is linked to the sample of establishments that were open in February 2020.

The first term on the right side of Equation (8) represents the employment change due to a shift since February in wage class j 's share of employment in each industry sector. If sectors across the economy shed low wage workers so that the share of low-wage workers within each sector changed, this would be reflected in the first term. If, instead, the employment change we observed above was entirely explained by specific low-wage sectors decreasing employment and the share of low-wage workers in each sector remaining the same, this first term would be zero.

The second term represents the change in employment due strictly to changes in employment across sectors. This term reflects how much of the decline in low-wage employment is due to the decline in employment for low-wage sectors initially employing a larger share of low-wage workers. The larger the decline in employment for low-wage sectors, the larger the second term will be.

The results from this decomposition are presented in Table 2, where the top portion shows the share of employment lost due to shifting employment across sectors, and the bottom portion of the table shows the share of employment due to shifting employment across wage classes within sectors.

Table 2 shows that only the lowest wage class had a consistently negative employment decline due to shifts in wage-class shares within sectors. Furthermore, the lowest wage class was the only class for which its within-sector employment share resulted in at least a 2-percentage point drop in overall employment. Thus, within sectors, employment has been moving away from the lowest-wage class and holding otherwise steady amongst the other four wage classes. As of

January 2021, 24% of overall employment loss for the lowest wage class was due to within-sector change, with across-sector share change accounting for the remaining 76%.

Table 2. CES Decomposition by Major Industry Sector

Decomposition component	Month	<20k	20k-40k	40k-60k	60k-80k	80k+
Percentage Employment Change Across Sectors	March 2020	-2.8	-1.7	-1.1	-1.0	-0.9
	April 2020	-29.2	-19.0	-13.2	-11.3	-9.4
	May 2020	-23.9	-15.5	-10.7	-9.2	-8.0
	June 2020	-15.5	-9.8	-7.3	-6.3	-5.7
	July 2020	-13.2	-8.4	-6.6	-5.9	-5.4
	August 2020	-12.6	-7.7	-6.2	-5.5	-5.2
	September 2020	-11.7	-7.3	-5.9	-5.3	-4.9
	October 2020	-10.2	-5.9	-4.8	-4.3	-4.1
	November 2020	-9.7	-4.9	-4.1	-4.0	-4.2
	December 2020	-9.9	-5.1	-4.2	-4.2	-4.4
	January 2021	-9.3	-4.7	-3.9	-3.8	-4.0
Percentage Employment Change Within Sectors, Across Classes	March 2020	-1.7	0	0.3	0.6	0.3
	April 2020	-9.2	-1.6	1.3	3.7	4.2
	May 2020	-7.5	-0.8	1.3	2.2	3.0
	June 2020	-4.3	-0.6	0.6	1.2	2.2
	July 2020	-3.4	-0.4	0.1	1.0	1.9
	August 2020	-3.1	-0.3	0.1	0.9	1.7
	September 2020	-3.7	-0.3	0.3	1.0	1.5
	October 2020	-3.3	0.1	0.4	0.4	1.1
	November 2020	-3.1	0.1	0.6	-0.2	1.1
	December 2020	-3.1	0.1	0.6	-0.2	1.1
	January 2021	-2.9	0.1	0.6	-0.3	1.1

Table 3 shows the decomposition using 4-digit industry instead of sector as the industry grouping.

This decomposition should show less employment loss due to within-industry share shifting. This is as expected since presumably 4-digit industries are more homogenous than establishments in

the same sector, the latter being a broader classification. Nevertheless, the same pattern observed in Table 2 also holds for Table 3. Even when using the more detailed industry classification, employment loss due to shifts away from the lowest-wage class within industry makes up nearly a fifth of the total 12.2% employment loss as of January 2021. Although across-sector employment change is the dominant factor, within-sector share shifting is sizeable and shows employment loss is happening in low-wage establishments across the economy.

Table 3. CES Decomposition by Detailed (4-digit) Industry

Decomposition component	Month	<20k	20k-40k	40k-60k	60k-80k	80k+
Percentage Employment Change Across 4-Digit Industries	March 2020	-3.4	-1.6	-1.0	-0.8	-0.8
	April 2020	-34.1	-18.9	-12.8	-9.7	-7.8
	May 2020	-27.1	-15.5	-10.3	-8.0	-7.3
	June 2020	-17.3	-9.8	-6.9	-5.7	-5.3
	July 2020	-14.5	-8.6	-6.3	-5.3	-5.0
	August 2020	-13.9	-7.8	-6.0	-5.1	-4.8
	September 2020	-13.0	-7.4	-5.6	-4.9	-4.6
	October 2020	-11.2	-5.9	-4.6	-4.1	-3.9
	November 2020	-10.3	-4.9	-3.9	-4.1	-4.1
	December 2020	-10.5	-5.1	-4.0	-4.2	-4.2
	January 2021	-9.9	-4.6	-3.7	-3.9	-3.9
Percentage Employment Change Within 4-Digit Industries, Across Classes	March 2020	-1.0	0	0.2	0.4	0.1
	April 2020	-4.3	-1.6	1.0	2.1	2.6
	May 2020	-4.3	-0.8	0.9	1.0	2.2
	June 2020	-2.5	-0.6	0.2	0.6	1.8
	July 2020	-2.0	-0.2	-0.1	0.5	1.4
	August 2020	-1.9	-0.2	-0.2	0.5	1.4
	September 2020	-2.4	-0.2	0.1	0.6	1.2
	October 2020	-2.3	0.1	0.2	0.2	0.9
	November 2020	-2.4	0.1	0.4	-0.2	1.0
	December 2020	-2.5	0.1	0.4	-0.2	0.9
	January 2021	-2.3	0.1	0.4	-0.2	1.0

CPS Analysis

Each household in the CPS is scheduled to be interviewed for four consecutive months and then, eight months later, is interviewed for another four consecutive months. Since questions about earnings are asked only in the fourth and eighth interviews, we use information collected in workers' fourth interview between January 2019 and February 2020 to determine, at the time of the interview, an employed worker's earnings, hours worked, occupation, and industry. We then examine the labor force status and hours of work for these workers for every month between February 2020 and December 2020.⁵ This yields a sample of approximately 18,500 individuals from February through November and 14,000 in December. The sample reduction in the final month is caused by the rotational nature of the CPS interview schedule. In December there are fewer individuals that provided earnings data from January 2019 to February 2020; some of those interviewed in December conducted their fourth interview in March 2020, making them ineligible for our sample. To account for the reduction of observations caused by the rotation pattern of interviewing and attrition, we adjusted the weights used in our analysis to preserve the average age, race, and gender distribution of workers in January 2019 to February 2020. Each worker is assigned a wage class on the basis of the weekly earnings they reported in their previous fourth interview.⁶ Table 4 shows the earnings breakdown by quintile.

⁵ Cortes and Forsythe (2020) carry out a similar analysis to examine earnings losses during the pandemic.

⁶ Earnings quintiles are defined based on real weekly earnings from January 2019 through February 2020. All weekly earnings were adjusted using the CPI-U to a February 2020 reference period.

Table 4. CPS Weekly Earnings Quintile Definitions

Quintile	Weekly Earnings
1	Less than \$432.39
2	\$432.39 - \$665.47
3	\$665.47 - \$960.09
4	\$960.09 - \$1,493.69
5	More than \$1,493.69

The sample each month consists of workers who were interviewed that month and also employed at their fourth interview between January 2019 and February 2020.⁷ Figure 4 displays the proportion of workers in each earnings quintile who were still employed each month from February 2020 to December 2020, thereby illustrating the evolution of employment during the pandemic by earnings quintile.⁸ The proportion of workers who were still employed in February 2020 increases by earnings quintile. Among those in the lowest earnings quintile, 82.4% were employed in February 2020, compared to 95.1% of those in the highest earnings quintile. As is discussed more below, these February rates are in line with historical rates of those remaining employed by quintile.

However, starting in March 2020, the proportion of workers who remained employed declined for all of the earnings quintiles, with the lowest earnings quintile suffering the largest decline in

⁷ Throughout the remainder of the discussion we refer to these workers as “still employed” or “remained employed”. Despite the use of these terms, we do not mean to imply that these workers were continuously employed, but rather these workers were employed the last time we observed them between January 2019 and February 2020 and in the month under discussion in 2020. Workers could have experienced a period of non-employment in between.

⁸ The February 2020 sample consists only of workers who had their fourth interview sometime prior to February 2020. All workers who had their fourth interview in February 2020 were not included in the analysis for February 2020.

employment. The proportion of workers in the lowest earnings quintile who remained employed dropped 3.9 percentage points between February and March and fell another 23.6 percentage points between March and April. In comparison, the proportion of those in the second earnings quintile who remained employed fell 1.1 percentage points between February and March and an additional 14.7 percentage points between March and April. The decline for the upper quintile was much less severe, with the proportion of those who remained employed falling 0.1 percentage points between February and March and an additional 5.1 percentage points between March and April.

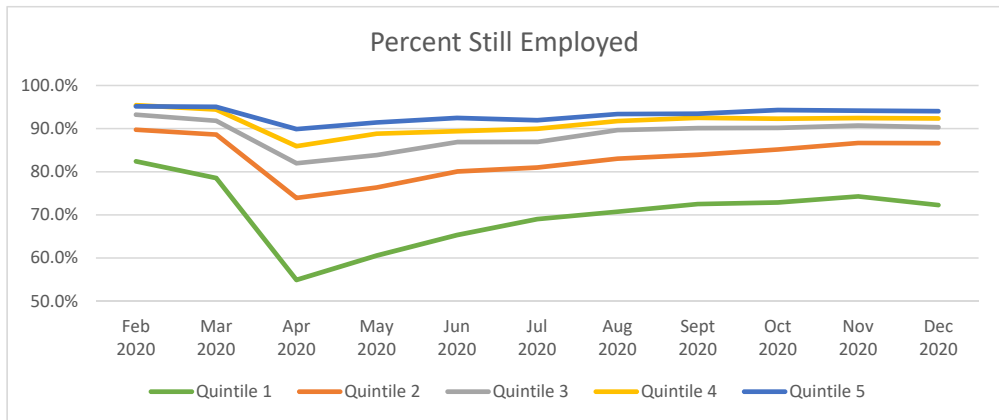


Figure 4. Percent of those Employed between January 2019 and February 2020 who are Employed in 2020 during the Pandemic.

Between April and November, employment partially recovered for all five quintiles, but as of November, employment loss was still greatest for the lowest two quintiles. By November only 74.3% of those in the lowest earnings quintile were working and 86.7% of those in the second

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lowest quintile. In comparison 94.1% of those in the highest earnings quintile and 92.4% of those in the fourth earnings quintile were working in November. Between November and December, the proportion of workers who remained employed in the top four wage quintiles stayed mostly unchanged; however, in the lowest wage quintile the proportion who remained employed dropped 2.0 percentage points. Consistent with research based on less representative private data, the estimates from the CPS thus indicate quite clearly that the employment declines during the pandemic have fallen disproportionately on workers in the lowest earnings quintiles. The CPS estimates also are in accord with the CES estimates that indicate that it was the establishments with the lowest average wages that experienced the largest decline in employment.⁹

To provide a frame of reference for the employment pattern in 2020, Figure 5 shows analogous results averaged for 2015 to 2019. The main takeaway is that even during normal economic times the proportion of individuals who are still employed from one year to the next varies across earnings quintiles. Individuals in the lowest quintile are less likely than individuals in the other four quintiles to be employed the following year. From February to December, the 5-year-average proportion still employed in the lowest quintile varies between 79.5% and 81.4% across months, while the proportion still employed for the other four quintiles varies between 89.4% and 95.4%. Figure 4 thus overstates the effect of the pandemic on employment, and this overstatement is largest for low-earning workers.

⁹ Even if employment declines were not concentrated among low-wage establishments, we would still see greater declines in the employment of low-wage workers if low-wage workers were more likely to be laid off than their higher-wage co-workers.

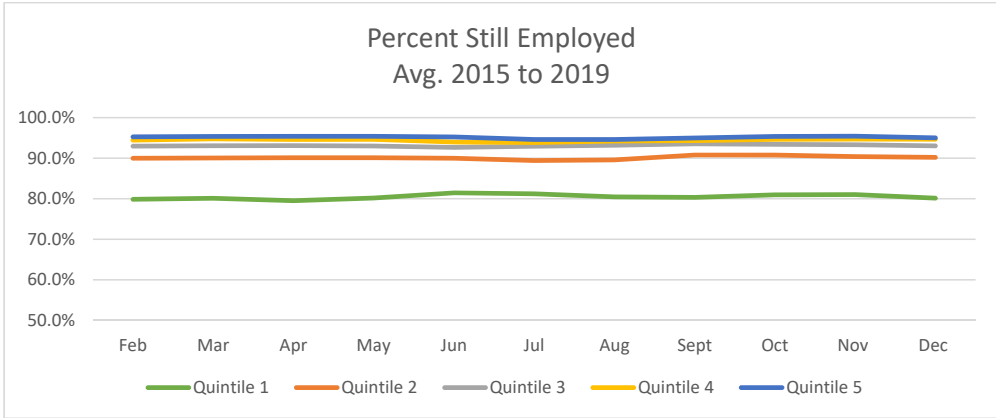


Figure 5. Average from 2015 to 2019 of the Percent of those Employed in the Previous Year who are Employed in the Current Year.

Figure 6 displays the proportion of workers who remained employed by earnings quintile normalizing the estimates by subtracting off the 5-year-average proportion remaining employed within a quintile. This normalization does not affect the overall pattern across the earnings quintiles. Workers in the lowest earnings quintile suffered the largest losses early in the recession. Although somewhat muted by the normalization, the decline in the proportion of workers who remained employed as of December was eight times larger for the lowest earnings quintile than for the highest earnings quintile (-7.8% vs. -1.0%). Given the persistent differences in the proportion of workers remaining employed by earnings quintile, the remaining analysis for 2020 is normalized by subtracting off the appropriate 5-year average proportion of those remaining employed.

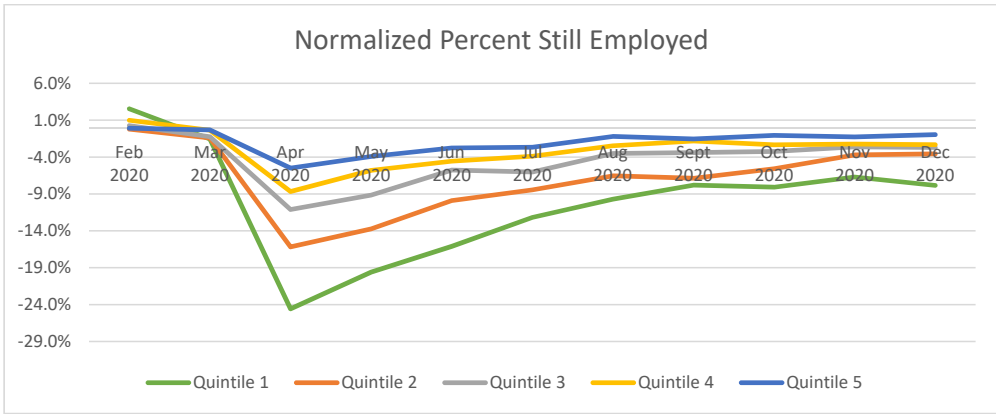


Figure 6. Percent of those Employed in 2019 who are Employed in 2020, Normalized Using Data from 2015-2019.

Figure 7 shows the employment rate by the major industry group that the respondent worked in during 2019, using the same earnings cutoffs across industries.¹⁰ Similar to the patterns observed in Figure 3 using the establishment data from the CES, and similar to the overall results observed in Figure 6 using the CPS, the key result holds: even within industry, the lowest earnings quintile had the biggest initial drop in its employment rate, as well as the most employment to recover as of December in order to return to the baseline February 2020 employment rate. As of December, the lowest earnings quintile’s biggest employment gaps relative to February are in Other Services, Leisure and Hospitality, Education and Health Services, and Information, a similar pattern to that in the CES data. Several of these sectors are low earnings sectors. Nevertheless, the finding that low earnings workers were disproportionately harmed in every sector provides further

¹⁰ In the CES, detailed industries are divided into NAICS sectors, while CPS uses major industry groups. These classifications are not exactly 1 to 1.

corroborating evidence that the worse employment outcomes for low earnings individuals are not just due to them being heavily concentrated in hard-hit industries. Low wage workers suffered larger employment losses within industries, too.

Decomposition of Employment Change in the CPS

Similar to our CES analysis, we decompose the change in CPS employment into across-industry and within-industry components. Note, however, that as discussed above, labor turnover means that not all workers employed in a given year will also be employed in the subsequent one even in normal times. Furthermore, the proportion of workers remaining employed varies by earning quintile. To isolate the effect of the pandemic, we normalize by subtracting the average over the previous 5 years of the proportion of workers employed between January (year $t-1$) and February (year t) who were still employed the following period through December (year t) from the proportion of workers employed between January 2019 and February 2020 who were still employed in 2020 during the pandemic. We modify our decomposition accordingly. Specifically, we perform a decomposition for both the year 2020 and a decomposition for each year from 2015 to 2019 (prior to the pandemic) and then subtract the average of the 2015 to 2019 components of employment change from the same components of change in 2020.

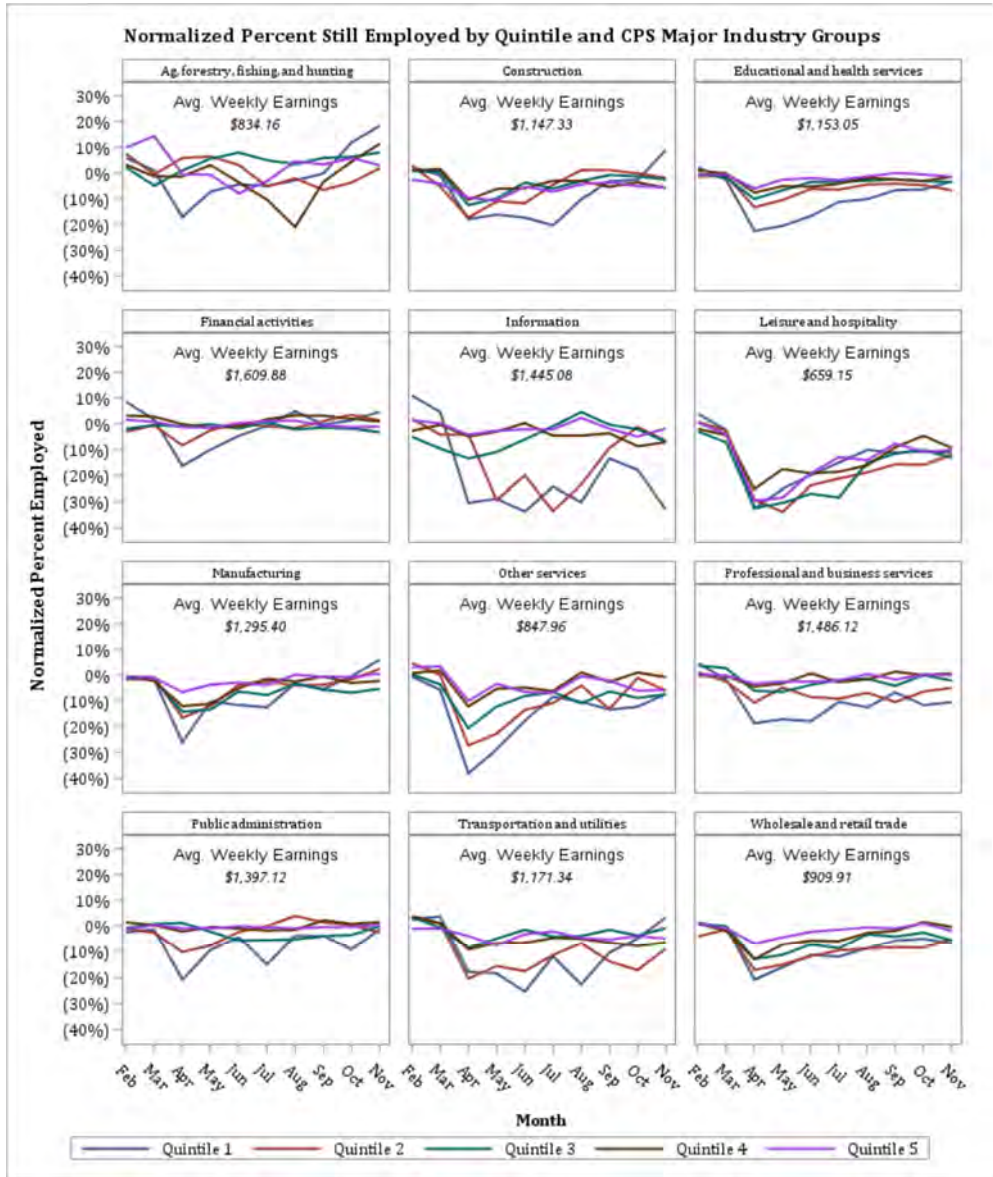


Figure 7. Industry Percent Employed, Normalized Using Data from 2015-2019.

Note: The Mining major industry group is excluded from Figure 7 due to an insufficient amount of sample.

Slightly modifying the notation used above, the shares for the CPS decomposition now have a year component such that the change in industry k 's share of still employed in year y vs. total employed in year $y-1$ for wage quintile j in month t is given by¹¹

$$s_{kjt_y} - s_{kjt_{y-1}} = \frac{E_{kjt_y}}{N_{kt_y}} - \frac{E_{kjt_{y-1}}}{N_{kt_{y-1}}} \tag{9}$$

Similarly, the change in still employed in year y vs. total employed in year $y-1$ in major industry group k in month t is given by

$$N_{kt_y} - N_{kt_{y-1}} \tag{10}$$

Equation (8) can then be written as

$$\% \Delta W_{jt_y} = \frac{\sum_k [(s_{kjt_y} - s_{kjt_{y-1}})N_{kt_y} + s_{kjt_{y-1}}(N_{kt_y} - N_{kt_{y-1}})]}{W_{jy-1}} \tag{11}$$

where the denominator, W_{jy-1} , is the annual CPS employment level for individuals in earnings quintile j , in the previous year $y - 1$.

Using the same form as Equation (11), the decomposition of the average percentage of workers who were employed a year earlier who are still employed can be written as

$$\% \Delta \bar{W}_{jt_{y-1}} = \frac{\sum_k [(\bar{s}_{kjt_{y-1}} - \bar{s}_{kjt_{y-2}})\bar{N}_{kt_{y-1}} + \bar{s}_{kjt_{y-2}}(\bar{N}_{kt_{y-1}} - \bar{N}_{kt_{y-2}})]}{\bar{W}_{jy-2}} \tag{12}$$

¹¹ Similar to CES, the totals for month t years y and $y-1$ are for workers in month t and year y who were also employed the last time they were in the sample in year $y-1$.

where the bar over a variable denotes a 5 year average. For example, $\bar{s}_{kjt_{y-1}}$ is the average share of industry k 's still employed in wage quintile j , in month t for reference year $y - 1$, where $y-1$ ranges over 2019 to 2015 and $\bar{s}_{kjt_{y-2}}$ is the average share of industry k 's total employed in wage quintile j , in month t for prior year $y - 2$, where $y-2$ equals the ranges over 2018 to 2014.

The final normalized decomposition is the difference between $\% \Delta W_{jty}$ and $\% \Delta \bar{W}_{jty-1}$, which yields

$$\begin{aligned} & \% \Delta W_{jty} - \% \Delta \bar{W}_{jty-1} \\ &= \sum_k \left[\frac{(s_{kjt_{y-1}} - s_{kjt_{y-2}}) N_{kt_{y-1}}}{W_{jy-1}} - \frac{(\bar{s}_{kjt_{y-1}} - \bar{s}_{kjt_{y-2}}) \bar{N}_{kt_{y-1}}}{\bar{W}_{jy-2}} \right] \\ &+ \sum_k \left[\frac{s_{kjt_{y-1}} (N_{kt_{y-1}} - N_{kt_{y-2}})}{W_{jy-1}} - \frac{\bar{s}_{kjt_{y-2}} (\bar{N}_{kt_{y-1}} - \bar{N}_{kt_{y-2}})}{\bar{W}_{jy-2}} \right] \end{aligned} \quad (13)$$

The first term in Equation (13) denotes the pandemic-induced employment change in earnings quintile j stemming from a shift in the share of employment in each major industry group attributed to earnings quintile j . The second term denotes change in employment due to changes in employment across industry groups.

The normalized decomposition results for the CPS are presented in Table 5. Similar to the CES results, for each earnings quintile across months, the majority of the employment loss is explained by changes in sectoral employment. For the two lowest earnings quintiles, the employment loss from shifting sectoral employment has been amplified by a loss stemming from reduced employment within major industry groups. For April, 32% of the decline in employment for workers in the lowest earnings quintile was due to these workers' employment shares declining

within industries. This is comparable to the 24% that we see in the CES during that same time period. A reduction in the within industry employment share continued to account for a substantial portion of the lowest wage quintile’s employment loss through December, where the percentage was 41%.

Table 5. Normalized CPS Decomposition by Major Industry Group

Decomposition component	Month	Weekly Earnings Quintile				
		1 Less than \$432.39	2 \$432.39 to \$665.47	3 \$665.47 to \$960.09	4 \$960.09 to \$1,493.69	5 More than \$1,493.69
Percentage Employment Change Across Major Industry Groups	February 2020	0.9	0.7	0.6	0.6	0.6
	March 2020	-1.4	-1.2	-0.9	-0.8	-0.7
	April 2020	-16.7	-13.7	-12.7	-12.0	-10.9
	May 2020	-14.1	-10.9	-9.9	-9.2	-8.1
	June 2020	-10.8	-8.2	-7.2	-6.9	-6.0
	July 2020	-9.4	-7.0	-6.0	-5.8	-5.1
	August 2020	-6.9	-5.0	-4.0	-4.1	-3.5
	September 2020	-6.0	-4.4	-3.8	-3.7	-3.5
	October 2020	-5.5	-4.1	-3.7	-3.7	-3.3
	November 2020	-4.5	-3.4	-3.0	-2.9	-2.8
	December 2020	-4.6	-3.7	-3.3	-2.9	-2.9
Percentage Employment Change Within Major Industry Groups, Across Wage Classes	February 2020	1.6	-0.9	-0.4	0.4	-0.7
	March 2020	-0.2	-0.3	-0.4	0.4	0.4
	April 2020	-7.9	-2.5	1.6	3.3	5.4
	May 2020	-5.5	-2.8	0.7	3.4	4.2
	June 2020	-5.3	-1.7	1.4	2.3	3.2
	July 2020	-2.8	-1.5	0	1.9	2.4
	August 2020	-2.8	-1.6	0.4	1.6	2.3
	September 2020	-1.8	-2.4	0.4	1.9	1.9
	October 2020	-2.6	-1.4	0.5	1.3	2.3
	November 2020	-2.2	-0.3	0.3	0.6	1.5
	December 2020	-3.2	0.1	0.6	0.6	1.9

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Working Part-Time for Economic Reasons in the CPS

Besides information on overall employment, the CPS has additional information that sheds light on workers who remained employed during the pandemic. For example, it is possible that these workers are negatively affected due to their inability to work as many hours as they wish. Figure 8 presents evidence that the pandemic led to an increase in the number of individuals working part-time for economic reasons in 2020.¹² Every earnings quintile experienced an increase in the percentage of those who worked full-time between January 2019 and February 2020 who were working part-time for economic reasons in 2020. However, the upward spike in this percentage was the largest and the most sustained for workers in the lowest earnings quintile. After increasing between February and April, the percentage of individuals working part-time for economic reasons dropped or remained stable cross all five wage quintiles between July and November. However, in December this trend reversed for the lowest two quintiles. Between November and December, the first and second quintiles saw an increase of 0.9 and 1.1 percentage points in the percentage of individuals working part-time for economic reasons, respectively, while the other three quintiles saw a decrease of 0.4 percentage points. This shows that even among those who remained employed, low wage workers were the most adversely affected by the pandemic.

¹² Respondents are classified as working part-time for economic reasons if they report that they want full-time employment (more than 35 hours per week), but work part-time (less than 35 hours per week) due to a lack of opportunity for full-time work.

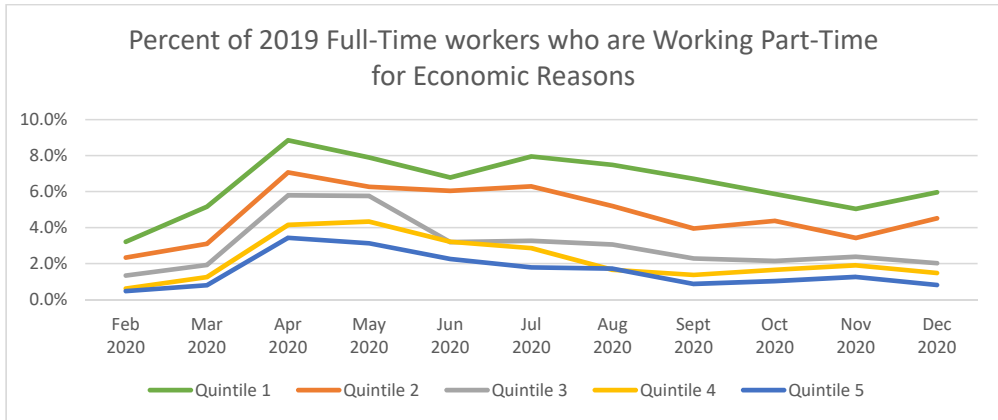


Figure 8. Percent of Individuals who were working Full-Time between January 2019 and February 2020 who are Reporting Working Part-Time for Economic Reasons in 2020 during the pandemic. Data from the Current Population Survey

Additional Evidence from a Special Establishment Survey about the COVID-19 Pandemic

A recent BLS survey provides additional insights into the experience of low wage workers during the pandemic. The Business Response Survey to the Coronavirus Pandemic (BRS) is a special survey of establishments conducted between the months of July and September 2020 using an online instrument to collect responses to a series of questions related to business experiences during and responses to the pandemic.¹³ The survey received responses from over 150,000 establishments to seven different questions. The sample was drawn from the QCEW universe of private establishments and was designed to be representative by state, sector, and size class.

¹³ More information can be found at <https://www.bls.gov/brs/>. Note, of course, that establishments that closed earlier during the pandemic are not present in the survey.

Besides presenting responses as to whether some workers were told not to work, we also present responses to three other questions collected in the survey:

- Did this business location continue to pay some or all employees who were told not to work as a result of the Coronavirus pandemic while they were not working?
- Did this business location continue to pay a portion of health insurance premiums for some or all employees who were told not to work as a result of the Coronavirus pandemic?
- Did this business location offer more opportunities for employees to telework (work remotely) as a result of the Coronavirus pandemic?

All responses are weighted using average annual employment from 2019. We classify respondents according to their industry and 2019 average wages recorded in the QCEW, as we did for the CES analysis.

Table 6 summarizes the results. The lowest-wage establishments were approximately 50 percent more likely than the highest-wage establishments to have told employees not to work. The highest-wage establishments were approximately 50 percent more likely than the lowest-wage establishment to have continued paying at least some employees that they told not to work. Furthermore, the highest-wage establishments were more than three times as likely as the lowest-wage establishments to have paid health insurance premiums for employees told not to work. Lastly, the highest-wage establishments were more than four times as likely to report increasing telework opportunities for employees, and for the vast majority of the lowest-wage establishments (74%), telework was not available for their employees.

Table 6. Percentage of Establishments Reporting Each in the Business Response Survey

Average Wage per Worker	Told Employees Not to Work	Continued Paying Employees Not Working	Paid Health Insurance for Employees Not Working	Increased Telework for Employees	No Telework Before or During Pandemic
<\$20k	60	38	20	13	74
\$20k-40k	56	50	39	23	63
\$40k-60k	52	58	60	39	46
\$60k-80k	47	60	68	52	29
\$80k+	39	57	66	58	17

The BRS results provide additional evidence that low wage workers have been hit very hard by the pandemic induced recession. Figure 9 shows that, again, these patterns are not isolated to one or two sectors – the pattern of hardship holds across most of the sectors. For each BRS response category, the figure shows a pair of up and down arrows corresponding to each sector (denoted by color). The down arrow indicates the percentage of establishments in a sector’s lowest wage class fitting into the corresponding category and the up arrow is the same but for the highest wage class. There are significant differences within sectors between the lowest and highest wage classes, providing further evidence that these effects persist throughout a broad portion of the economy and are not isolated to a few sectors. Note too that the option for telework provides a partial explanation for the employment disparity across wage classes. Telework may be an important pathway for maintaining employment throughout the pandemic. Even within sectors, high wage establishments are considerably more likely than low wage establishments to offer telework and to have increased telework during the pandemic.

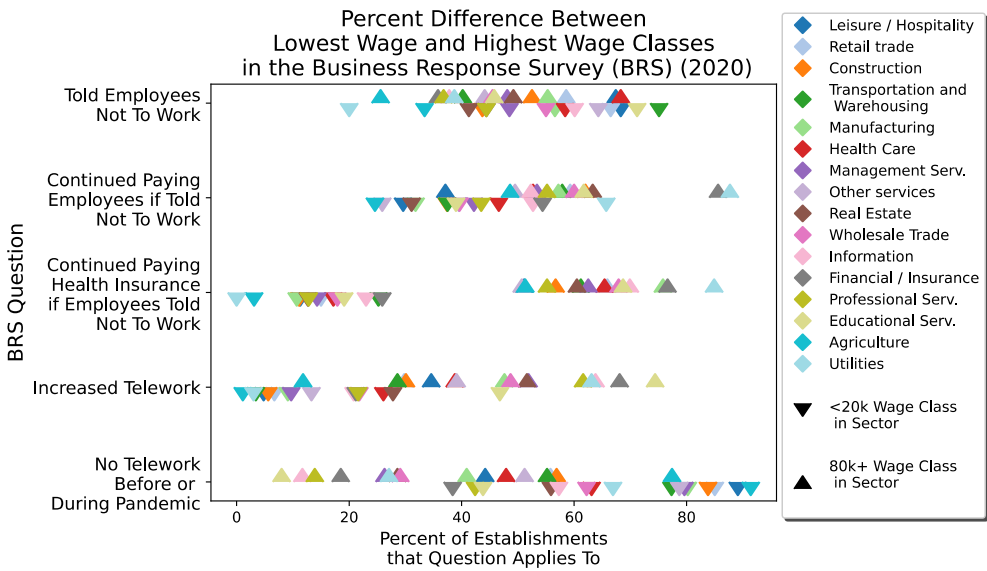


Figure 9. Differential Responses within Sector in the Business Response Survey to the Coronavirus Pandemic.

Conclusion

Our analysis of the CES establishment data and the CPS worker data demonstrates that the lowest average wage establishments and the lowest earning workers have borne the brunt of the recession induced by the Coronavirus pandemic. The lowest wage establishments and the lowest wage workers both saw the steepest initial declines in employment at the start of the recession and experienced the slowest subsequent recovery in employment. Further, our results indicate that these effects were not confined to a few low wage sectors, but rather that the decrease in

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employment for the lowest wage workers was widespread throughout the economy – a result particularly evident in the establishment-level data. Within the majority of industries, the lowest wage establishments and the lowest wage workers suffered a larger share of employment declines at the beginning of the recession and continued to experience slower employment growth once employment began to recover.

A decomposition of the overall employment decline of low wage establishments into the reduction stemming from declines in industries' shares of total employment and the reduction stemming from declines in the employment shares of low wage establishments within industries shows that although the majority of the overall employment decline has been due to low wage industries' declining employment shares, declining employment shares of low wage establishments within industries account for a substantial portion of the overall decline. Specifically, the establishment decomposition indicates that more than a fifth of the decline in employment among establishments in the lowest wage quintile was due to a decrease of these establishments' employment shares within industries as of January 2021, and this percentage has remained fairly steady since April, varying between 20% and 25%.

A decomposition of the overall employment decline of low wage workers yields a similar result. The decline in employment shares within industries was particularly true for both low wage workers and low wage establishments at the start of the recession. As of April, the decomposition for workers shows that 32% of the decline in employment for workers in the lowest earnings quintile was due to these workers' employment shares declining within industries; this percentage has steadily climbed from 23% in September to 41% in December.

The CPS data also indicate that even low wage workers who managed to hold onto their jobs have been hard hit during the pandemic induced recession. Low earning workers have been much more likely to work part time for an economic reasons than have workers in other earnings quintiles.

Examination of data from the Business Response Survey to the Coronavirus Pandemic further illustrates the disparity between low wage and high wage workers. Among establishments that reduced their workforce, low wage establishments were much less likely to pay a portion of workers' health insurance premiums. Low wage establishments were also less likely to pay workers who were told not to work. Analysis by industry again shows that these effects are not confined to establishments in the lowest wage sectors of the economy. A comparison of the lowest and highest average wage establishments within industries shows that even in the same industry a smaller percentage of the lowest wage establishments paid either wages to or health insurance for workers who were told not to work.

Altogether our findings suggest that the pandemic has increased economic inequality over the nine months we observe in the data. To the extent that lack of employment causes long-term earnings reductions, weakened savings, and loss of human capital, increased inequality due to the pandemic may persist for years to come.

References

Bartik, Alexander W., Marianne Bertrand, Feng Lin, Jesse Rothstein, and Matthew Unrath. 2020. “Measuring the Labor Market at the Onset of the COVID-19 Crisis.” Paper presented at the Brookings Papers on Economic Activity conference on June 25.

Cajner, Tomaz, Leland D. Crane, Ryan A. Decker, John Grigsby, Adrian Hamins-Puertolas, Erik Hurst, Christopher Kurz, and Ahu Yildirmaz. 2020. “The U.S. Labor Market during the Beginning of the Pandemic Recession.” NBER Working Paper 27159. June.

Chetty, Raj, John N. Friedman, Nathaniel Hendren, Michael Stepner, and the Opportunity Insights Team. 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. June.

Chetty, Raj, et al. 2016. “The Association between Income and Life Expectancy in the United States, 2001-2014.” *JAMA* 315 (16): 1750-1766.

Cortes, Guido Matias, and Eliza Forsythe. 2020. “Impacts of the Covid-19 Pandemic and the CARES Act on Earnings and Inequality.” Working Paper. December.

Dalton, Michael, Elizabeth Weber Handwerker, and Mark A. Loewenstein. 2020. “Employment changes by employer size during the COVID-19 pandemic: a look at the Current Employment Statistics survey microdata.” *Monthly Labor Review*, October.

<https://doi.org/10.21916/mlr.2020.23>

Davis, Steven J., and Till von Wachter. 2011. "Recessions and the Costs of Job Loss." *Brookings Papers on Economic Activity* 43 (2): 1-72.

Dey, Matthew, and Mark A. Loewenstein. 2020. "How Many Workers are Employed in Sectors Directly Affected by Covid-19 Shutdowns, Where Do They Work, and How Much Do They Earn?" *Monthly Labor Review*, April. <https://doi.org/10.21916/mlr.2020.6>

Dey, Matthew, Mark A. Loewenstein, David S. Piccone Jr., and Anne E. Polivka. 2020. "Demographics, Earnings, and Family Characteristics of Workers in Sectors Initially Affected by Covid-19 Shutdowns." *Monthly Labor Review*, June. <https://doi.org/10.21916/mlr.2020.11>

Heathcote, Jonathan, Fabrizio Perri, and Giovanni L. Violante. 2020. "The Rise in US Earnings Inequality: Does the Cycle Drive the Trend?" *Review of Economic Dynamics* 37: S181-S204.

Sullivan, Daniel, and Till Von Wachter. 2009. "Job Displacement and Mortality: An Analysis using Administrative Data." *Quarterly Journal of Economics* 124 (3): 1265-1306.

Yagan, Danny. 2019. "Employment Hysteresis from the Great Recession." *Journal of Political Economy* 127 (5): 2505-2558.

Misfortunes never come alone: From the financial crisis to the Covid-19 pandemic¹

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Is there a connection between the 2007-2009 financial crisis and the COVID-19 pandemic? To answer this question we examine the relation between both macroeconomic and financial losses derived from the financial crisis and the health outcomes associated with the first wave of the pandemic. At the European level, countries more affected by the financial crisis had more deaths relative to coronavirus cases. We find an analogous significant relation across Spanish provinces and a transmission mechanism running from finance to health outcomes through cross-sectional differences in health facilities.

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More than a decade apart, the 2007-2009 Great Financial Crisis and 2020-2021 COVID-19 pandemic battered a similar set of countries particularly hard, in the process socially and economically challenging households, firms, financial institutions, and policymakers alike. Potentially connecting these two calamities is their similarity in terms of global reach and the magnitude of their socio-economic damage as well as the likelihood that for many countries, the impact of the financial crisis may have compounded the effects of the COVID-19 pandemic.¹

In this paper, we aim to measure the connection between the financial crisis and the COVID-19 pandemic. Costly bank bailouts,² SME credit which became more constrained, and bank regulation that became stricter in the wake of the crisis all led to a slowing of economic growth, fiscal consolidation (e.g., Fatás and Summers (2018)) and an accumulation of sovereign debt relative to GDP. Cuts in public health spending followed.³ These cuts exacerbated the COVID-19 pandemic severity in terms of higher death rates at impact.⁴

¹ On the compounding of risks, see for example Monasterolo, Billio and Battiston (2020).

² “The notion of finance adding value has run increasingly hollow in the long shadow of the global financial crisis that began in 2008. This required governments around the world to rescue major banks whose ‘net worth’ had turned out to be fictitious; with the bailouts continuing to impose heavy social costs ten years on, in the form of squeezed public budgets, heavy household debt and negative real returns for savers” (Mazzucato (2018), p. 102).

³ “European leaders boasted of the superiority of their world-class health systems but had weakened them with a decade of cutbacks” (Kirkpatrick, Apuzzo and Gebrekidan (2020); see also Mazzucato (2018), p. 152). Complicating the picture is that “many European leaders felt so secure after the last pandemic — the 2009 swine flu — that they scaled back stockpiles of equipment and faulted medical experts for overreacting.” See Moreno, Ongena, Ventula Veghazy and Wagner (2020) for a discussion, also of other channels such as the transmission within households between young and old, a living arrangement which may have become more prevalent after the financial crisis as unemployed youngsters could not leave the parental home or even had to return to it.

⁴ A by now voluminous literature in progress, some of which is published in *Covid Economics, Vetted and Real-Time Papers* assesses the path of the COVID-19 pandemic and its economic impact. Particularly relevant to this study are studies exploiting the forward-looking nature of financial markets. For example, Gerding, Martin and Nagler (2021) find that countries with higher debt levels had worse stock price developments in the crisis, with the presumed channel that investors anticipate that their fiscal capacity is too weak to deal with the crisis (much like highly indebted companies suffered in the crisis Ramelli and Wagner (2020)). Second, Andrieş, Ongena and Sprincean (2021) and Augustin, Sokolovski, Subrahmanyam and Tomio (2021) show that COVID-19 increased sovereign CDS (thus making it more difficult for a

We analyze this possible connection between the financial crisis and pandemic outcomes across countries and across provinces in Spain. As measures of the severity of the financial crisis, we employ output gaps, real GDP growth, and sovereign debt accumulation measures at either the national or the provincial level. To measure pandemic outcomes, we look at deaths over cases at various points of the immediate impact of the pandemic's first wave in March 2020.

The estimates at the cross-country and cross-province level are strikingly similar in sign and in economic magnitude. Consider a two standard deviation increase in the severity of the financial crisis. In the half-decade following the financial crisis, this implies an output gap of 20 percent, a negative output growth of one to two percent per year, or a local debt tripling. Roughly, this analysis contrasts Germany with Spain, or the Spanish provinces of Zaragoza with Cádiz.

This difference in severity results in one to three more deaths (per 100 cases), across countries and provinces, respectively. This is a sizeable effect given that the mean is equal to one and a half deaths across countries and four deaths across provinces. It also results, across Spain, in a build-down of curative beds, with up to a third of a standard deviation in that number. This effect may sound modest. However, on the margin this factor may have played a prominent role in worsening the local death rate. We test and confirm this conjecture in a two-stage estimation. Specifically, the increase in local debt in the half-decade following the financial crisis partly explains the local number of curative beds in 2018, which in turn explains pandemic death rates in 2020.

government to finance itself, with possible further health consequences). There are also a plethora of studies on optimal public investment and health responses in pandemics (e.g., Adda (2016); Surico and Galeotti (2020); European Investment Bank (2021); Gourinchas, Kalemli-Özcan, Penciakova and Sander (2021)). An earlier (but still expanding) literature studies the repercussions of financial crises and policies preventing and dealing with them (e.g., Allen and Carletti (2010)).

We are not the first to link the financial crisis to public health performance. Maruthappu, Da Zhou, Williams, Zeltner and Atun (2015), for example, link the global economic downturn in 2009, increased unemployment and reduced public-sector expenditures, to HIV mortality. They find that a 300 percent increase in unemployment and a ten percent decrease in public sector expenditures for example,⁵ is associated with an increase in male HIV deaths per 100K population by 54 and 5, respectively.⁶

Compared to extant work, our study contributes as follows. We take a decisive step towards identifying the causal impact of a financial crisis on ensuing public health performance by linking measures of the severity of the financial crisis to the immediate impact of a later occurring pandemic (before the pandemic itself starts affecting local financial and economic outcomes and before major public health and other policies are implemented). We also study the causal chain within one country, where much is common except the financial crisis severity and the local spending on public health.

The rest of the paper proceeds as follows. Section I introduces the cross-country analysis, while Section II focuses on the impact across Spanish provinces. Section III clarifies the channel with an IV estimation. Section IV concludes.

⁵ In Spain (our focus in the main part of our analysis), the unemployment rate went from 8 percent in 2007 to 18 percent in 2009 to almost 25 percent in 2014, while public expenditure dropped by almost 7 percent from its peak of 502B euro in 2012 to 468B in 2013.

⁶ Unfortunately, these death rates are not immediately comparable to our findings as we measure deaths over cases at impact, not deaths over population over a longer period in the more advanced stages of a pandemic.

I. Cross-country Analysis

A. *Dependent Variable: Pandemic Deaths*

Assessing a potential connection between the financial crisis and the COVID-19 pandemic comes with at least two main challenges: (1) Despite the dramatic impact of the financial crisis on economic growth and sovereign debt, it is possible that with the passing of time stretching for over more than a decade and with many other developments and policy actions occurring, no exacerbation of the pandemic outcomes is discernible. Put differently, it is essential to adequately control for all developments during this time period and even then the impact-to-noise ratio over such an eventful time period may be simply too small. (2) Once the pandemic was under way, public health and other policy responses were unprecedented and may blur any assessment of the financial crisis – pandemic nexus.

To address the first concern we must have reliable measures of the impact of the financial crisis and try to control for other characteristics of the economy that were changing during this passage of time. While an omitted variable concern may continue to linger, at least we can comfortably argue that the financial crisis predates and hence is well pre-determined to the pandemic.

To deal with the second concern, we must measure the immediate impact of the pandemic, before unprecedented public health policy responses such as lock-downs were implemented (the timeliness and the optimal calibration of such policy responses may also have been an outcome of past public health expenditures in expertise).

For the analysis in this section we collect data from 23 European countries. We focus on Europe because outside Asia, Europe was hit by the spreading virus first. By contrast, North America, Latin America, and South America were able to observe the

developments in Europe and could (or could have) set up their policy responses accordingly.

Our aim is to assess if the severity of the financial crisis in a country a decade later results in a more severe pandemic outcome in terms of deaths per infections. Hence, our main dependent country variable, which is called *(Deaths / Cases) when (Cases / Population) > 100/1M*, measures the three-day moving average of the number of deaths over the number of cases, in percent, immediately after the number of cases per one million population surpassed 100 in March 2020 or before.⁷ We take three-day moving averages throughout our analysis as pandemic statistics are somewhat "jumpy" due to data reporting and collection issues. We focus on the number of deaths as the measure of the ultimate (and at the individual level, irreversible) measure of failure of a public health system to help and cure its people. And, we measure this at the point of the first major impact of the pandemic, i.e., the first "blow". 100 cases per one million is about the number when Italy as the first nation outside of China went into lock-down and many nations followed within a couple of weeks.

B. *Independent Variables: Financial Crisis Severity*

There are four main country-level financial crisis explanatory variables of interest, *Output Gaps* measured over two different periods, *Real GDP Growth* and the *CDS Premium Growth*. Each one measures different aspects of the severity of the financial crisis that took place in the country.

Output Gap (2008-13) is the output gap for 2008 to 2013, i.e., the difference between actual and potential Gross Domestic Product accumulated between 2008 and

⁷ Countries that surpassed this number only after March include Bulgaria, Hungary, Poland, Romania, and Slovakia.

Table 1. Variable Names and Definitions and Data Sources for Cross-Country Regressions

Variable Name	Units	Variable Definition	Data Source
<i>Dependent Country Variable</i>			
(Deaths / Cases) when (Cases / Population) > 100/1M	%	The three-day moving average of the number of deaths over the number of cases immediately after the number of cases per one million population surpassed 100 in March 2020 or before	OWID
<i>Main Independent Country Variables</i>			
Output Gap (2008-13)	%	The output gap for 2008 to 2013, i.e., the difference between actual and potential Gross Domestic Product accumulated between 2008 and 2013, as a percent of potential Gross Domestic Product	AMECO
Output Gap (2009-13)	%	The output gap for 2009 to 2013, i.e., the difference between actual and potential Gross Domestic Product accumulated between 2009 and 2013, as a percent of potential Gross Domestic Product	AMECO
Real GDP Growth (2008:09-2012:06)	%	The percent growth in real Gross Domestic Product between 2008:09 and 2012:06	AMECO
CDS Premium Growth (2008:09-2012:06)	%	The growth rate in the CDS premium in basis points on the country's five-year maturity sovereign debt between end-of-month 2008:09 and 2012:06	Refinitiv
<i>Independent Country Control Variables</i>			
GDP / Capita 2019	000 Euros	Gross Domestic Product per capita in 2019	ECB-SDW
# Curative Beds 2007	%000	The number in curative beds per one hundred thousand population at year-end 2007	Eurostat
Population Density 2018	-	The population per square kilometer at year-end 2018	Eurostat
# Tests	-	The three-day moving average of the number of COVID-19 tests per one thousand population that were performed prior to reaching the number of cases per one million population surpassing 100 in March 2020 or before	OWID
Death Rate 2018	%0	The death rate per one thousand population in 2018	Eurostat
Δ Curative Beds 2007-17	%000	The change in the number of curative beds per one hundred thousand population between 2007 and 2017	Eurostat

Notes. The table provides the variable names, definitions and data sources for the cross-country regressions. AMECO = the annual macro-economic database of the European Commission's Directorate General for Economic and Financial Affairs; ECB-SDW = European Central Bank - Statistical Data Warehouse; Eurostat = the statistical office of the European Union; OWID = <https://ourworldindata.org/coronavirus-source-data>; Refinitiv = <https://www.refinitiv.com/>.

2013, as a percent of potential Gross Domestic Product, while the Output Gap (2009-13) covers the period 2009 to 2013. *Real GDP Growth (2008:09-2012:06)* is the percent growth in real Gross Domestic Product between 2008:09 and 2012:06, while the *CDS Premium Growth (2008:09-2012:06)* is the growth rate in the CDS premium in basis points on the country's five-year maturity sovereign debt between end-of-month 2008:09 and 2012:06.⁸

C. Control Variables

As independent country-level control variables, we curate the following set. *GDP / Capita 2019* is the Gross Domestic Product per capita in 2019. This variable captures the overall state of the economy just prior to the pandemic.

Curative Beds 2007 is the number in curative beds per one hundred thousand population at year-end 2007. We include this variable to capture the state of the public health system just prior to the financial crisis. In this way, our crisis variables of interest stand for the deterioration in the public health system since then.

The variable *Population Density 2018* measures the population per square kilometer at year-end 2018. Density is expected to play a role in infectious disease transmission.

Tests captures the three-day moving average of the number of COVID-19 tests per one thousand population that were performed prior to reaching the number of cases per one million population surpassing 100 in March 2020 or before. The reason for including this variable is to make sure the number of cases across countries are comparable, in the sense that more intense testing could lead to more cases counted.

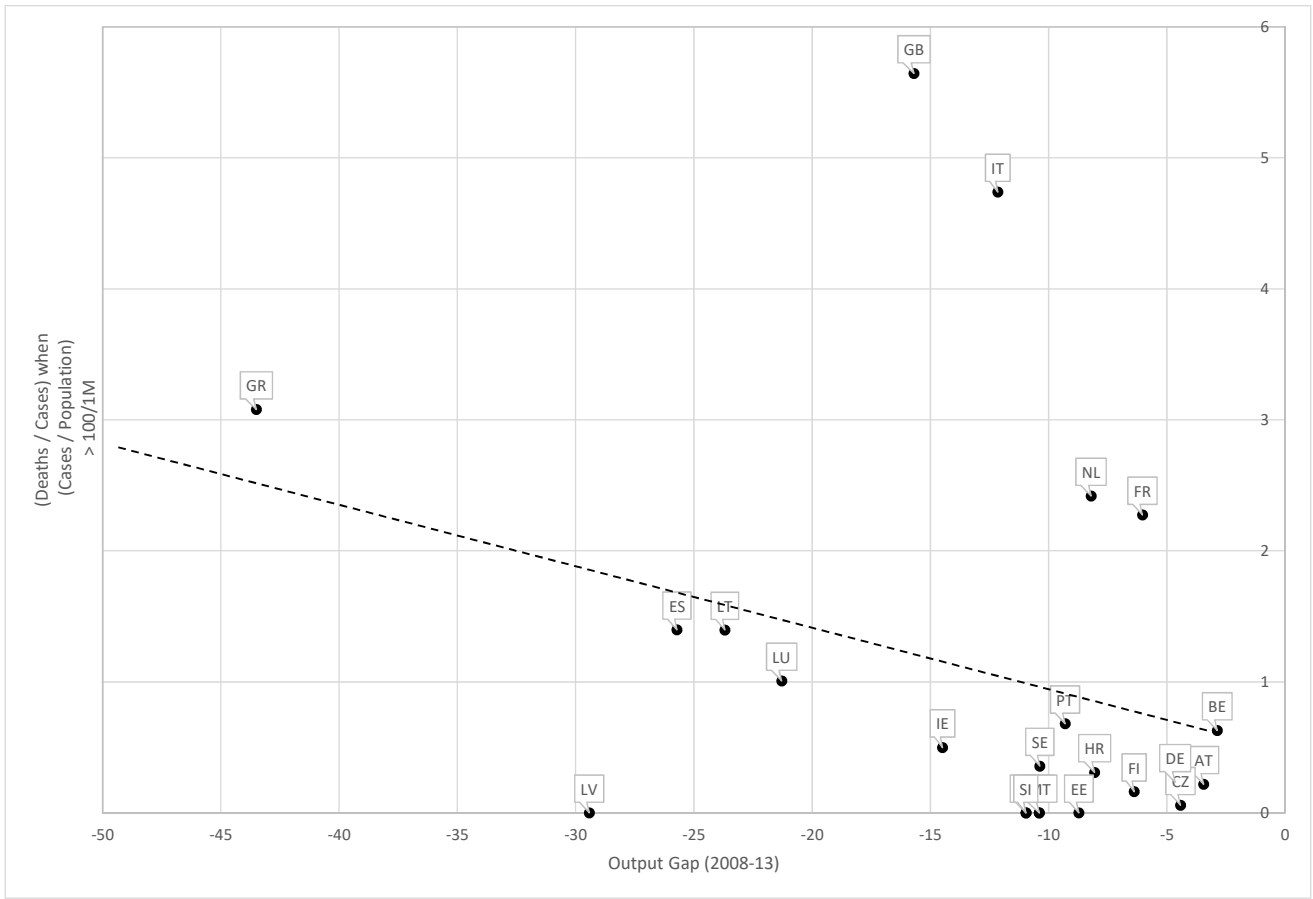
⁸ Recall that on September 15, 2008, Lehman declared bankruptcy and that on July 26, 2012, the President of the European Central Bank, Mario Draghi, delivered his "Whatever it takes" speech. These two dates bracket the most intense period of the financial crisis.

The variable *Death Rate 2018* is the death rate per one thousand population in 2018. This is the "normal" death rate in the year prior to the origination year of the pandemic. Including this variable further enhances comparability of the COVID-19 death rate per cases.

Finally, Δ *Curative Beds 2007-17* is the change in the number of curative beds per one hundred thousand population between 2007 and 2017. This measure narrowly captures the change in curative beds during this period. Controlling for this change ensures that our financial crisis impact variables measure components of the weakening of the public health sector that may have taken place after the financial crisis due to the curtailing of government expenditures on public health, such as the lack in growth in the number and the quality in curative beds, and including the training and compensation of health care workers, the investment in technology and equipment, and the administrative and strategic agility of the public health sector.

D. *First Estimates*

Figure 1 provides a first visual inspection of the data. On the vertical axis is the number of deaths over the number of cases, in percent, immediately after the number of cases per one million population surpassed 100 in March 2020 or before. Across countries, the average equals around 1.5 percent, but there is substantial variation with a range spanning from 0 in six countries to more than 5 percent in the UK. On the horizontal axis is the output gap between 2008 and 2013, with Greece experiencing a gap of almost 45 percent and Belgium a gap of only close to 2 percent. Overall, the relationship between pandemic deaths and output gap seems negative, with Greece however potentially a high-leverage point.



Code	Country Name
AT	Austria
BE	Belgium
BG	Bulgaria
CY	Cyprus
CZ	Czechia
DE	Germany
DK	Denmark
EE	Estonia
ES	Spain
FI	Finland
FR	France
GB	United Kingdom
GR	Greece
HR	Croatia
HU	Hungary
IE	Ireland
IT	Italy
LT	Lithuania
LU	Luxembourg
LV	Latvia
MT	Malta
NL	Netherlands
PL	Poland
PT	Portugal
RO	Romania
SE	Sweden
SI	Slovenia
SK	Slovakia

Figure 1. Financial Crisis Severity and COVID-19 Death Rate

The figure plots the output gap accumulated between 2008 and 2013 and the number of deaths over the number of cases, in percent, immediately after the number of cases per million of population surpassed 100 in the country. The two-letter country codes (ISO 3166-1 alpha-2) are explained in the two columns adjacent to the figure. The estimated regression equals: $Y = 0.46 - 0.047 X$.

Table 2 then simply regresses deaths over cases on one of the crisis severity measures and a constant, and depending on the specification a set of control variables. Starting with the six-year output gap in Column (1), the estimated coefficient equals -0.048**,⁹ which implies that for an additional minus 20 percentage points (pp) in output gap, which is around two standard deviations, the number of deaths over a 100 cases increases by one person. This increase in the death rate by one pp is sizable effect as the mean death rate was equal to 1.5 percent, and the range between one and five percent. The financial crisis in countries like Spain, Greece, Lithuania and Latvia did result in a six-year output gap that was even more negative than that (i.e., minus 26, 44, 24 and 29 pp, respectively).

Next, in Model (2) we add the first control variable, which is per capita GDP, followed in Models (3) to (9) by the other control variables in various combinations and for the countries for which we could collect the relevant information. The loading of the output gap remains mostly statistically significant and of equal or slightly larger size, implying one and a quarter additional deaths (per 100 cases) for an additional minus 20 pp output gap. What is remarkable is that, despite our judicious curation of controls, none of the estimated coefficients are statistically significant. The stability of the estimated coefficient on the output gap across the nine models provides some relief about potential biases from omitted variables.

In Column (10) we introduce the second financial crisis measure, which is the five-year output gap between 2009 and 2013. The reason for this shortening of the gap period is that in some countries the financial crisis and the corresponding arrived approximately

⁹ As in the Tables we indicate statistical significance in the text as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2. Cross-Country Regression Estimates of Pandemic Mortality Rate on Financial Crisis Severity Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Samples	All Countries											Countries with Deaths > 0			Without Greece			
Dependent Variable	<i>(Deaths / Cases) when (Cases / Population) > 100/1M</i>																	
Output Gap (2008-13)	-0.048** (0.020)	-0.048** (0.021)	-0.039* (0.022)	-0.039* (0.022)	-0.038 (0.023)	-0.067*** (0.014)	-0.066*** (0.014)	-0.067*** (0.015)	-0.064*** (0.016)				-0.060** (0.019)	-0.080** (0.017)	-0.078* (0.029)	-0.075 (0.053)	-0.084* (0.044)	-0.077 (0.055)
Output Gap (2009-13)												-0.061*** (0.017)						
Real GDP Growth (2008:09-2012:06)												-0.106** (0.030)						
CDS Premium Growth (2008:09-2012:06)													0.00013** (0.000)					
GDP / Capita 2019	0.002 (0.009)		-0.002 (0.008)	-0.002 (0.008)	-0.022 (0.020)	-0.018 (0.022)	-0.023 (0.021)	-0.015 (0.019)	-0.008 (0.022)	0.001 (0.023)	-0.001 (0.025)	-0.001 (0.025)	0.014 (0.033)	-0.015 (0.020)	0.035 (0.050)	-0.021 (0.031)	-0.024 (0.023)	-0.019 (0.031)
# Curative Beds 2007			-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.003 (0.003)	-0.003 (0.005)	-0.003 (0.004)	-0.003 (0.005)	-0.004 (0.005)	-0.003 (0.005)	-0.005 (0.005)	-0.005 (0.006)	-0.004 (0.005)	-0.007 (0.008)	-0.003 (0.004)	-0.003 (0.004)	-0.003 (0.005)
Population Density 2018					-0.000 (0.001)	0.008 (0.005)	0.008 (0.006)	0.007 (0.006)	0.008 (0.007)	0.008 (0.006)	0.008 (0.007)	0.006 (0.007)	0.008 (0.007)	0.008 (0.007)	0.010 (0.009)	0.008 (0.007)	0.008 (0.007)	0.008 (0.007)
# Tests						-0.510* (0.240)	-0.530 (0.303)	-0.503* (0.256)	-0.538 (0.293)	-0.550 (0.309)	-0.599 (0.337)	-0.484 (0.338)	-0.738 (0.771)	-0.262 (0.583)	-0.400 (0.672)	-0.542 (0.355)	-0.546 (0.330)	-0.554 (0.345)
Death Rate 2018							0.059 (0.269)		0.119 (0.246)	0.164 (0.257)	0.252 (0.247)	0.362 (0.238)	0.451 (0.495)		0.544 (0.623)	0.018 (0.262)		0.069 (0.268)
Δ Curative Beds 2007-17								0.002 (0.006)	0.003 (0.005)	0.003 (0.005)	0.003 (0.006)	0.002 (0.006)		-0.009 (0.013)	-0.013 (0.014)		0.003 (0.005)	0.003 (0.005)
Observations	23	23	21	21	21	15	15	15	15	15	15	15	11	11	11	14	14	14
R-squared	0.089	0.090	0.147	0.149	0.150	0.562	0.564	0.566	0.572	0.558	0.532	0.517	0.650	0.619	0.687	0.445	0.454	0.456

The table reports cross-country regression estimates of the pandemic mortality rate on financial crisis severity measures. The dependent variable is the three-day moving average of the number of deaths over the number of cases immediately after the number of cases per one million population surpassed 100 in March 2020 or before. The output gap for 2008 to 2013 (2009 to 2014) is the difference between actual and potential Gross Domestic Product accumulated between 2008 and 2013 (2009 and 2014). The other independent variables are defined in Table 1. A constant is included but not reported. Robust standard errors are listed in parentheses below the coefficient estimates. *** p<0.01, ** p<0.05, * p<0.1

a year later than in other countries. However the estimated coefficient equals -0.0061^{***} which is very similar to those we estimated for the six-year output gap.

In Column (11) we include *Real GDP Growth (2008:09-2012:06)* as the financial crisis variable. The estimated coefficient now equals -0.106^{**} , which implies that for a two standard deviation decrease in growth (which equals minus 13 percent), one and a quarter additional deaths (per hundred cases) occur.

Finally, in Model (12) we feature the crisis variable the *CDS Premium Growth (2008:09-2012:06)*. An increase in this variable captures a deterioration in the solvability of the sovereign, which may correspond to the ability of the sovereign to fund public health, among many other categories of spending. The estimated coefficient equals 0.00013^{**} , which implies that for a two standard deviation increase in premium growth, which equals around 6,500, there is almost one additional death (per 100 cases).

So far, the evidence suggests that the financial crisis may have worsened the initial blow of the pandemic. Returning to the six-year output gap as a representative crisis measure, in Models (13) to (15) we check whether removing the countries with zero deaths in the beginning of the pandemic, i.e., countries where the pandemic arrived later, alters the estimates. We find this removal does not change the estimates by much.

Finally, in Models (16) to (18) we remove Greece, as it may be a high-leverage observation as could be seen from Figure 1. We are left with only fourteen observations and despite the loss of some statistical significance, the estimated coefficients remain similar in sign and size. Nevertheless, concerns about this one country determining our findings makes us turn to a more detailed within-country analysis, the Spanish case.

II. Spain, the Financial Crisis, and COVID-19

A. *Motivation*

We turn to Spain for multiple reasons. First, following a real-estate boom before 2007, fueled by low interest rates and money from abroad, Spain was hit hard by the financial crisis, with an output gap between 2008 and 2013 of minus 26 percent, and importantly a severe worsening of government public finances, with the ratio of government debt to GDP increasing from 37% in 2007 to 100% in 2014. Hence the crisis possibly led to a weakening of the public health sector in the ensuing decade.¹⁰ Second, there are 50 provinces in Spain and substantial autonomy at the regional level when it comes to public finance and spending on public health, among other categories. Finally, following Italy, Spain was one of the countries hit hardest by the initial wave of the pandemic. In this respect, we assess the impact at the initial stages, but also after lockdown on March 14 and other public health measures were put in place. If such measures are successful, the flow of the pandemic should become increasingly disconnected from the severity of the financial crisis.

B. *Dependent Variables for Spanish Provinces*

In our preceding country analysis we selected as our main dependent country-level variable (*Deaths / Cases*) when (*Cases / Population*) > 100/1M, which recall measures the three-day moving average of the number of deaths over the number of cases, in percent, immediately after the number of cases per one million population surpassed 100

¹⁰ For example on March 22nd, 2020, in a prominent article in the newspaper *El País*, Boi Ruiz, MD, who was formerly in charge of the Health Department of Cataluña, was quoted as saying: “Not only have public (health) resources not grown at the pace of needs, but they still suffer from the previous economic crisis, as does the whole public sector” (<https://elpais.com/espana/catalunya/2020-03-22/la-gestion-de-una-pandemia.html>).

Table 3. Variable Names and Definitions and Data Sources for Spanish Province Regressions

Variable Name	Units	Variable Definition	Data Source
<i>Dependent Spanish Province Variable</i>			
(Deaths / Cases) when (Cases / Population) = X/100K	%	The three-day moving average of the number of deaths over the number of cases immediately after the number of cases per one hundred thousand population equals X	E19d
(Deaths / Cases) when (Cases / Population) At Peak	%	The three-day moving average of the number of deaths over the number of cases immediately after the number of new cases peaks before May 2020	E19d
(Deaths / Cases) on 14.03 (or 28.03)	%	The three-day moving average of the number of deaths over the number of cases on March 14 (or 28)	E19d
<i>Main Independent Spanish Province Variables</i>			
Real GDP Growth (2009-2013)	%	The percent growth in real provincial Gross Domestic Product between 2009 and 2013	INE
Real GDP Growth (2008-2013)	%	The percent growth in real provincial Gross Domestic Product between 2008 and 2013	INE
Provincial Debt Growth (2008-2013)	%	The percent growth in per-capita nominal provincial debt between 2008 and 2013	DME
Provincial Debt Growth (2008-2012)	%	The percent growth in per-capita nominal provincial debt between 2008 and 2012	DME
<i>Independent Spanish Province Control Variables</i>			
GDP / Capita 2019	000 Euros	Gross Domestic Product per capita in the province in 2019	INE
# Curative Beds 2018	%	The number in curative beds per one thousand population at year-end 2018	MdS
Temperature	°Celsius	The average yearly temperature in the province	INE
Population Density 2020	-	The population per square kilometer at year-end 2020	W-INE
Population Age 2018	Years	The average age of the population in the province	INE
Population Exposed to Infection	%	The percent of the population that is working in sectors exposed to infection by the virus (branches of activity G-J) including hostelry, shopping-commerce	INE
Population	-	The total size of the population in the province in 2020	INE

Notes. The table provides the variable names, definitions and data sources for the Spanish province regressions. DME is the Datos Macro Expansión; E19d is the Escovid19data dataset which can be found in the following repository: <https://github.com/montera34/escovid19data>; INE is the Instituto Nacional de Estadística / National Bureau of Statistics; MdS is the Ministerio de Sanidad (España) / Health Ministry of Spain; W-INE is Wikipedia but based on the Instituto Nacional de Estadística / National Bureau of Statistics.

in March 2020 or before. For Spain, we want to assess the performance of the independent variables more carefully across different points of the impact curve of the pandemic wave, because now lockdown is set nationally for all provinces that may be in different stages of the wave build-up. The pandemic also hit Spain much earlier and harder than many countries so far analyzed.

Therefore, we redefine the dependent variable as *(Deaths / Cases) when (Cases / Population) = X/100K*, which measures the three-day moving average of the number of deaths over the number of cases, in percent, immediately after the number of cases per one hundred thousand population equals X, and situated in the range [30-50], [50-70], [70-90], or [90-110]. We also assess the three-day moving average of *(Deaths / Cases) At Peak*, and *On 14.03* and fifteen days later *On 28.03*.

C. *Independent Variables for Spanish Provinces: Financial Crisis Severity*

We focus on four main financial crisis severity measures, with the periods of measurement covering the main crisis impact period in Spain. *Real GDP Growth (2009-2013)* is the percent growth in real provincial Gross Domestic Product between 2009 and 2013. We also feature a similar variable starting one year earlier. We alternate these two GDP growth variables with *Provincial Debt Growth (2008-2013)*, which is the percent growth in per-capita nominal provincial debt, and a similar one ending one year earlier.

D. *Control Variables for Spanish Provinces*

As a first control variable, we feature *GDP / Capita 2019*, which is the Gross Domestic Product per capita in the province in 2019, in thousands of Euros. This variable captures the local per capita level of economic activity prior to the pandemic.

A key control variable for our purposes is *# Curative Beds 2018*, which is the number in curative beds per one thousand population at year-end 2018, in percent. This variable

captures the capacity of the local hospitals to deal with the pandemic. In a later step we will instrument this variable with the severity measures to assess if indeed part of the effect of the financial crisis went through the cross-province build-down in the number of beds.

We feature four control variables that capture potential differences in the local intensity of the pandemic: *Temperature* is the average yearly temperature in the province, in °Celsius (as temperature may play a role in the spreading of the virus); *Population Density 2020* is the population per square kilometer at year-end 2020 (a higher density speeds transmission);¹¹ *Population Age 2018* is the average age of the population in the province, in years (older people will die more frequently when contracting the virus); and *Population Exposed to Infection* is the percent of the population that is working in sectors exposed to infection by the virus (branches of activity G-J) including hostelry, shopping, and commerce, in percent (before lock-down transmission occurred more often in these sectors). In sum, lower temperatures, and higher population density, age, and exposure may lead to a stronger impact of the pandemic. Finally, we control for the total size of the *Population* in the province in 2020 as well.

E. Estimates

In Table 4 in Column (1) we regress $(Deaths / Cases)$ when $(Cases / Population) = X/100K$, with X situated in the range]30-50] on the five-year GDP growth, without controls. The estimated coefficient equals -0.285^{**} . This implies that for a decrease in growth by 5.6 pp, which is two standard deviations, the number of deaths over a 100 cases increases by 1.6 persons. This is a very similar, though slightly higher impact compared to what we estimated across countries.

¹¹ We acknowledge this measure is not perfectly pre-determined to the pandemic outbreak in March 2020, but we conjecture that the still relatively low number of deaths the pandemic caused leave the cross-province variation in density mostly unaltered.

Table 4. Spanish Province Regression Estimates of Pandemic Mortality Rate on Financial Crisis Severity Measures

Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	
	<i>(Deaths / Cases)</i>																								
	<i>When (Cases / Population) = X / 100K</i>							<i>When (Cases / Population) = X / 100K</i>							<i>When (Cases / Population) > X / 100K</i>							<i>When (Cases / Population) > X / 100K</i>			
<i>X =</i>	<i>[30-50]</i>	<i>[50-70]</i>	<i>[70-90]</i>	<i>[90-110]</i>	<i>At Peak</i>	<i>On 14.03</i>	<i>On 28.03</i>	<i>[30-50]</i>	<i>[50-70]</i>	<i>[70-90]</i>	<i>[90-110]</i>	<i>At Peak</i>	<i>On 14.03</i>	<i>On 28.03</i>	<i>[50-70]</i>	<i>[70-90]</i>	<i>At Peak</i>	<i>On 14.03</i>	<i>On 28.03</i>	<i>[50-70]</i>	<i>[70-90]</i>	<i>At Peak</i>	<i>On 14.03</i>	<i>On 28.03</i>	
Real GDP Growth (2009-2013)	-0.285**	-0.334***	-0.258**	-0.191*	-0.349*	-0.086	-0.082	-0.283*	-0.321**	-0.263*	-0.211	-0.260	-0.096	0.026											
Real GDP Growth (2008-2013)	(0.140)	(0.095)	(0.105)	(0.106)	(0.183)	(0.222)	(0.229)	(0.156)	(0.117)	(0.139)	(0.136)	(0.190)	(0.241)	(0.248)	-0.275**	-0.225*	-0.119	0.041	0.120	-0.278*	-0.246	-0.103	0.025	0.145	0.218
GDP / Capita 2019								-0.131	-0.075	0.009	0.029	-0.042	-0.086	-0.047											
# Curative Beds 2018								(0.077)	(0.062)	(0.086)	(0.082)	(0.099)	(0.074)	(0.090)											
Temperature								(0.917)	(0.855)	(0.805)	(1.007)	(1.259)	(1.043)	(1.742)											
Population Density 2018								(0.393)	(0.315)	(0.320)	(0.323)	(0.407)	(0.332)	(0.583)											
Population Age 2018								0.002	0.000	-0.003	-0.006**	-0.004	0.005	-0.001											
Population Exposed to Infection								(0.003)	(0.002)	(0.003)	(0.002)	(0.004)	(0.004)	(0.003)											
Population								-0.031	-0.010	0.040	-0.044	-0.370	0.137	-0.276											
								(0.210)	(0.175)	(0.253)	(0.263)	(0.327)	(0.252)	(0.305)											
								0.057	0.048	0.027	0.005	0.188	0.028	0.408*											
								(0.123)	(0.098)	(0.118)	(0.108)	(0.143)	(0.134)	(0.234)											
								0.000	0.000	0.000	0.000*	0.000	0.000	0.000											
								(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)											
Observations	38	38	38	38	44	45	47	38	38	38	38	44	45	47	38	38	44	45	47	38	38	44	45	47	47
R-squared	0.101	0.205	0.107	0.058	0.071	0.006	0.003	0.218	0.278	0.129	0.152	0.340	0.185	0.346	0.166	0.099	0.010	0.002	0.008	0.260	0.133	0.312	0.179	0.356	0.356

The table reports Spanish province regression estimates of the pandemic mortality rate on financial crisis severity measures. The dependent variable is the three-day moving average of the number of deaths over the number of cases immediately after the number of cases per one hundred thousand population falls into a bracket, at peak within March or April 2020, or on March 14 or 28, respectively. All independent variables are defined in Table 3. A constant is included but not reported. Robust standard errors are listed in parentheses below the coefficient estimates. *** p<0.01, ** p<0.05, * p<0.1

In Columns (2) to (7), we then assess the results along the impact curve, and at peak, March 14 and 28. The estimate ranges between -0.334^{***} and -0.082 , implying between 1.9 and 0.5 extra deaths. The latter smaller and insignificant impact occurs on March 28 when the national lockdown had been in place for fifteen days, which indicates that this lockdown altered the trajectory of the pandemic.

In Columns (8) to (14) we add in all control variables and find that the estimated coefficients are mostly unaffected, though at times somewhat less significant. The estimated coefficients on the control variables are hardly ever significant, with the exception of temperature in some specifications. A temperature that is higher by five extra degrees (which is two standard deviations) decreases the number of deaths by over five persons per 100 cases. This is a large impact, which is in line with the casual observation that in the Northern Hemisphere in many countries (though not all) the first wave of the pandemic ended when summer arrived.

In Columns (15) to (24) we replicate the entire analysis for the six-year real GDP growth between 2008 and 2013. Estimates for this financial crisis severity measure are similar, though again less significant.

In Table 5 we turn to the growth in provincial debt over six and five year periods, respectively, as our measure for the severity of the financial crisis. We now at once include controls (without controls estimates are similar). The estimates range between 0.015^{**} and 0.006 , implying that a tripling of provincial debt (which is shy of two standard deviations in growth) results in up to three additional deaths (over 100 cases). Once more these estimates are comparable in size to those found for the other financial crisis severity measures.

Table 5. Spanish Province Regression Estimates of Pandemic Mortality Rate on Provincial Debt Growth as a Financial Crisis Severity Measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent Variable	<i>(Deaths / Cases)</i>											
<i>X =</i>	<i>When (Cases / Population) = X / 100K</i>				<i>At Peak</i>	<i>On 14.03</i>	<i>On 28.03</i>	<i>When (Cases / Population) > X / 100K</i>		<i>At Peak</i>	<i>On 14.03</i>	<i>On 28.03</i>
	<i>]30-50]</i>	<i>]50-70]</i>	<i>]70-90]</i>	<i>]90-110]</i>			<i>]50-70]</i>	<i>]70-90]</i>				
Provincial Debt Growth (2008-2013)	0.006 (0.005)	0.007* (0.003)	0.007 (0.004)	0.007 (0.004)	0.008* (0.004)	0.009* (0.005)	0.015** (0.007)					
Provincial Debt Growth (2008-2012)								0.007*** (0.003)	0.007* (0.004)	0.008* (0.004)	0.009* (0.005)	0.011* (0.006)
GDP / Capita 2019	-0.184** (0.083)	-0.132* (0.066)	-0.046 (0.092)	-0.022 (0.082)	-0.050 (0.088)	-0.090 (0.080)	-0.053 (0.086)	-0.138** (0.065)	-0.046 (0.090)	-0.042 (0.088)	-0.075 (0.078)	-0.030 (0.087)
# Curative Beds 2018	-0.374 (0.879)	-0.427 (0.848)	-0.052 (0.797)	0.438 (0.972)	0.690 (1.242)	0.817 (1.057)	0.093 (0.865)	-0.516 (0.854)	-0.168 (0.797)	0.644 (1.221)	0.487 (1.006)	-0.716 (1.358)
Temperature	-0.384 (0.436)	-0.419 (0.354)	-0.106 (0.332)	0.082 (0.328)	-1.081*** (0.357)	-0.065 (0.347)	-1.257*** (0.360)	-0.439 (0.342)	-0.118 (0.327)	-1.062*** (0.350)	-0.122 (0.349)	-1.421*** (0.481)
Population Density 2018	0.001 (0.003)	-0.000 (0.002)	-0.003 (0.002)	-0.006*** (0.002)	-0.005 (0.003)	0.004 (0.005)	-0.002 (0.003)	-0.001 (0.002)	-0.003 (0.002)	-0.006* (0.003)	0.003 (0.005)	-0.002 (0.003)
Population Age 2018	-0.054 (0.200)	-0.036 (0.189)	0.016 (0.263)	-0.067 (0.270)	-0.290 (0.317)	0.172 (0.250)	-0.193 (0.239)	-0.062 (0.190)	-0.006 (0.272)	-0.296 (0.315)	0.177 (0.254)	-0.221 (0.248)
Population Exposed to Infection	0.083 (0.128)	0.078 (0.109)	0.051 (0.122)	0.024 (0.111)	0.213 (0.140)	-0.030 (0.118)	0.321** (0.149)	0.077 (0.107)	0.050 (0.122)	0.211 (0.139)	0.003 (0.122)	0.381* (0.205)
Population	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Observations	38	38	38	38	44	45	47	38	38	44	45	47
R-squared	0.167	0.167	0.091	0.151	0.362	0.297	0.525	0.179	0.082	0.372	0.289	0.432

The table reports Spanish province regression estimates of the pandemic mortality rate on provincial debt growth as financial crisis severity measures. The dependent variable is the three-day moving average of the number of deaths over the number of cases immediately after the number of cases per one hundred thousand population falls into a bracket, at peak within March or April 2020, or on March 14 or 28, respectively. All independent variables are defined in Table 3. A constant is included but not reported. Robust standard errors are listed in parentheses below the coefficient estimates. *** p<0.01, ** p<0.05, * p<0.1

III. Reduction in Public Health Spending

In the final part of our analysis we want to shed some light on a potential channel through which the financial crisis may have affected the pandemic outcomes. What we have in mind is that slowing or reductions in public health care spending on curative beds causes hospitals to have a limited ability to care for the COVID-19 infected patients.

To investigate this channel, in Table 6 in a first stage we regress the number of curative beds in 2018 in the province on our provincial debt measures. We then use the explained part of this number to explain pandemic deaths over cases.

The first stage estimate varies between -0.002^{***} and -0.001^{**} ,¹² implying that a tripling of provincial debt results in a reduction in the number of beds per 1K of population by 0.4 to 0.2 beds, or one-third to one-sixth a standard deviation, or six to three percent of the mean of beds.

The second stage estimate varies between -8.975^{***} and -4.469^* , though the estimate is not always precisely estimated. These estimates imply that the financial crisis driven reduction in beds may have increased deaths (per 100 cases) by 3.6 to 0.9 deaths, so possibly a substantial portion of the extra deaths that we documented in the previous section.

¹² Though the coefficients on the instrument are usually statistically significant, and the R-squared statistics are around 0.5, the F-statistics remain below or are equal to ten. However, notice that we are not concerned about reverse causality here, as it seems unlikely that death rates in 2020 influence the number of curative beds in 2018 across Spanish provinces, even in expectation. Very few people worried about an upcoming pandemic (with the exception of public health officials and philanthropists with public health concerns like Bill Gates) and even those that did, could not foresee its eventual timing, spreading and path.

Table 6. Spanish Province Regression Estimates of Pandemic Mortality Rate on Changes in the Number of Curative Beds Instrumented by Provincial Debt Growth as a Financial Crisis Severity Measure

Dependent Variable	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)		(9)		(10)		(11)		(12)	
	<i>At Peak</i>																							
	<i>On 14.03</i>																							
	<i>On 28.03</i>																							
	First Stage		Second Stage		First Stage		Second Stage		First Stage		Second Stage		First Stage		Second Stage		First Stage		Second Stage		First Stage		Second Stage	
	# Curative Beds 2018		(Deaths / Cases)		# Curative Beds 2018		(Deaths / Cases)		# Curative Beds 2018		(Deaths / Cases)		# Curative Beds 2018		(Deaths / Cases)		# Curative Beds 2018		(Deaths / Cases)		# Curative Beds 2018		(Deaths / Cases)	
Provincial Debt Growth (2008-2013)	-0.001**								-0.002***									-0.002***						
	(0.001)								(0.000)									(0.000)						
Provincial Debt Growth (2008-2012)					-0.001**									-0.001***								-0.001***		
					(0.000)									(0.000)								(0.001)		
# Curative Beds 2018		-5.090				-6.553					-4.469*				-5.869*						-8.975***			-8.610**
		(3.778)				(4.928)					(2.306)				(3.426)						(3.433)			(4.389)
GDP / Capita 2019	-0.008		-0.095		-0.009		-0.104		-0.014		-0.163		-0.018		-0.188		-0.011		-0.148		-0.148		-0.014	
	(0.018)		(0.135)		(0.018)		(0.152)		(0.015)		(0.118)		(0.016)		(0.139)		(0.016)		(0.166)		(0.166)		(0.016)	
Temperature	-0.160***		-2.009***		-0.163***		-2.238**		-0.143***		-0.822*		-0.139***		-1.007*		-0.157***		-2.683***		-2.683***		-0.153***	
	(0.049)		(0.720)		(0.050)		(0.899)		(0.046)		(0.467)		(0.049)		(0.604)		(0.044)		(0.697)		(0.697)		(0.047)	
Population Density 2018	0.001**		0.002		0.001***		0.003		0.001**		0.010		0.001**		0.012		0.001***		0.009		0.001***		0.009	
	(0.000)		(0.009)		(0.000)		(0.010)		(0.000)		(0.007)		(0.001)		(0.008)		(0.000)		(0.010)		(0.000)		(0.010)	
Population Age 2018	0.037		-0.078		0.041		-0.003		0.058		0.477		0.063*		0.580		0.034		0.116		0.116		0.040	
	(0.037)		(0.356)		(0.037)		(0.420)		(0.037)		(0.338)		(0.037)		(0.416)		(0.036)		(0.414)		(0.414)		(0.036)	
Population Exposed to Infection	0.046**		0.481*		0.048**		0.553*		0.047**		0.216		0.043**		0.279		0.043**		0.708***		0.708***		0.040*	
	(0.021)		(0.255)		(0.022)		(0.312)		(0.020)		(0.182)		(0.021)		(0.229)		(0.020)		(0.255)		(0.255)		(0.021)	
Population	-0.000**		-0.000		-0.000**		-0.000		-0.000*		-0.000		-0.000*		-0.000		-0.000**		-0.000		-0.000**		-0.000**	
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Observations	44				44				45				45				47				47			
R-squared	0.470				0.454				0.531				0.480				0.492				0.445			

The table reports Spanish province regression estimates of the pandemic mortality rate on the changes in the number of curative beds in 2018 instrumented by provincial debt growth as the financial crisis severity measure. The dependent variable is the three-day moving average of the number of deaths over the number of cases at peak or on March 14 or 28. All independent variables are defined in Table 3. A constant is included but not reported. Robust standard errors are listed in parentheses below the coefficient estimates. *** p<0.01, ** p<0.05, * p<0.1

IV. Conclusion

Financial crisis tend to produce economic hysteresis, with output permanently wandering away from the previous output trend (Jordà, Schularick and Taylor (2011)). This has wide negative implications in an economy, with lower public investment in a wide range of sectors, such as research and development (e.g., Abbritti and Weber (2019)), education and health, among others. In the context of an unexpected pandemic, the initial health response has proved key to fight the coronavirus pandemic. But this response crucially depended on the initial health capacity of the different provinces and countries. In this respect, this paper shows that the 2008 financial crisis loomed large during the initial 2020 coronavirus shock, as countries and provinces more economically and financially affected by the 2008 crisis experienced significantly more life losses relative to the number of cases.

The Spanish case reveals that provinces which lost significantly more output or which saw their debt levels increase more during the 2008 crisis experienced a more significant shortage of curative beds and, in turn, a higher ratio of deaths per cases during the initial COVID outbreak. While Spain was one of the countries with a more severe financial crisis in the 2008-2013 period, differences in terms of funding and health capabilities across provinces remain. Our results thus suggest the importance of not diminishing the level public investment in health facilities and personnel during recessions in order to hedge against potentially negative future disease sprouts.

References

- Abbritti, M., Weber, S., 2019. Market Regulation, Cycles and Growth in a Monetary Union. International Monetary Fund, Washington DC.
- Adda, J., 2016. Economic Activity and the Spread of Viral Diseases: Evidence from High Frequency Data. *Quarterly Journal of Economics* 131, 891-941.
- Allen, F., Carletti, E., 2010. An Overview of the Crisis: Causes, Consequences, and Solutions. *International Review of Finance* 10, 1-26.
- Andrieș, A.M., Ongena, S., Sprincean, N., 2021. The COVID-19 Pandemic and Sovereign Bond Risk. Alexandru Ioan Cuza University of Iasi, Iasi.
- Augustin, P., Sokolovski, V., Subrahmanyam, M.G., Tomio, D., 2021. In Sickness and in Debt: The COVID-19 Impact on Sovereign Credit Risk. *Journal of Financial Economics*, Forthcoming.
- European Investment Bank, 2021. Investment Report 2020/2021: Building a Smart and Green Europe in the COVID-19 Era. Economics Department, Luxembourg LX.
- Fatás, A., Summers, L.H., 2018. The Permanent Effects of Fiscal Consolidations. *Journal of International Economics* 112, 238-250.
- Gerding, F., Martin, T., Nagler, F., 2021. Sovereign Debt and Equity Returns in the Face of Disaster. Bocconi University, Milano IT.
- Gourinchas, P.-O., Kalemli-Özcan, Ş., Penciakova, V., Sander, N., 2021. COVID-19 and SMEs: A 2021 "Time Bomb"? *American Economic Review Papers & Proceedings* 111, Forthcoming.
- Jordà, Ò., Schularick, M., Taylor, A.M., 2011. Financial Crises, Credit Booms, and External Imbalances: 140 Years of Lessons. *IMF Economic Review* 59, 340-378.
- Kirkpatrick, D.D., Apuzzo, M., Gebrekidan, S., 2020. Europe Said It Was Pandemic-Ready. Pride Was Its Downfall. *New York Times*
- Maruthappu, M., Da Zhou, C., Williams, C., Zeltner, T., Atun, R., 2015. Unemployment, Public-sector Health Care Expenditure and HIV Mortality: An Analysis of 74 Countries, 1981-2009. *Journal of Global Health* 5, 1-9.
- Mazzucato, M., 2018. The Value of Everything. Making and Taking in the Global Economy. PublicAffairs, New York NY.
- Monasterolo, I., Billio, M., Battiston, S., 2020. The Importance of Compound Risk in the Nexus of COVID-19, Climate change and Finance. Department of Economics, University of Venice "Ca' Foscari", Venice IT.
- Moreno, A., Ongena, S., Ventula Veghazy, A., Wagner, A.F., 2020. The Global Financial Crisis and the COVID-19 Pandemic. In: Billio M & Varotto S (eds.) *A New World Post COVID-19. Lessons for Business, the Finance Industry and Policy Makers*. Ca' Foscari University Press, Venice IT, pp. 23-34.
- Ramelli, S., Wagner, A.F., 2020. Feverish Stock Price Reactions to COVID-19. *Review of Corporate Finance Studies* 9, 622-655.
- Surico, P., Galeotti, A., 2020. The Economics of a Pandemic: The case of Covid-19. London Business School, London UK.

Can Covid-19 induce governments to implement tax reforms in developing countries?¹

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We estimate that the short to medium-term fiscal impact of previous pandemics has been significant in 170 countries (including low-income countries) during the 2000-2018 period. The impact has varied, with pandemics affecting government expenditures more than revenues in advanced economies, while the converse applies to developing countries. Using a subset of 45 developing countries for which tax reform data are available, we find that past pandemics have propelled countries to implement tax reforms, particularly in corporate income taxes, excises and property taxation. Pandemics do not drive revenue administration reforms.

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1. Introduction

The Covid-19 pandemic has cost lives and disrupted economic activity worldwide. To prevent the spread of the virus, governments have imposed lockdowns with varying degrees of stringency. The general population has also sought to reduce exposure to the virus through voluntary social distancing. The result has been a dramatic contraction in economic activity in 2020 with global GDP estimated to have declined by 3.5 percent (IMF, 2021). The projected rebound in 2021 is not expected to restore the pre-crisis GDP in 2019 in advanced, emerging and developing economies until 2022. The global reduction in work hours in the second quarter of 2020 compared with the fourth quarter of 2019 was equivalent to 400 million full-time jobs; already 155 million full-time jobs were lost in the first quarter (ILO, 2020).

In an environment where most countries still face near zero interest rates (so monetary policy lacks effectiveness), fiscal policy has a crucial role in mitigating the pandemic's overall economic impact and promoting a quick recovery. It can help save lives and shield the most-affected segments of the population. To counter income losses arising from the pandemic, countries have taken steps to help households and firms by implementing discretionary revenue and spending measures. In addition, they have provided liquidity support to the economy in the form of equity injections, asset purchases, loans, and credit guarantees. Together with lower projected output growth, these measures would reduce revenues in relation to GDP in 2020 and possibly beyond with important implications for public spending at a time when the overall spending has been scaled up. These developments are likely to result in larger budget deficits and rising debt-to-GDP ratios in the foreseeable future. Understanding empirically how public finances are affected is therefore important for policy makers notably once the unwinding of economic support measures begin and the “new-normal” is attained.

In this paper, we systematically study the short to medium-term fiscal impact of past pandemics in 170 countries, including low-income countries. We show that the fiscal impact is substantial in all countries. As low-income countries have limited fiscal space to accommodate the shock, we examine whether pandemic has created conditions for them to implement much-needed

tax reforms to raise revenues over the longer term.¹ For this purpose, we rely on tax reform data from 45 emerging and low-income countries during 2000-2015.

This paper relates to two main strands of literature.

The first is the literature on the economic effects of pandemics. Studies of the macroeconomic impact of past pandemics and of other major diseases (such as SARS and HIV/AIDs) have typically quantified the resulting short-term loss in output and growth.²³ However, there is little consensus on economic consequences of pandemics. Results critically depend on the models used and on the availability of data (Bell and Lewis, 2004). A study by Brainerd and Siegler (2003), one of the few on the economic effects of the Spanish flu, suggested that the 1918/19 pandemic in the US actually increased growth in the 1920s. In contrast, Almond and Mazumber (2005) argued that the Spanish flu had long-term negative effects through its impact on fetal health. Using a theoretical model, Young (2004) argued that the AIDS epidemic in South Africa would increase net future per capita consumption, while Bell and Gersbach (2004) found strong negative effects. Jonung and Roeger (2006) estimated the macroeconomic effects of a pandemic using a quarterly macro-model constructed and calibrated for the EU-25 as a single economic entity. The recent literature on this topic, motivated by the Covid-19 pandemic, provides evidence of large and persistent effects on economic activity (see e.g. Atkeson, 2020; Barro et al., 2020; Eichenbaum et al., 2020). In fact, Ma et al. (2020) in an empirical analysis of the economic effects of past pandemics, found that real GDP is 2.6 percent lower on average across 210 countries in the year the outbreak is officially declared and remains 3 percent below pre-shock level five years later. Moreover, according to Jorda et al. (2020), significant macroeconomic after-effects of pandemics persist for decades, with real rates of return substantially depressed. Pandemics induce relative labor scarcity in some areas and/or a shift to greater precautionary savings.

¹ Note however that to support aggregate demand following crises, typically countries in the short-run cut taxes despite being mindful of the need for long term reforms. At the same time, countries also take measures to offset some of the adverse effects of pandemics on revenues and budget deficits.

² Even then, direct measures based on data from past episodes are not generally available (e.g. in the US, see Meltzer, Cox and Fukuda, 1999). An alternative would be to look at microeconomic outcomes for a given population in response to episodes for which high-quality administrative data are available (e.g. in Sweden Karlsson, Nilsson and Pichler, 2014). Absent such data, economic historians have to use more aggregated data at the regional or national level to study the relationship between pandemic incidence and economic outcomes (e.g., the 1918 flu epidemic across the US states, see Brainerd and Siegler, 2003).

³ For a historic view of pandemics, see Kenny (2021).

The second strand of the literature is on the role of crises and recessions in affecting fiscal variables (European Commission (2009a)). Financial crises have induced governments around the globe to take decisive action in terms of sustaining economic activity and preventing the meltdown of the financial sector. These actions had direct and indirect fiscal costs. Direct fiscal costs from actions from financial system rescue packages (such as capital injections, purchases of toxic assets, subsidies, payments of called upon guarantees) resulted in permanent decreases in government's net worth (Such interventions result in higher public debt, which either show up as an increase in stock flow debt-deficit adjustments or as higher deficits (Attinasi et al., 2010; European Commission, 2009b)). There also are indirect fiscal costs, i.e., due to the feedback loop from the crisis to economic activity. These involve lower revenues due to falling profits and asset prices, higher expenditure to counter the impact of the crisis, as well as interest rate and exchange rate effects due to market reactions (European Commission, 2009b). European Commission (2009b) building on fiscal reaction functions in the spirit of Gali and Perotti (2003) found that the bulk of the effect of crises on debt changes takes place during the first 2 years. Moreover, the impact of financial crises on debt was larger in emerging market economies than for the EU or other OECD countries. Building on a banking crises dataset by Laeven and Valencia (2008), several empirical studies have investigated the effect of crises on the debt-to-GDP ratio and GDP growth (Furceri and Zdzienicka, 2010, 2012; Reinhart and Rogoff, 2008, 2009, 2011). Furceri and Zdzienicka (2010) using a panel of 154 countries from 1980-2006 showed that banking crises are associated with a significant and long-lasting increase in government debt and that such increase is a positive function of higher initial indebtedness levels – so initial conditions matter. Employing different modelling techniques, Tagkalakis (2013) found significant econometric evidence that fiscal positions deteriorated during financial crises in 20 OECD countries over the 1990-2010 period. Several other studies investigated the direct fiscal implications of past banking system support schemes (Honohan and Klingebiel, 2003), the determinants of fiscal recovery rates (European Commission, 2009b), as well as whether costly fiscal interventions reduced output loss (Claessens et al., 2005; Detragiache and Ho, 2010).⁴

⁴ Claessens et al. (2005) explored the relationship between intervention policies and the economic and fiscal costs of crises. Costs were measured by the output loss relative to trend during the crisis episode. Detragiache and Ho (2010) found that crisis response strategies that commit more fiscal resources did not lower the economic costs of crises, and in some cases, they led to worse post crisis performance.

While the macroeconomic effects of pandemics have been studied, a deeper and more disaggregated assessment of their fiscal consequences is lacking. Past studies have focused on the fiscal costs of financial sector rescue packages. This paper looks in more detail on what happens to revenues and spending and not just the cost of rescue packages. Using a dataset put together by Ma et al. (2020), we first estimate the short to medium-term response of fiscal variables to major pandemic shocks.⁵ As Ma et al. (2020) conclude, the impact of pandemic events on economic activity is likely to vary across episodes and countries' initial conditions.

This paper finds that the short to medium-term fiscal impact of pandemics is significant in our sample of 170 countries (including low-income countries) during the 2000-2018 period. The impact varies, with pandemics affecting government expenditures more than revenues in advanced economies, while converse applies to developing countries, reflecting the size of automatic stabilizers in advanced economies. A deeper analysis of a subset of 45 developing countries for which tax reform data are available shows that past pandemics have propelled countries to implement tax reforms, particularly in corporate income taxes, excises and property taxation. Pandemics do not drive reforms in revenue administration.

The remainder of the paper is structured as follows. Section 2 presents the empirical strategy followed to study the dynamic response of fiscal variables to past pandemic shocks and lays out the strategy to examine whether these fueled tax reforms. Section 3 presents the data and key stylized facts. Section 4 discusses our empirical results while sensitivity and robustness checks are available in an online annex. Section 5 concludes and elaborates on the policy implications.

2. Econometric Methodology

a. Dynamic impact of Pandemics on Fiscal Outcomes

In order to estimate the response of fiscal variables to major pandemic shocks, we follow the local projection method proposed by Jordà (2005) to estimate impulse-response functions. This

⁵ Historically, there were three influenza pandemics in the last century occurring in 1918/19 (A/H1N1), 1957 (A/H2N2) and 1968/69 (A/H3N2) (HPA, 2006). The most serious of these pandemics was A/H1N1 known as "Spanish flu", which occurred in 1918/19 causing serious illness and a high number of deaths (20-40 million worldwide). The other two pandemics were less severe and had less impact on those in prime age with mortality occurring mainly amongst the elderly. Because these pandemics occurred at a time when data quality and coverage was poor, this paper focuses on the last 30 years to maximize country coverage.

approach has been advocated by Auerbach and Gorodnichenko (2013) and Romer and Romer (2019) as a flexible alternative, better suited to estimating a dynamic response—such as, in our context, interactions between pandemic shocks and macroeconomic and fiscal conditions. The baseline specification is:

$$y_{t+k,i} - y_{t-1,i} = \alpha_i + \tau_i + \beta_k \text{pand}_{i,t} + \theta X_{i,t} + \varepsilon_{i,t} \quad (1)$$

in which y is the dependent fiscal variable of interest; β_k denotes the (cumulative) response of the variable of interest in each k year after the pandemic shock; α_i, τ_i are country and time fixed effects respectively, included to take account for cross-country heterogeneity and global shocks; $\text{pand}_{i,t}$ denotes the pandemic shock from Ma et al. (2020).⁶ $X_{i,t}$ is a set of control variables including two lags of pandemic shocks, two lags of real GDP growth and two lags of the relevant fiscal dependent variable.

Equation (1) is estimated using OLS.⁷ ⁸ Pandemic shocks are treated as exogenous events as they cannot be anticipated nor correlated with past changes in economic activity. In large scale epidemics, effects will be felt across whole economies, or across wider regions, for two reasons: either because the infection itself is widespread or because trade and market integration eventually propagate the economic shock across borders.

b. Do pandemic events trigger structural tax reforms?

A structural tax reform (*STR*) for country i at time t takes the value one as identified in the narrative database—the next section provides details on data. All other non-reform years take the value zero.⁹ Based on this binary characterization, our main exercise consists of estimating logistic

⁶ All pandemic shocks featured in our analysis are country-wide shocks.

⁷ Another advantage of the local projection method compared to vector autoregression (autoregressive distributed lag) specifications is that the computation of confidence bands does not require Monte Carlo simulations or asymptotic approximations. One limitation, however, is that confidence bands at longer horizons tend to be wider than those estimated in vector autoregression specifications.

⁸ Impulse response functions (IRFs) are then obtained by plotting the estimated β_k for $k=0,1,..5$ with 90 (68) percent confidence bands computed using the standard deviations associated with the estimated coefficients β_k —based on robust standard errors clustered at the country level.

⁹ The database also includes what we call “tax reversals”, that is, reforms that reduce revenue collection. Note that the database considers large tax revenue changes in the aggregate but also identifies tax reforms by sub-category. Some

regressions to assess the likelihood of a tax reform by testing specifically the pandemic channel, while controlling for other variables identified in the literature affecting the implementation of reforms.¹⁰ In particular, we estimate the following reduced-form model:¹¹

$$\text{Prob}(\text{STR} = 1|X) = \Phi(\lambda_i + \text{pand}'\alpha + X'\beta) \quad (2)$$

where α , β are vectors of the parameters to be estimated, pand is the pandemic shock, X is a vector of exogenous control variables, and $\Phi(\cdot)$ is the logistic function.¹² λ_i denote country fixed effects to capture unobserved heterogeneity and different initial conditions or underlying structural characteristics. Our list of control variables includes: real GDP growth, inflation rate, trade openness and the unemployment rate. Such structural forces have also been put forward as influencing the reform momentum. For instance, small open economies may be more amenable to reform due to greater exposure to competitive pressures and international policy diffusion (see e.g. Belloc and Nicita, 2011). The structural model associated with (2) can be written as:

$$\text{STR} = \lambda_i + \alpha \text{pand}_{it} + \beta X_{it} + \varepsilon_{it} \quad (3)$$

The STR variable can take the value one if there is a reform in any area of taxation, including revenue administration.¹³

$\text{STR}_{it} = 1$ if $\text{STR}_{it}^* > 0$, and 0 otherwise.

with $i = 1, \dots, N$; $t = 1, \dots, T$; λ_i captures the unobserved individual effects; and ε_{it} is an error term.

3. Data

of the reforms using tax specific instruments may be revenue decreasing. These are identified in Akitoby et al. (2020) Appendix table 4. Overall, their database identifies 163 reforms associated with positive revenue changes against 36 reforms associated with negative revenue changes, that is, the latter corresponds to 18 percent of the total 199 major tax reforms. Given the low proportion of “tax reversals” in the total universe of observations, we decided to drop them.

¹⁰ This is akin to the methodology proposed by Aoyagi and Ganelli (2015), who considered – looking at another issue, namely inclusive growth - the direct impact of a fixed block of structural determinants, coupled with a set of controls.

¹¹ For details on this binary choice model see, for example, Greene (2012, Ch. 17).

¹² We should note that, as probit models do not render themselves well to the fixed-effects treatment due to the incidental parameter problem (Wooldridge, 2002, Ch. 15, p. 484), we estimate a logit model with fixed-effects.

¹³ Eight categories are considered and detailed in the next section, namely reforms in the area of: personal income tax, corporate income tax, general goods and service tax, value added tax, excises, trade taxes, property taxes and revenue administration.

Our empirical analysis consists – as explained above – of two related but separate steps. The first makes use of a heterogeneous unbalanced sample of 170 countries from 2000-2018. The key regressor in the study of fiscal consequences of pandemics is taken from the dataset on pandemics/epidemics put together by Ma et al. (2020); this dataset starts in 2000 and covers SARS in 2003; H1N1 in 2009; MERS in 2012; Ebola in 2014; and Zika in 2016. Among the five events, the most widespread one is H1N1 (Swine Flu Influenza). We constructed a dummy variable, the pandemic event or shock, which takes the value 1 when the World Health Organization declares a pandemic for the country and zero otherwise. The list of countries that are affected by each event is given in Table 1 below.

Table 1. List of Pandemic and Epidemic Episodes

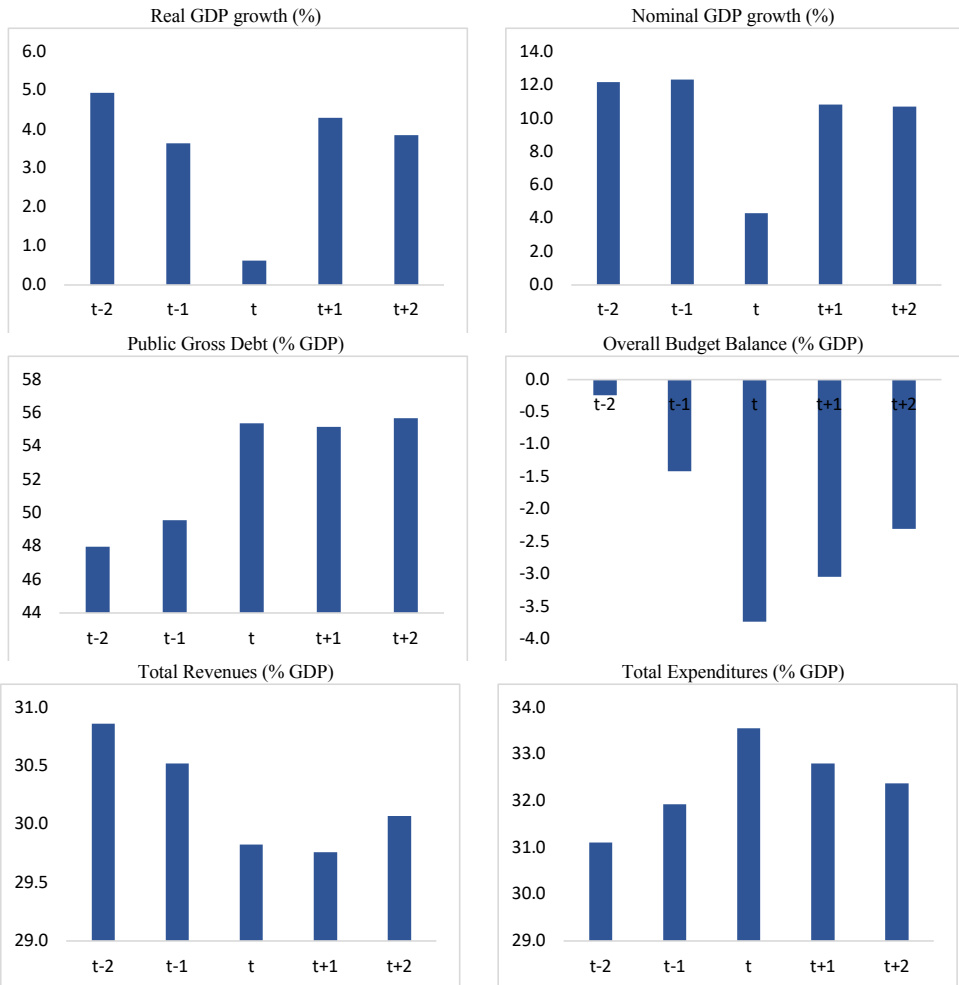
Starting year	Event Name	Affected Countries	Number of countries
2003	SARS	AUS, CAN, CHE, CHN, DEU, ESP, FRA, GBR, HKG, IDN, IND, IRL, ITA, KOR, MNG, MYS, NZL, PHL, ROU, RUS, SGP, SWE, THA, TWN, USA, VNM, ZAF	27
2009	H1N1	AFG, AGO, ALB, ARG, ARM, AUS, AUT, BDI, BEL, BGD, BGR, BHS, BIH, BLR, BLZ, BOL, BRA, BRB, BTN, BWA, CAN, CHE, CHL, CHN, CIV, CMR, COD, COG, COL, CPV, CRI, CYP, CZE, DEU, DJI, DMA, DNK, DOM, DZA, ECU, EGY, ESP, EST, ETH, FIN, FJI, FRA, FSM, GAB, GBR, GEO, GHA, GRC, GTM, HND, HRV, HTI, HUN, IDN, IND, IRL, IRN, IRQ, ISL, ISR, ITA, JAM, JOR, JPN, KAZ, KEN, KHM, KNA, KOR, LAO, LBN, LCA, LKA, LSO, LTU, LUX, LVA, MAR, MDA, MDG, MDV, MEX, MKD, MLI, MLT, MNE, MNG, MOZ, MUS, MWI, MYS, NAM, NGA, NIC, NLD, NOR, NPL, NZL, PAK, PAN, PER, PHL, PLW, PNG, POL, PRI, PRT, PRY, QAT, ROU, RUS, RWA, SAU, SDN, SGP, SLB, SLV, STP, SVK, SVN, SWE, SWZ, SYC, TCD, THA, TJK, TON, TUN, TUR, TUV, TZA, UGA, UKR, URY, USA, VEN, VNM, VUT, WSM, YEM, ZAF, ZMB, ZWE	148
2012	MERS	AUT, CHN, DEU, EGY, FRA, GBR, GRC, IRN, ITA, JOR, KOR, LBN, MYS, NLD, PHL, QAT, SAU, THA, TUN, TUR, USA, YEM	22
2014	Ebola	ESP, GBR, ITA, LBR, USA	5
2016	Zika	ARG, BOL, BRA, CAN, CHL, COL, CRI, DOM, ECU, HND, LCA, PAN, PER, PRI, PRY, SLV, URY, USA	18
		Total Pandemic and Epidemic Events	220

Source: based on Ma et al. (2020)

Other macroeconomic and fiscal variables come from the IMF's World Economic Outlook (WEO) database. Specifically, in addition to real GDP, the following fiscal variables are analyzed as main dependent variables: public gross debt, total government revenues, total government expenditures, overall budget balance, public consumption expenditure, public investment expenditure, social spending, direct taxes, indirect taxes and non-tax revenue (all expressed in percent of GDP).

Figure 2 plots the evolution of key macro and fiscal aggregates before, during and after the pandemic shock. This unconditional association shows that economic growth goes down while debt goes up and the overall balance deteriorates as a result of both a fall in revenues and an increase in expenditure. These movements are somewhat persistent over time.

Figure 2. Evolution of fiscal variables around Pandemics



Note: x-axis in years; t=0 is the year of the pandemic shock.

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In the second empirical exercise, due to data availability, we focus on the sample of a smaller group of 45 developing countries. We use a new “narrative” database of major tax reforms implemented in 45 developing economies (23 emerging and 22 low-income) during the 2000-2015 period (Akitoby et al., 2020). An important novelty and strength of this database is the precise timing and nature of key legislative tax actions that took place over the 15-year period under scrutiny. Figure 3 provides the number of years of tax reforms identified in the sample and illustrates the heterogeneity of reforms efforts by type. Excise reforms have been more frequently implemented. In general, fewer major reforms have been implemented in the areas of property taxes. Reforms in tax administration have been more the rule than the exception, accompanying a specific tax policy measure. Out of 119 years of tax reforms, only 17 corresponded to tax policy measures not accompanied by improvements in revenue administration.

Figure 3. Number of country-years with tax revenue reforms by type
(45 developing economies, 2000-2015)

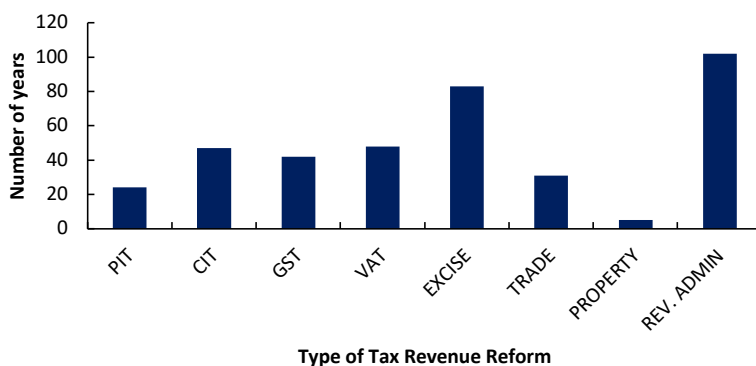
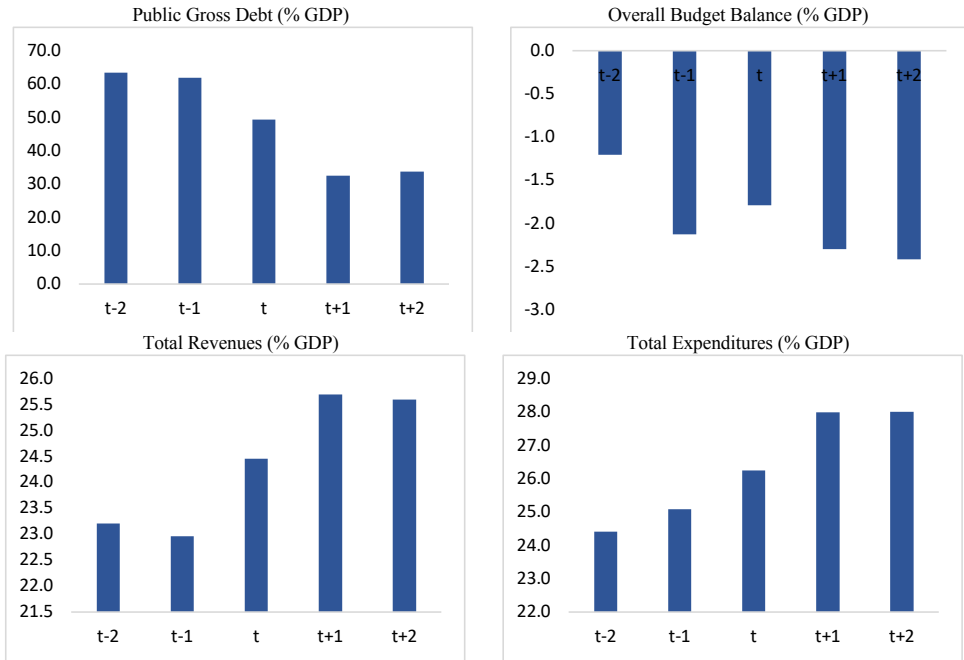


Figure 4 plots the evolution of key fiscal aggregates before, during and after the tax reform event. This unconditional association shows that government’s overall balance improves in the year of the reform as a result of an increase in revenues suggesting that these reforms were effective revenue-enhancing structural changes.

Figure 4. Evolution of fiscal variables around tax reforms



Note: x-axis in years; t=0 is the year of the tax reform event.

Control variables used in equation 3 enter with a one-year lag to minimize reverse causation issues. The inclusion of real GDP growth, inflation rate, trade openness and the unemployment rate as explanatory variables is motivated by a model selection analysis conducted by Duval et al. (2020) exploring key correlates driving reforms (cf. footnote1). They also relate to the fiscal policy literature (for recent review studies see Bergh and Henrekson, 2011 and Halkos and Paizanos, 2015). The appendix presents a table with summary statistics of the explanatory variables used in the regressions.

4. Empirical Results

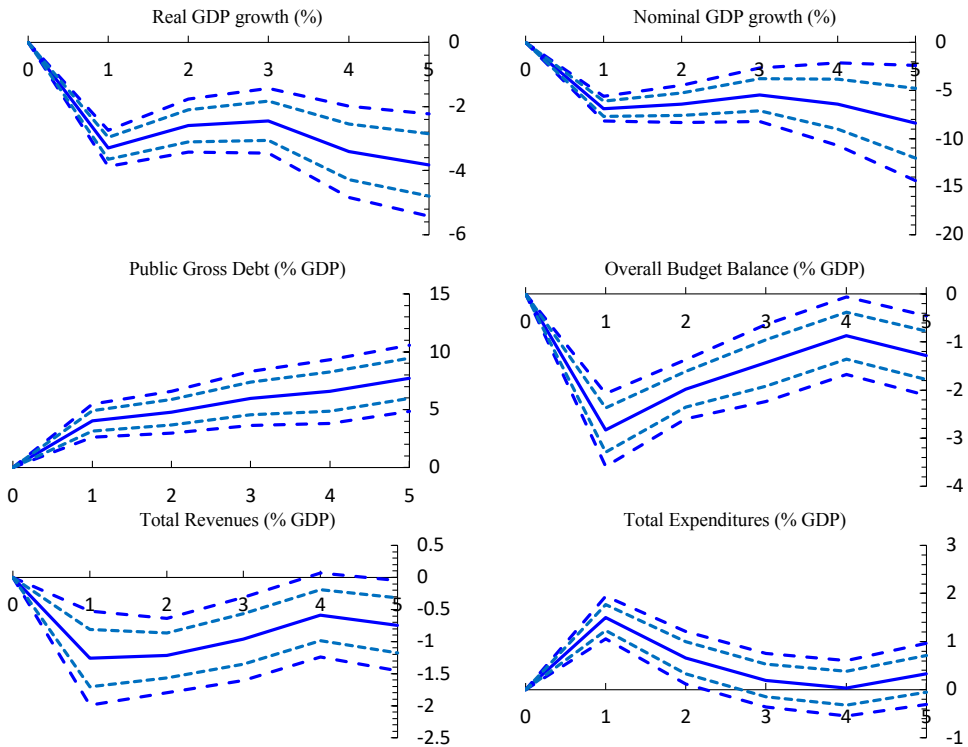
A. Fiscal Consequences of Pandemics

Figure 5 shows the results of estimating equation (1) for alternative fiscal dependent variables. Both the 90 and 68 percent confidence bands are shown together with the fiscal response.

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Public debt rises close to 4 percentage points of GDP in the first year after the pandemic event and reaching a cumulative of close to 8 percentage points of GDP after 5 years, meaning that the pandemic impact is non-negligible and long-lasting. At the same time, the budget balance deteriorates immediately reaching a deficit of 2.4 percent of GDP but improves subsequently until it stabilizes at a level worse than before the pandemic at about -1.3 percent of GDP. This deterioration in the fiscal position reflects a combined effect of fall in revenues and an increase in expenditure of about 1 percent of GDP. The effect on expenditure dissipates from the third year onwards, while for revenues it takes about five years for the negative impact to become statistically not different from zero.

Figure 5. Impact of Pandemics on Macro and Fiscal Variables, all countries (% GDP)



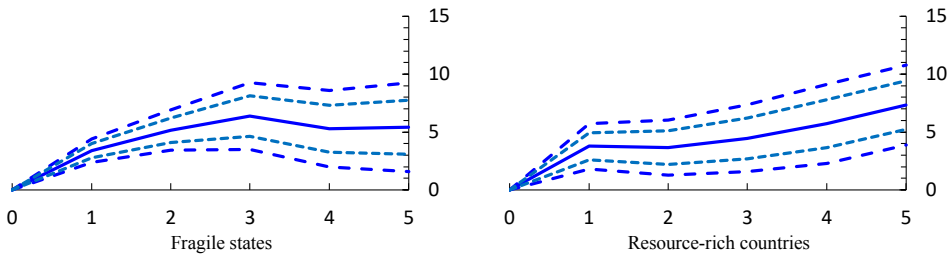
Note: Impulse response functions are estimated using a sample of 170 countries over the period 1980-2018. The graph shows the response and both the 90 and 68 percent confidence bands. The x-axis shows years (k) after pandemic events; t = 0 is the year of the pandemic event. Estimates based on equation 1. Standard errors in parentheses are clustered at the country level.

Splitting the sample of 170 countries between advanced and developing economies and performing sensitivity with respect to country characteristics (such as being a fragile state or a resource-rich economy) yields results shown in Figures 6a-d.¹⁴ Analyses of two key groups of low-income countries, resource-rich and fragile states (countries defined by the World Bank as having less good policy performance or institutions) is important because:

- in fragile states crises typically create a revenue shortfall for only some countries, because others already have very low revenue levels to start with. Moreover, in many countries fiscal deterioration results from ensuing spending increases.
- resource-rich countries typically suffer a massive fiscal deterioration because of the fall in global oil and commodity prices, but also due to spending increases.¹⁵

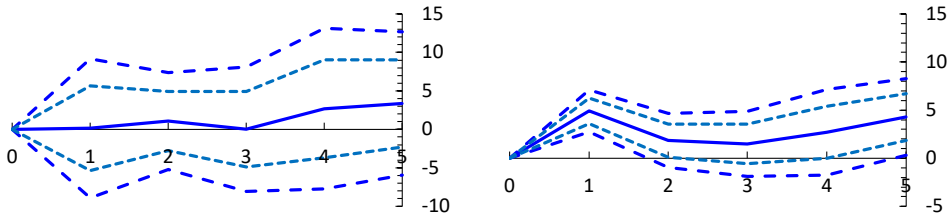
We observe that pandemics' effect on debt ratios is relatively small in the sub-sample of fragile states and begins to rise after tapering off in the initial years in resource-rich countries. That said, the negative toll pandemics have on the budget is long-lasting in the case of developing countries, explained largely by a significant fall in revenues. This contrasts with advanced economies where revenues are not affected as much but expenditures increase owing to the natural operation of automatic stabilizers which are larger in this group of countries.

Figure 6.a Impact of Pandemics on Public Gross Debt by Group of countries (% GDP)



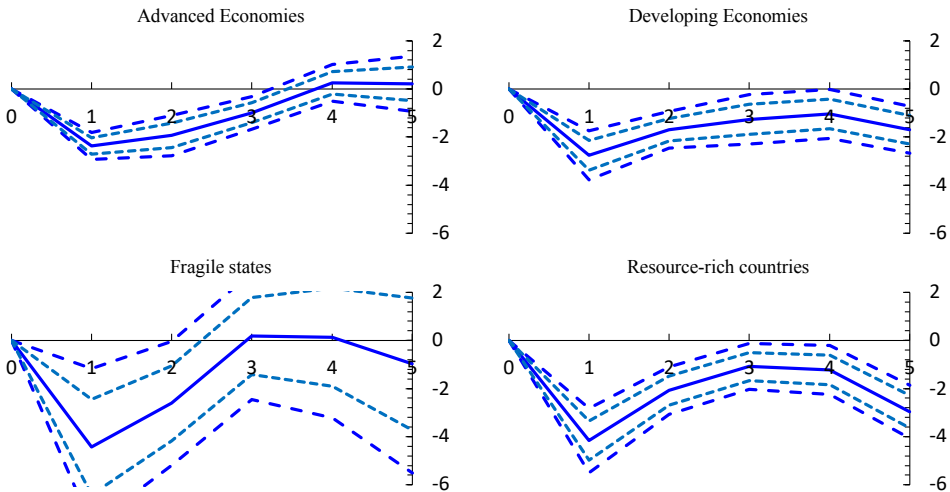
¹⁴ We separately estimated the impact of pandemics on sub-Saharan Africa. Results reported in Appendix Figure A1 show that pandemics worsen the overall fiscal balance more than for the entire sample mainly because of a much larger decline in region's revenues.

¹⁵ For evidence on the impact of the last global financial crisis on the budgets of low-income countries, see Kyrili and Martin (2010).



Note: Impulse response functions are estimated using a sample of 170 countries over the period 1980-2018. The graph shows the response and both the 90 and 68 percent confidence bands. The x-axis shows years (k) after pandemic events; t = 0 is the year of the pandemic event. Estimates based on equation 1. Standard errors in parentheses are clustered at the country level.

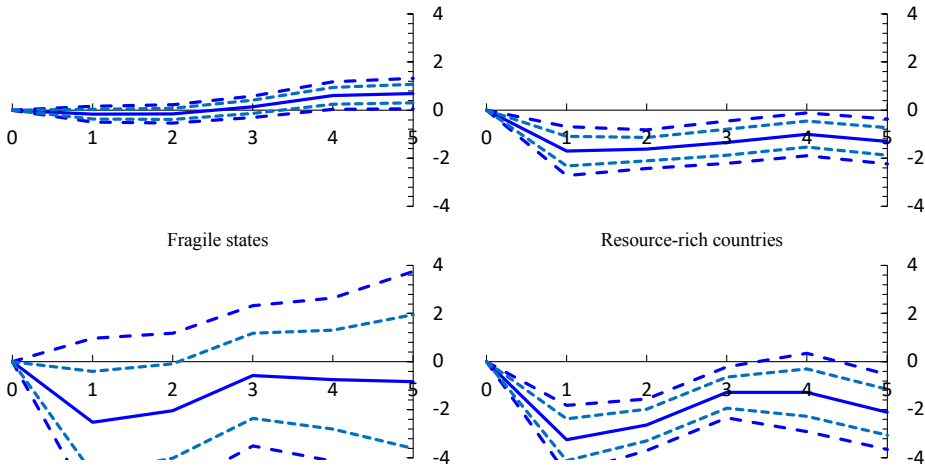
Figure 6.b Impact of Pandemics on Overall Budget Balance by Group of countries (% GDP)



Note: Impulse response functions are estimated using a sample of 170 countries over the period 1980-2017. The graph shows the response and both the 90 and 68 percent confidence bands. The x-axis shows years (k) after pandemic events; t = 0 is the year of the pandemic event. Estimates based on equation 1. Standard errors in parentheses are clustered at the country level.

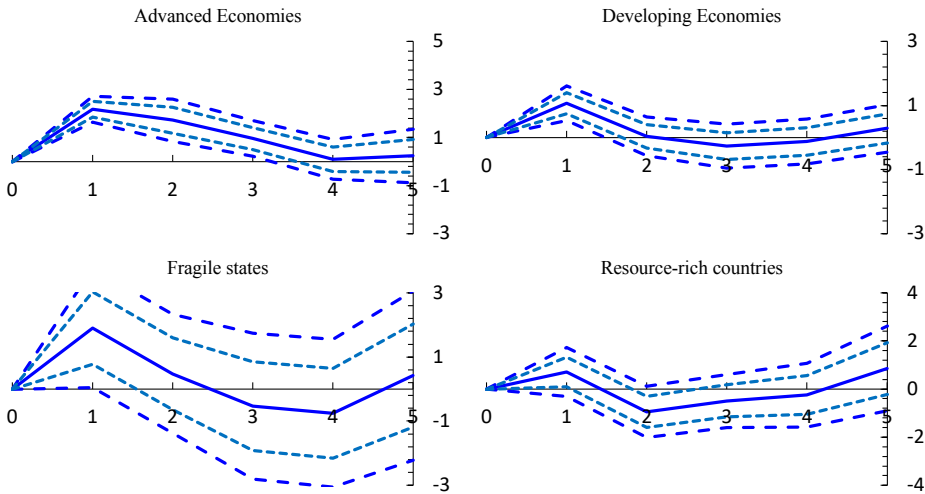
Figure 6.c Impact of Pandemics on Total Revenues by Group of countries (% GDP)

Advanced Economies Developing Economies



Note: Impulse response functions are estimated using a sample of 170 countries over the period 1980-2018. The graph shows the response and both the 90 and 68 percent confidence bands. The x-axis shows years (k) after pandemic events; t = 0 is the year of the pandemic event. Estimates based on equation 1. Standard errors in parentheses are clustered at the country level.

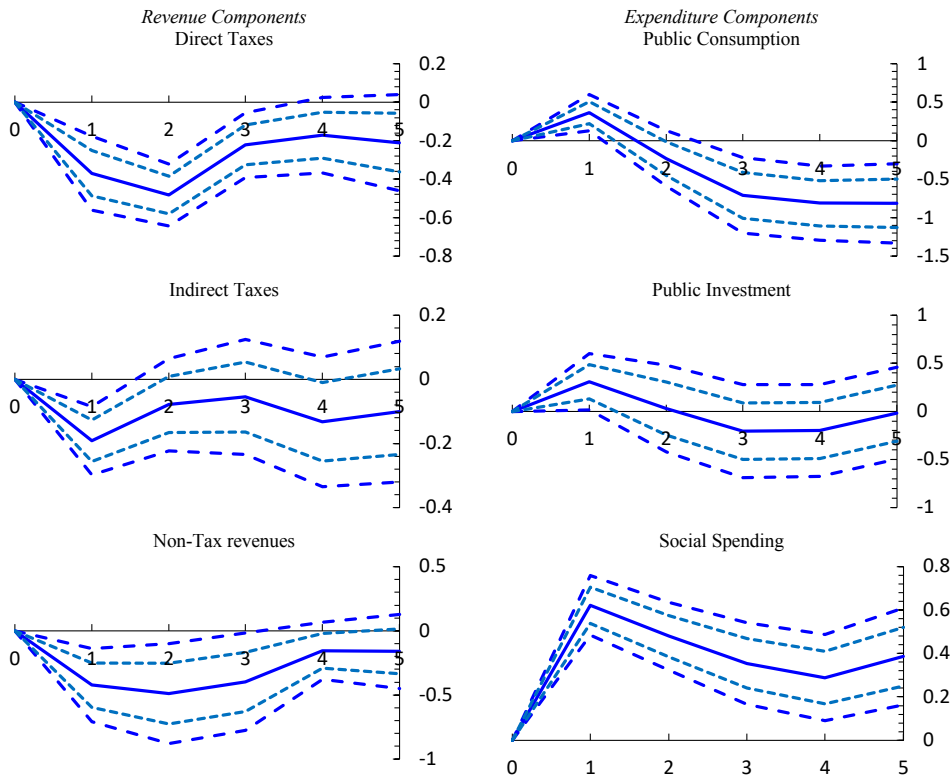
Figure 6.d Impact of Pandemics on Total Expenditures by Group of countries (% GDP)



Note: Impulse response functions are estimated using a sample of 170 countries over the period 1980-2018. The graph shows the response and both the 90 and 68 percent confidence bands. The x-axis shows years (k) after pandemic events; t = 0 is the year of the pandemic event. Estimates based on equation 1. Standard errors in parentheses are clustered at the country level.

A relevant question is whether the effect on the budget is being driven by a particular component of revenues and expenditure. In this regard, we decompose revenues into direct taxes, indirect taxes and non-tax revenues and expenditures into public consumption, public investment and social spending (all expressed in percent of GDP). Looking at Figure 7 – for the entire sample - we observe that the fall in revenue is mostly driven by a drop in direct taxes followed by a decline in non-tax revenues (such as grants). Expenditure increase in turn is mostly the result of the operation of automatic stabilizers, that is, the jump in social spending.

Figure 7. Impact of Pandemics on Revenue and Expenditure Components, all countries (% GDP)



Note: Impulse response functions are estimated using a sample of 170 countries over the period 1980-2018. The graph shows the response and both the 90 and 68 percent confidence bands. The x-axis shows years (k) after pandemic events; t = 0 is the year of the pandemic event. Estimates based on equation 1. Standard errors in parentheses are clustered at the country level.

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B. Do Pandemics propel Tax Reforms?

Table 2 reports estimation of baseline equation 3. We observe that pandemics increase the likelihood of tax reforms happening – the effect is positive and statistically significant when all 45 countries are considered. Results suggest that crisis situations present an opportunity for a country to implement tax reforms. The statistical effect is lost—while maintaining the correct sign—when countries are further subdivided into two groups of emerging market and low-income economies, possibly due to smallness of sample size (see specifications 2 through 5 in Table 2). Regarding controls, the more developed a country is, the more likely it is to implement tax reforms as reflected in statistical significance of real GDP variable, although the pandemic variable is significant in the small sample of fragile states with relatively low real GDP. In contrast, countries characterized by high inflation tend to implement fewer tax reforms possibly due to the availability of seigniorage and heightened economic volatility that makes the outcome of a given reform more uncertain. A country more open to trade seems to be associated with a higher likelihood of tax reforms taking place (consistent with the findings by Belloc and Nicita, 2011). We tried income distribution and corruption variables as controls as well. The former is included to determine whether tax reforms are perceived as benefiting the rich. The latter tests whether perception of high levels of corruption is a deterrent to reforming tax systems. Both variables turned out to be statistically insignificant. As their inclusion greatly reduced the number of observations, in what follows next these controls are not included.

Table 2: Determinants of structural tax reforms, baseline model

Specification	(1)	(2)	(3)	(4)	(5)	(6)
Sample	all	EME	LIC	exc. fragile	only fragile	exc. resource rich
Real GDP	0.036 (0.036)	0.086* (0.049)	0.014 (0.056)	0.061 (0.045)	-0.087 (0.085)	-0.001 (0.043)
Inflation rate	-2.496*** (0.842)	-6.734*** (2.015)	-1.247 (0.864)	-1.895 (1.581)	5.328** (2.540)	-0.084 (1.343)
Trade openness	0.006*** (0.002)	-0.003 (0.004)	0.011*** (0.003)	0.001 (0.004)	0.004 (0.005)	0.000 (0.003)
Unemployment rate	-0.150 (0.104)	-0.621** (0.291)	-0.070 (0.140)	-0.020 (0.141)	-0.086 (0.287)	-0.047 (0.129)
Pandemic shock	0.807** (0.357)	0.619 (0.467)	0.843 (0.580)	0.232 (0.420)	1.274* (0.783)	0.307 (0.384)
Observations	785	394	391	413	137	476
Pseudo-R2	0.041	0.087	0.041	0.008	0.060	0.001

Note: All models are estimated by logit. Dependent variable is the structural tax reform binary variable. Standard errors are reported in parenthesis. Country fixed effects estimated but omitted. The constant term is not reported for parsimony. *, **, *** denote statistical significance at the 10, 5, and 1 percent levels, respectively.

The previous table did not distinguish tax reforms between tax policy and revenue administration. In Table 3, we remedy this and study the likelihood of reforms of different taxes/measures. For this purpose, we re-run specification (3) in Table 2 for alternative binary-type dependent variables. We find that pandemics seem to trigger reforms in CIT, excises and property taxes. Also, VAT and excise reforms are more likely when inflation is lower as one would expect.

Table 3: Determinants of structural tax reforms, by tax category

Specification Dependent variable (tax reform)	(1) PIT	(2) CIT	(3) GST	(4) VAT	(5) Excises	(6) Trade	(7) Property	(8) Revenue Administration.
Real GDP	0.093 (0.062)	0.035 (0.058)	0.043 (0.074)	0.031 (0.051)	0.067 (0.047)	-0.309*** (0.091)	0.246* (0.134)	0.077** (0.038)
Inflation rate	-0.946 (0.884)	-1.726* (1.049)	-2.105* (1.273)	-2.034** (0.967)	-1.676** (0.843)	-1.726 (1.321)	-2.678* (1.473)	-2.141*** (0.820)
Trade openness	0.017*** (0.003)	0.012*** (0.003)	0.014*** (0.004)	0.004 (0.003)	0.005 (0.003)	-0.011 (0.008)	0.002 (0.008)	0.008*** (0.002)
Unemployment rate	0.402** (0.200)	0.512** (0.200)	-0.086 (0.219)	0.056 (0.149)	0.152 (0.137)	0.272 (0.328)	0.303 (0.333)	-0.181* (0.108)
Pandemic shock	-0.847 (1.031)	0.847* (0.516)	0.382 (0.760)	0.362 (0.501)	0.730* (0.421)	1.086* (0.664)	0.000 (0.000)	0.519 (0.383)
Observations	785	785	785	785	785	785	750	785
Pseudo-R2	0.092	0.079	0.066	0.020	0.025	0.097	0.047	0.043

Note: All models are estimated by logit. Dependent variables identified in the second row. Standard errors are reported in parenthesis. Country fixed effects estimated but omitted. The constant term is not reported for parsimony. *, **, *** denote statistical significance at the 10, 5, and 1 percent levels, respectively.

Revenue administration reforms typically cover multiple areas. We re-did the previous exercise by zooming into the 8 specific areas of revenue administration for which we have information. Coefficient estimates attached to the pandemic variable in Table 4 come out statistically insignificant. It appears pandemic events boost the possibility of certain tax policy reforms but not that of revenue administration.

Table 4: Determinants of revenue administration reforms

Specification Dependent variable (Rev. Adm. area/reform)	(1) Management & HR	(2) Large taxpayers' office	(3) IT system	(4) Registration & filing	(5) Audit & verification	(6) Management payment obligations	(7) Improving compliance	(8) Customs clearance
Real GDP	0.012 (0.046)	0.080 (0.053)	-0.037 (0.045)	-0.057 (0.047)	0.003 (0.043)	-0.018 (0.053)	-0.074 (0.056)	-0.095* (0.054)
Inflation rate	-0.360 (1.446)	-2.046 (1.998)	-2.505 (1.805)	-2.350 (1.895)	0.045 (1.319)	-0.972 (1.854)	-5.183** (2.535)	0.117 (1.629)
Trade openness	0.004 (0.003)	0.003 (0.004)	0.002 (0.003)	0.007** (0.003)	0.006** (0.003)	0.005 (0.003)	-0.010** (0.004)	0.004 (0.003)
Unemployment rate	-0.238* (0.130)	0.081 (0.152)	0.029 (0.139)	-0.325** (0.138)	-0.102 (0.125)	-0.385** (0.150)	-0.138 (0.161)	-0.663*** (0.153)
Pandemic shock	0.280 (0.425)	0.061 (0.504)	-0.138 (0.467)	0.006 (0.474)	-0.118 (0.440)	0.391 (0.480)	-0.192 (0.553)	-0.157 (0.575)
Observations	550	550	550	550	550	550	550	550
Pseudo-R2	0.011	0.008	0.010	0.029	0.010	0.023	0.030	0.050

Note: All models are estimated by logit. Dependent variables identified in the second row. Standard errors are reported in parenthesis. Country fixed effects estimated but omitted. The constant term is not reported for parsimony. *, **, *** denote statistical significance at the 10, 5, and 1 percent levels, respectively.

C. Sensitivity and Robustness

We have carried out several robustness checks of the previous findings—see the Online Annex for detailed description and discussion.

Regarding the first empirical exercise, first, we re-estimated equation (1) excluding country fixed effects (Tuelings and Zubanov, 2010). Then, we included country-specific time trends as additional controls (see Figure A2 in the Online Annex). Results are similar to, and not statistically different from the baseline results. Given the possible concern that results may suffer from omitted variable bias we expanded the set of controls to include growth expectations and observed that results were in line with the ones presented in Figure 4 (see Figure A3 in the Online Annex). We also explored whether business cycle conditions at the time of the pandemic affect fiscal outcomes. Results available in Figure A4 in the Online Appendix suggest that the response of key fiscal aggregates to pandemics does not vary significantly with prevailing business conditions.

Further, we re-estimated equation (3) using 4 alternative estimators: Ordinary Least Squares, probit, ordered logit and the rare events relogit model. Results available in Table A1 in the Online Annex confirm the positive and significant coefficient estimate of pandemic shocks, meaning that such events increase the likelihood of tax reforms in the sample of developing countries under scrutiny.

5. Conclusion and Policy Implications

Results presented in this paper indicate that the fiscal landscape of countries is likely to alter as a result of the COVID19 pandemic, although there is a great deal of uncertainty about its likely impact on economic variables. We believe that this paper's findings provide a lower bound to what the current pandemic is likely to inflict on countries. While all country groups would see a rising debt and widening of budget deficits, the revenue position of developing countries (and sub-Saharan Africa in particular) would worsen more than that of advanced economies—an effect that is likely to persist. This outcome has important implications for low-income countries where average tax-to-GDP ratio is around 15 percent, and in many instances lower than the level necessary to achieve a significant acceleration in growth and development (Mullins, Gupta and Liu, 2020). The COVID-19 pandemic will significantly affect the tax bases of these countries for several years (Gupta and Liu, 2020). This means that policymakers in these countries should reconsider their revenue-raising strategy in favor of an approach that embraces a comprehensive reform package, including policies that have encountered political opposition in the past.

The paper showed that the fiscal effect varies, with pandemics affecting government expenditures more than revenues in advanced economies, while the converse applies to developing countries. The two sources of revenues that are affected the most are direct taxes and non-tax revenues. The former plays a bigger role in advanced and the latter in developing economies. An analysis of a subset of 45 developing economies for which tax reform data are available suggests that past pandemics have pushed countries to implement tax reforms, particularly in corporate income taxes, excises and property taxation. Unfortunately, pandemics do not drive developing countries to implement revenue administration reforms.

References

1. Akitoby, B., Baum, A., Hackney, C., Harrison, O., Primus, K., Salins, V. (2019), “Tax revenue mobilization episodes in developing countries”, **Policy Design and Practice**, 3(1).
2. Almond, D. and Mazumber, B. (2005), “The 1918 Influenza Pandemic and Subsequent Health Outcomes: an analysis of SIPP data”, **American Economic Review**, 95(2), 258-262
3. Aoyagi, C. and Ganelli, G. (2015), “Asia’s Quest for Inclusive Growth Revisited”. IMF Working Papers No. 15.
4. Atkeson, A. (2020). “What Will Be the Economic Impact of COVID-19 in the US? Rough Estimates of Disease Scenarios,” NBER WP 26867.
5. Attinasi, M.G., Checherita, C. and Nickel, C. (2010), “What explains the surge in euro area sovereign spreads during the Financial Crisis 2007-2009?” **Public Finance and Management**, 10, 595-645.
6. Auerbach, A., and Gorodnichenko, Y. (2013), “Fiscal Multipliers in Recession and Expansion” in Fiscal Policy after the Financial Crisis, Alberto Alesina and Francesco Giavazzi, eds., University of Chicago Press.
7. Barro, R., Ursua, J., 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 WP 26866.
8. Bell, C. and Lewis, M. (2005). The Economic Implications of Epidemics Old and New. SSRN Electronic Journal.
9. Belloc, F. and Nicita, A. (2010), “The Political Determinants of Liberalization: Do Ideological Cleavages Still Matter?”, **International Review of Economics**. 58. 121-145.
10. Bergh, A. and Henrekson, M. (2011), “Government Size and Growth: A Survey and Interpretation of the Evidence”. **Journal of Economic Surveys**. 25. 872-897
11. Brainerd, E. and Siegler, M. (2003), “The economic effects of the 1918 influenza epidemic”, CEPR Discussion Papers No. 3791.
12. Claessens, S, D. Klingebiel and L Laeven (2005), “Crisis resolution, policies, and institutions: empirical evidence”, in P Honohan and L Laeven (eds), Systemic financial crises: containment and resolution, Cambridge University Press, 169–94.
13. Duval, R., Furceri, D., Miethe, J. (2018). “The Needle in the Haystack: What Drives Labor and Product Market Reforms in Advanced Countries?”, IMF Working Papers 18/101, International Monetary Fund.
14. Eichenbaum, M. S., S. Rebelo, and M. Trabandt (2020). “The Macroeconomics of Epidemics,” NBER WP 26882.
15. European Commission, 2009a. European Economic Forecast: Autumn, European Commission: Brussels.
16. European Commission, 2009b. Public Finances in EMU. European Economy No 3. European Commission: Brussels.
17. Furceri, D., Zdzienicka, A. (2010), “The consequences of banking crisis for public debt”. OECD, Working Paper, No. 81.
18. Furceri, D., Zdzienicka, A. (2012), “How costly are debt crises?” **Journal of International Money and Finance**, 31(4), 726-742

19. Kenny, C. (2021), “The Plague Cycle: The Unending War Between Humanity and Infectious Disease,” Scribner.
20. Gali, J. Perotti, R. (2003), “Fiscal policy and monetary integration in Europe”. **Economic Policy**, 18, 533-572.
21. Greene, W. (2012), “Econometric Analysis”, 7th edition, Prentice Hall.
22. Gupta, S., and Liu, J. (2020), “The Covid-19 Crisis and Fiscal Reform in Low-Income Countries”. CGD Note, June.
23. Halkos, G. and Paizanos, E. (2015), “Fiscal policy and economic performance: A review of the theoretical and empirical literature”, MPRA Paper No. 67737
24. Ho, G. and Detragiache, E. (2010), “Responding to Banking Crises: Lessons from Cross-Country Evidence”. International Monetary Fund, IMF Working Papers. 10.
25. Honohan, P. and D. Klingebiel (2003), “The Fiscal Cost Implication of an Accommodating Approach to Banking Crises.” **Journal of Banking and Finance**. 27(8), 1539-1560.
26. ILO (2020). ILO Monitor 6th edition: COVID-19 and the world of work.
27. IMF (2021). World Economic Outlook - Update, January, Washington DC. IMF Publishing
28. Jonung, L. and Roeger, W. (2006), The Macroeconomic Effects of a Pandemic in Europe – A Model-Based Assessment’, European Economy Economic Papers No. 251, European Commission, Directorate-General for Economic and Financial Affairs, June.
29. Jordà, O. (2005). “Estimation and inference of impulse responses by local projections,” **American Economic Review**, 95, 161–182.
30. Jordà, O. Singh, S. and Taylor, A. (2020), “Longer-Run Economic Consequences of Pandemics”. Federal Reserve Bank of San Francisco, Working Paper Series. 01-16.
31. Karlsson, M., Nilsson, T. and Pichler, S. (2014), “The Impact of the 1918 Spanish Flu Epidemic on Economic Performance in Sweden – An Investigation into the Consequences of an Extraordinary Mortality Shock”, **Journal of Health Economics**, 36, 1-19.
32. Kyrili, K. and Martin, M. (2010) “The hidden crisis: Armed conflict and education: Monitoring the impact of the financial crisis on national education financing: A cross country study,” A Background Paper prepared for the Education for All Global Monitoring Report 2011.
33. Laeven, L. and Valencia, F.. (2008), “Systemic Banking Crises: A New Database”. International Monetary Fund, IMF Working Papers. 08.
34. Ma, C., J. Rogers and S. Zhou (2020). “Global Financial Effects”. **Covid Economics**, 5, 56-78.
35. Meltzer, M. I., Cox, N. J., and Fukuda, K. (1999), “The economic impact of pandemic influenza in the United States: Priorities for intervention”. **Emerging Infectious Diseases**, 5(5), 659–671.
36. Peter Mullins, Sanjeev Gupta and Jianhong Liu (2020), “Domestic Revenue Mobilization in Low Income Countries: Where to From Here?” CGD Policy Paper 195.
37. Reinhart, Carmen M. and Kenneth S Rogoff, This Time is Different: Eight Centuries of Financial Folly. (Princeton: Princeton University Press, October 2009).
38. Reinhart, Carmen M., and Kenneth S. Rogoff, —This Time is Different: A Panoramic View of Eight Centuries of Financial Crisesl, NBER Working Paper 13882, March 2008.
39. Romer, C. and Romer, D. (2019), “Fiscal Space and the Aftermath of Financial Crises: How It Matters and Why.” **Brookings Papers on Economic Activity**, 239–313.

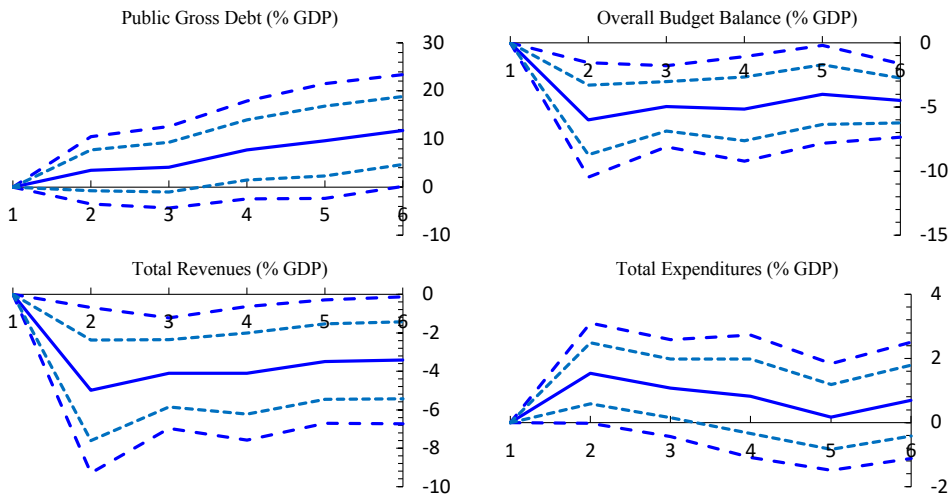
40. Tagkalakis, A. (2013), “Audits and tax offenders: Recent evidence from Greece”. **Economics Letters**, 118, 519–522.
41. Teulings, C. and N. Zubanov (2010), “Economic Recovery a Myth? Robust Estimation of Impulse Responses,” CEPR Discussion Paper 7300 (London: CEPR).
42. Wooldridge, J. (2002), *Econometric Analysis of Cross Section and Panel Data*, MIT Press

APPENDIX

Table A1. Summary Statistics

Variable	observations	Mean	Standard deviation	minimum	maximum
<i>IRF analysis</i>					
Public Debt	3143	55.32	39.14	0.07	495.20
Overall balance	3496	-1.9	5.022	-39.03	125.13
Government revenues	3576	28.57	12.76	0.036	164.05
Government expenditures	3511	31.041	12.77	3.78	104.46
<i>Binary Models Analysis</i>					
Real GDP (log)	1165	5.10	3.01	-0.809	10.90
CPI (log)	1165	4.65	2.16	-7.58	17.84
Trade openness (% GDP)	1109	84.02	41.34	19.68	321.63
Unemployment (log)	1008	1.94	0.84	-2.30	3.62
Pandemic shock	882	0.043	0.203	0	1

Figure A1. Impact of Pandemics on Fiscal Variables, SSA (% GDP)



Note: Impulse response functions are estimated using a sample of sub-Saharan African countries over the period 1980-2018. The graph shows the response at both 90 and 68 percent confidence bands. The x-axis shows years (k) after pandemic events; t = 0 is the year of the pandemic event. Estimates based on equation 1. Standard errors in parentheses are clustered at the country level.

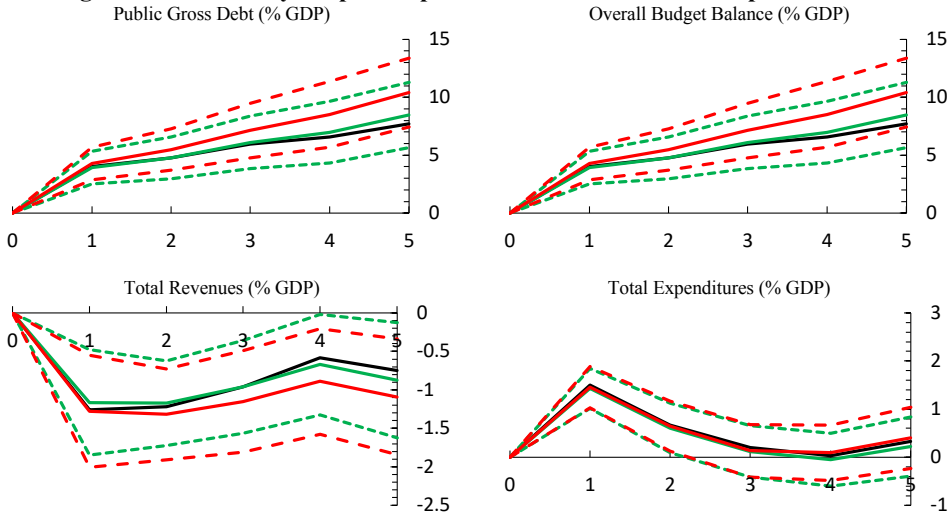
ONLINE ANNEX

Sensitivity and Robustness checks

A possible bias from estimating equation (1) using country-fixed effects is that the error term may have a non-zero expected value, due to the interaction of fixed effects and country-specific developments (Tuelings and Zubanov, 2010). This would lead to a bias of the estimates that is a function of k . To address this issue, equation (1) was re-estimated by excluding country fixed effects from the analysis. Results in Figure A1 (green lines) suggest that this bias is negligible.

To try and estimate the causal impact of pandemics on fiscal outcomes, it is important to control for previous trends in dynamics of the fiscal variables. The baseline specification attempts to do this by controlling for up to two lags in the dependent variable.¹⁶ To further mitigate this concern, we re-estimate equation (1) by including country-specific time trends as additional control variables. Results in Figure A1 (red lines) keep the main thrust of our previous findings.

Figure A2. Sensitivity: Impact of pandemics under alternative specifications

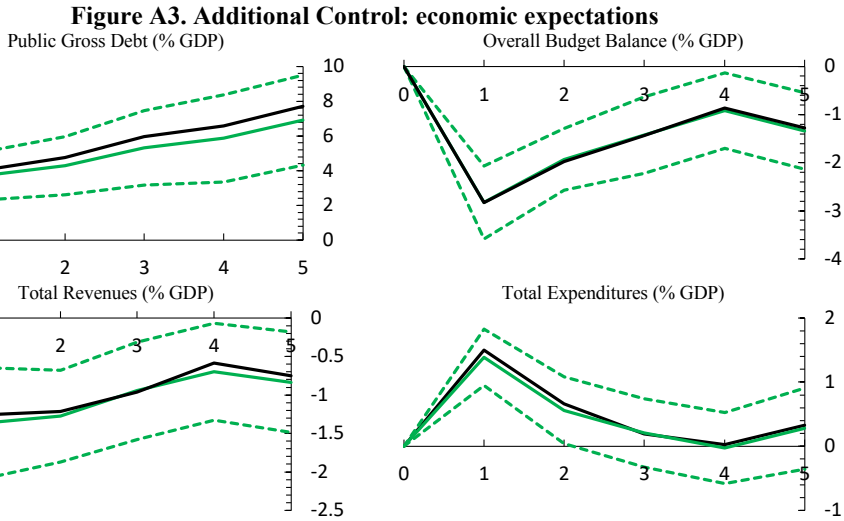


Note: Impulse response functions are estimated using a sample of 170 countries over the period 1980-2018. Black solid line corresponds to the baseline result in Figure 4. Green lines denote the exercise dropping country fixed effects. Red lines denote the exercise adding country time trends. The graph shows the response and the 90 confidence bands for the two exercises conducted. The x-axis shows years (k) after pandemic events; $t = 0$ is the year of the pandemic event. Estimates based on equation 1. Standard errors in parentheses are clustered at the country level.

Another possible concern regarding the analysis is that the results may suffer from omitted variable bias, as fiscal policies may be carried out because of concerns regarding future evolution of economic activity. To address this issue, we control for the expected values in $t-1$ of future real GDP growth over periods t to $t+k$ —that is, the time horizon over which the impulse response functions are

¹⁶ Similar results are obtained when using alternative lag parametrizations. Results for zero, one and three lags (not shown) confirm that previous findings are not sensitive to the choice of the number of lags.

computed. These are taken from the fall issue of the IMF WEO for year $t-1$. Figure A2 shows the results from considering growth expectations in our baseline specification. We observe that these are in line with those presented in Figure 4.



Note: Impulse response functions are estimated using a sample of 170 countries over the period 1980-2018. Black solid line corresponds to the baseline result in Figure 3. Green lines denote the exercise augmented with growth expectations. The graph shows the response and the 90 confidence bands for the two exercises conducted. The x-axis shows years (k) after pandemic events; $t = 0$ is the year of the pandemic event. Estimates based on equation 1. Standard errors in parentheses are clustered at the country level.

We also explored whether business cycle conditions at the time of the pandemic affect fiscal outcomes. That means the response is allowed to vary with the state of the economy:

$$y_{i,t+k} - y_{i,t-1} = \alpha_i + \tau_i + \beta_L^k F(z_{i,t}) \text{pand}_{i,t} + \beta_H^k (1 - F(z_{i,t})) \text{pand}_{i,t} + \theta M_{i,t} + \varepsilon_{i,t} \quad (A1)$$

with

$$F(z_{it}) = \frac{\exp(-\gamma z_{it})}{1 + \exp(-\gamma z_{it})}, \quad \gamma > 0$$

in which z_{it} is an indicator of the state of the economy (the real GDP growth) normalized to have zero mean and unit variance.¹⁷ The coefficients β_L^k and β_H^k capture the fiscal impact of pandemics at each horizon k in cases of extreme recessions ($F(z_{it}) \approx 1$ when z goes to minus infinity) and booms ($1 - F(z_{it}) \approx 1$ when z goes to plus infinity), respectively.^{18 19} Results in Figure A3 suggest

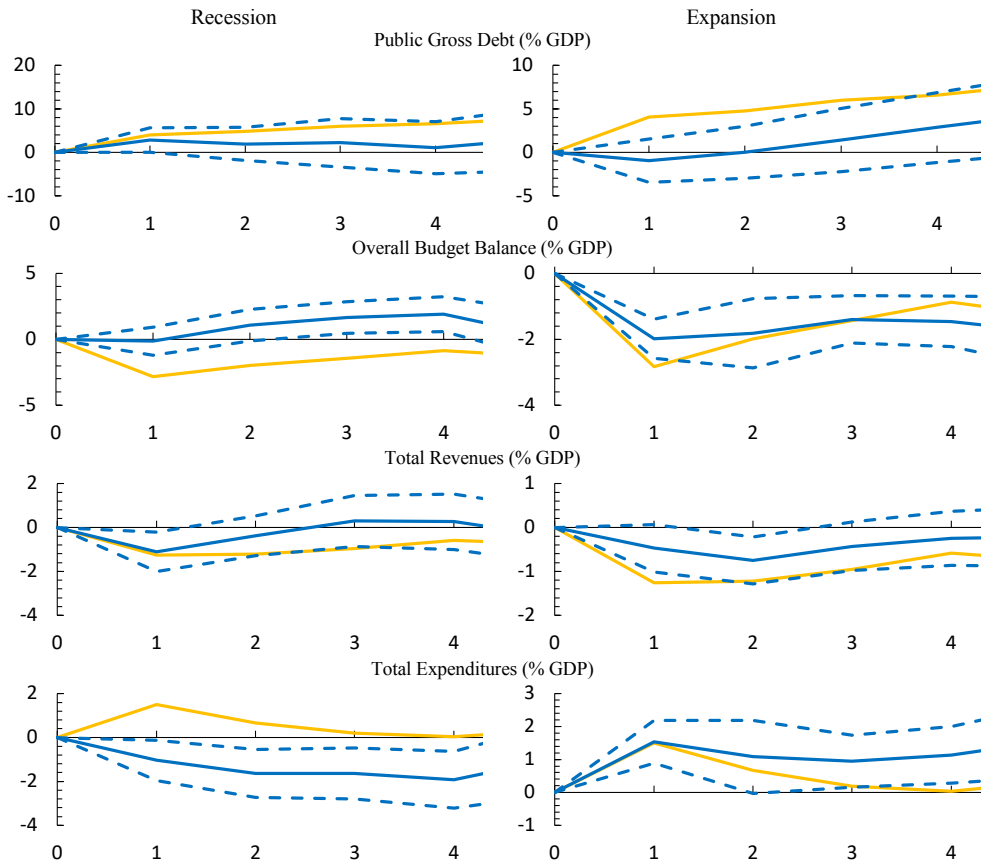
¹⁷ The weights assigned to each regime vary between 0 and 1 according to the weighting function $F(\cdot)$, so that $F(z_{it})$ can be interpreted as the probability of being in a given state of the economy.

¹⁸ $F(z_{it})=0.5$ is the cutoff between weak and strong economic activity.

¹⁹ We choose $\gamma = 1.5$, following Auerbach and Gorodnichenko (2012), so that the economy spends about 20 percent of the time in a recessionary regime—defined as $F(z_{it}) > 0.8$. Our results hardly change when using alternative values

that the response of key fiscal aggregates to pandemics does not vary significantly with prevailing business conditions. The two exceptions are the response of the overall fiscal balance, which becomes statistically insignificant in bad times (in contrast with a negative response in the baseline or unconditional specification); and that total expenditure actually falls in bad times (in contrast with a positive response in the baseline or unconditional specification).²⁰

Figure A4. State Contingent Regression: Impact from Pandemics on Fiscal Outcomes over the Business Cycle



Note: Impulse response functions are estimated using a sample of 170 countries over the period 1980-2018. Yellow solid lines correspond to the baseline result in Figure 4. The graph shows the response and the 90 confidence bands.

of the parameter γ , between 1 and 6. Auerbach and Gorodnichenko (2012, 2013) discuss the advantages of using the local projection approach to estimating non-linear effects.

²⁰ Results are also robust to re-estimating equation (4) more simply through a dummy variable that takes value 1 when the GDP growth rate of the country considered is below its sample average and zero otherwise (results available upon request).

The x-axis shows years (k) after pandemic events; t = 0 is the year of the pandemic event. Estimates based on equation 1. Standard errors in parentheses are clustered at the country level.

To test for the robustness of the results of the logistic regressions, we re-estimated the baseline model with a number of alternative estimators. First, we re-estimate the baseline specification resorting to an Ordinary Least Squares (OLS) approach. Second, we use a probit approach. Third, we employed an ordered logit model under the assumption that the larger the number of tax reforms the better in our context. Finally, we employ a rare events logit (or relogit) estimator. In a logistic regression, the Maximum Likelihood estimates are consistent but only asymptotically unbiased. The basic problem is having a number of units (structural tax reforms) in a panel that has no events. This means that the country-specific indicators corresponding to the all-zero countries perfectly predict the zeroes in the outcome variable (Gates, 2001; King, 2001).²¹ The simplest way of dealing with this problem is decreasing the rareness of the event of interest: by lowering the threshold of what constitutes the event of interest or expanding the data selection period, for example, there is less need to correct for rareness. Alternatively, the King and Zeng’s (2001) bias correction method, the relogit estimator, can be used.²² The relogit estimator for dichotomous dependent variables provides a lower mean square error in the presence of rare events and can be defined as follows:

$$\text{Prob}(STR_{it} = 1|Z_{it}) = \Phi(Z'_{it}\vartheta) \Leftrightarrow \text{Prob}(STR_{it} = 1|S_{it}, X_{it}) = \Phi(\alpha_i + Pol_{it}'\eta + X_{it}'\gamma) \quad (1)$$

with $i = 1, \dots, N; t = 1, \dots, T$, where $\Phi(\cdot) = \frac{1}{1+e^{-(Z'_{it}\vartheta)}} = \frac{1}{1+e^{-(\alpha_i + Pol_{it}'\eta + X_{it}'\gamma)}}$, α, η, γ are the vectors of the parameters to be estimated, and $\Phi(\cdot)$ is the logistic function.

The parameters can be estimated by maximum likelihood.²³ However, as pointed out by King and Zeng (1999a, 1999b, 2001), the estimates of $\Phi(\cdot)$ and $\Phi(\cdot) \cdot [1 - \Phi(\cdot)]$ among observations that include rare events (in our case, for which $STR = 1$) will be typically larger than those among observations that do not include rare events (i.e., for which $STR = 0$). Consequently, their contribution to the variance will be smaller, rendering additional ‘rare’ events more informative than additional ‘frequent’ events. Therefore, we follow King and Zeng (1999a, 1999b) and correct for the small sample and rare events biases and estimate a relogit model where the sampling design is random or conditional on Z_{it} .²⁴

The regression results of these alternative estimators are reported in Table A1.

²¹ This is a well-known phenomenon in the statistical literature (for an overview see Gao and Shen, 2007).

²² King and Zeng (2001) describe rare events as “dozens to thousands of times fewer ones [...] than zeroes”.

²³ And the variance of the estimated coefficients can be expressed as $Var(\hat{\vartheta}) = (Z'VZ)^{-1}$, where V is a diagonal matrix, with diagonal entries equal to $\Phi(\cdot) \cdot [1 - \Phi(\cdot)]$. In the case of rare events, $\Phi(\cdot)$ will be generally small.

²⁴ We use the software package “relogit” provided by Tomz et al. (1999).

Table A1: Determinants of structural tax reforms: robustness to alternative estimators

Specification Estimator	(1) Probit	(2) OLS	(3) Relogit	(4) Ordered Logit
Real GDP	0.023 (0.021)	0.006 (0.006)	0.036 (0.035)	0.192*** (0.041)
Inflation rate	-1.462*** (0.439)	-0.105*** (0.037)	-2.328** (0.965)	-0.436* (0.231)
Trade openness	0.004*** (0.001)	0.001*** (0.000)	0.006*** (0.002)	-0.002 (0.003)
Unemployment rate	-0.091 (0.062)	-0.028 (0.019)	-0.149 (0.101)	0.153 (0.106)
Pandemic shock	0.493** (0.219)	0.188*** (0.073)	0.813** (0.370)	1.009*** (0.350)
Observations	785	785	785	785
R2	0.274	0.033		
Pseudo-R2	0.042			0.029

Note: estimator identified in the second row. Standard errors are reported in parenthesis. Country fixed effects estimated but omitted. The constant term is omitted for parsimony. *, **, *** denote statistical significance at the 10, 5, and 1 percent levels, respectively.

Coping with Covid: Australian women's coping responses during the Covid-19 pandemic

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The current Covid-19 pandemic is a stochastic shock that impacts all Australian women irrespective of individual difference. While not every person will contract coronavirus, every Australian woman has experienced a stress reaction impacting their psychological, regulatory, or behavioural responses. Our study employs a repeated measures survey from (n=420) Australian women in June (n=207) and September 2020. We analyse the relationship between women's demographics, personality, mental and physical health, their Covid-19 knowledge and stated risk preferences, to identify factors impacting coping behaviors employed using the BriefCope scale. We find that both age and personality are key factors impacting both choice and type of coping strategy employed. With younger Australian women (compared to older) more likely to engage a coping strategy. Interestingly, women's income and self-rated general health showed no statistically significant relationship with any of the 14 strategies in the BriefCope scale. Further our repeated measures analysis shows that women aged 40 years and below report greater increases in the use of avoidant (denial, substance use, venting and self-blame) and approach coping (emotional and instrumental support) compared to older women in our cohort. We also find that across time, younger Australian women exhibit higher propensities for risk compared with older Australian women. Our findings of key age & time effects for Australian women's willingness or choice to enact a coping strategy warrants further research into the underlying drivers of such pronounced generational difference.

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Introduction

In Australia, the threat of the coronavirus has been largely contained by government enforced lockdowns, social distancing measures, and track and trace state level health protocols (López & Rodó, 2020). As a wealthy first world country the infection and fatality rates in Australia are relatively low compared to world averages (Roser, Ritchie, Ortiz-Ospina, & Hasell, 2020). Therefore, there is a need to move beyond the easily observable epidemiological impacts and address the growing concerns regarding the economic and social impact of Covid-19 (Burki, 2020; Madgavkar, White, Krishnan, Mahajan, Azcue, 2020; UNCTAD, 2020). We take particular interest with women, who historically have endured greater burdens to their economic conditions, agency and access to endowments during and post exogenous shocks (World Bank Group, 2020).

The Covid-19 pandemic is a universal health shock causing a major interrupting on people's lives requiring a response to stress. For women, physiological factors, through increased exposure through work or care, disruption to service and, social norms of care responsibilities, mean that on a global scale, existing gender differences in work, health and care are amplified for women during the pandemic (United Nations, 2020; McLaren, Wong, Nguyen & Mahamadachchi, 2020; Gausman & Langer, 2020). This ignites an interest into how Australian women are coping as a response to stress with Covid-19.

Coping is the appraisal of stressful situations that result in a style focused on approach or avoidant strategies (Lazarus & Folkman, 1984; Carver & Scheier, 1994). Coping strategies and gender differences are plentiful in the literature (Goubet & Chrysikou, 2019; Hobfall, Dunahoo, Ben-Porath & Monnier, 1994; Matud, 2004) however, conventions regarding male or femaleness to coping strategy, such as the socialisation hypothesis (Pearlin & Schooler, 1978) do not fully investigate the emotional function or in other words, the gendered coping response, such as the use of denial or emotional support.

The purpose of this study is twofold, first it investigates the relationship between women's coping responses using a unique sample of women, to identify factors impacting approach or avoidant coping responses at the end of the 'first wave' peak (June, 2020). Secondly, it assesses change in the same women's coping responses by reporting data captured during viral resurgence (September 2020), using a repeated measures survey.

Background

Females and males face fundamentally different biological, socio-economic, institutional, and cultural constraints (Trivers 1972; Whyte et al. 2018; 2018; Whyte & Torgler 2020). During stochastic shocks like the Covid-19 pandemic, male and female differences may be further illuminated by historically socialised gender roles (Chan et al., 2020). Particularly in heteronormative relationships where evidence suggests women revert to traditional gender norms through increased unpaid labour and furthering disparities in terms of economic progress and socialised stress (BehaviourWorks, 2020; Krentz et al., 2020). Early nationwide indicators suggest that Australian women were more likely to reduce their paid employment opportunities or continue with current employment commitments, whilst increasing their hours in domestic, unpaid labour roles (ABS, 2020; AIHW, 2020). Further to that, early indicators show that women's experience of psychological distress exceeded men's during the first six months of the pandemic¹ (ABS, 2020; Rahman et al. 2020).

Approach and avoidance coping strategies are the process of repressing or becoming sensitised to a threat that is currently felt, or a threat that could be felt in the future (Roth and Cohen, 1986). The approach avoidance coping model is broad in its method as it not only assesses actualised threat but also deals with anticipatory threat (Roth and Cohen, 1986). That

¹ See Australian Bureau of Statistics Household Impacts <https://www.abs.gov.au/statistics/people/people-and-communities/household-impacts-covid-19-survey/latest-release#key-statistics>

is, the coming to terms with a potential future problem, such as those faced during the Covid-19 health pandemic. Whilst it is normal for individuals to oscillate between coping strategies, long term reliance on avoidant coping is associated with long term negative mental health outcomes (Panayiotou, Karekla & Leonidou, 2017). Our level of knowledge and propensity for risk are also both key factors in how we evaluate and make choices relating to stress (Porcelli & Delgado, 2017).

There are underlying pejorative stereotypes of coping that women are “emotional” and men “problem solvers” rather than coping mechanisms being a by-product of the stressful setting (Hobfoll et al., 1994; Panayiotou, Karekla & Leonidou, 2017; Li & Graham, 2017). Irrespective of whether coping responses are innate or learned, research has shown there are clear differences between male and female coping (Tamres, Janicki & Helgeson, 2002). One suggestion is that this difference is caused by the frequency of daily stressful situations women encounter, particularly when investigating women who manage paid and unpaid labour roles. Frequency of ‘daily hassles’ on account of multiple roles translates to increased stress on the decision process, and impacts wellbeing (Chopra & Zambelli, 2017; Seib et al., 2014).

Stress negatively impacts wellbeing when demanding situations or unpredictable events or tasks threaten an individual’s sense of self-worth (Baumann, Kaschel, & Kuhl, 2005; Gillett & Crisp, 2017). As such, the competing priorities experienced by women during the pandemic accentuate pressure on women’s wellbeing and life satisfaction, warranting investigation into what coping strategies women currently employ and the underlying factors associated (ABS, 2020; Cain Miller, 2020, ALWHS, 2020).

Research has shown that women and men employ different coping styles (Kelly, Tyrka, Price, & Carpenter, 2008; Kiely, Brady & Byles, 2019, Samulowitz, Gremyr & Hensing, 2018), that an individual’s coping choice needs to be considered both in terms of the situation and the

style (Steed, 1998). The inclusion of situation and style when investigating coping behaviour is paramount to exploring the strategy enacted. Characteristics of context influence the coping style because ones “*coping strategy is moderated by the nature, duration, context and controllability of the stressor*” (Carver & Connor-Smith, 2010, p.694). This is because being able to identify situations where the stressor is controllable or not can be associated with the use of either an approach or avoidant response. The current Covid-19 pandemic creates a scientifically unique natural field experiment for exploring women’s coping strategies based on their own individual differences. In that the stressor is essentially a quasi-uniform stochastic shock for all women, in that all women have essentially zero direct control over the spread or severity of the pandemic.

The coping literature has also (and in the recent context of Covid-19) demonstrated significant sex differences in adult cohorts, with (particularly younger) women exhibiting higher levels of both stress and anxiety no matter the coping style (Mahmoud et al. 2012; Gurvich et al. 2020; Peck, 2020; Loxton et al., 2020; Gausman & Langer, 2020). Additionally, research has shown that coping responses can change with age, owing to developed stress appraisal thresholds that adjust with life experiences (Skinner, Edge, Altman, & Sherwood, 2003; Yeung & Fung, 2007; Charles, 2010).

Both personality (Jang et al. 1996; Almund et al. 2011) and coping style have been shown to be heritable to an extent (Jang et al., 2007). A genetic adaption passed on in some part to each new generation. Of-course coping and stress are dichotomously interdependent and both mediated or exacerbated by one’s own inherent personality traits. This is because personality and coping with stress can be seen as both a top down and bottom up model of behaviour (Segerstrom & Smith, 2019). Bolger (1990, p.525) stated that coping is “*personality in action under stress*”, because personality dimensions exert consistent influence on how we choose to cope with stress. Personality plays a significant role in how individuals experience

and evaluate stress with research showing a systematic relationship between such traits as emotional stability and openness and the choice of coping mechanisms humans employ (McCrae & Costa 1986). Indeed, all traits of the Five-Factor model have shown predictive power for specific coping strategies (Connor-Smith & Flachsbart 2007).

Using a purposively recruited sample of Australian women, the study identifies factors impacting approach or avoidant coping responses at the end of the ‘first wave’ peak (June). And then assesses if these coping responses change by using a repeated measures survey to capture data during the viral resurgence in September 2020.

Material and Methods

Procedures

These data were captured using a repeated measures survey across two time periods 10 June and 12 June 2020 and 10 September until 28 September, 2020. The timeframe for the data collection in June overlapped with the Australian federal government enforced nationwide lockdown. For the first capture some state and territory schools had begun to return school students to classrooms, “*stay at home*” orders were in place for the majority in the public and private workforce. Restrictions were still in place for social occasions, meaning restaurants, bars, clubs were closed to dine in patrons.

The secondary data capture coincided with state and territory boarder closures for interstate travel. Federal government economic stimulus packages were widely available for citizens impacted by loss of work and income. Participants in Victoria were experiencing critical restrictions as the state attempted to gain control of secondary infection spread and New South Wales was in early stages of considering needs for a secondary lockdown. Queensland and South Australia had managed approximately 2,000 recovered cases with few fatalities. Tasmania, Northern Territory and Western Australia had managed a suppression strategy after initial ‘first wave’ of infections.

Qualtrics Panels survey management services were used to recruit participants. All data collection & promotion was conducted in accordance with the university human research ethics on clearance approval number 2000000364.

Measures

The study is descriptive in nature and scales from behavioural science are used to build a holistic picture of Australian women's coping in the context of Covid-19. The BriefCOPE scale includes 28 items that measure 14 conceptually different coping responses – self distraction, active coping, denial, substance use, emotional support, instrumental support, behavioural disengagement, venting, positive reframing, planning, humour, acceptance, religion and self-blame. The BriefCOPE scale is appropriate for examination of coping in naturally occurring settings and can be used to study an individual's coping based on style and situation. The study computes the 28 items following the abbreviated process outlined by Carver (1997) and although items can be spared depending on context, the current study includes each of the items to garner a meaningful understanding of women's coping process during Covid-19. Each coping reaction is measured on a four-point scale that ranges from 1. "I have not been doing this at all" to 4. "I have been doing this a lot". This means that coping response, be it primarily avoidant or approach is not a binary outcome. Respondents are not one or another in terms of their coping response, rather a mixture of both with greater proclivity towards one over the other.

There have been some suggestions that Covid-19 knowledge and sense of being information are correlated with coping because it increases efficacy when dealing with the virus (Wanberg, Csillag, Douglass, Zhou and Pollard, 2020; Wang et al. 2020). Therefore, this study incorporates three items from the national Australian *Survey of COVID19 Responses to*

Understand Behaviour (SCRUB)² to measure citizen's Covid-19 knowledge, sense of information and experience with infection (BehaviourWorks, 2020).

Personality was measured using Saucier (1994) mini-marker subset and followed the inventory reduction method to result in the Big Five factors: Openness, Conscientiousness, Extraversion, Agreeableness and Emotional Stability.

Women's subjective wellbeing was measured by asking participants to evaluate their perception of overall life satisfaction, mental health, and general health. The three-measure provision allows for inferences about subjective wellbeing to be made at a global and domain specific level (Kahneman & Krueger, 2006). Our study also includes a 0 -100 scale to measure overall propensity for risk willingness.

Method

First we assess the relationships between coping responses and demographics, risk willingness and personality variables. We utilise a multivariate regression model to examine the factors associated with Australian women's coping responses during the Covid-19 lockdown period. Table 1 lists the coping responses and independent variables, age is included as a control for each regression. The analysis identifies the relationship between the 14 coping styles and the predictors of self-reported wellbeing, risk, Covid-19 knowledge and personality traits over two time periods.

Repeated measures analysis

To investigate the changes in the 14 responses over two time periods we use a repeated measures ANOVA. The analysis is threefold, firstly it identifies main effects of time, secondly assesses the interaction between age (younger or older) and time, and finally a pairwise comparison indicating the direction of coping changes between age and time. The bimodal

² Survey of COVID-19 Responses to understand Behaviour <https://www.behaviourworksaustralia.org/survey-of-covid-19-responses-to-understand-behaviour-scrub-project/>

distribution is incorporated into the analysis by splitting participants into two groups, younger (18-40 years old) or older (41-70 years old). These age cohorts become the grouping variable and each coping strategy at (T1) and (T2) is the factor in the repeated analysis.

Descriptive Statistics

The study recruited via a commercial recruitment company (Qualtrics) one sample of women in June ($n=420$), where approximately 50% of participants completed a secondary survey in September 2020 ($n=207$). Participants for this study which included $n=420$ Australian women, 18 years and over. Completed surveys resulted in a sample total of 406, a further eight participants were removed from the study based on their Covid-19 infection status. Of these, two reported having been infected with Covid-19, four participants reported that they believe they had been infected with Covid-19 without test confirmation, a further two were awaiting results. The final sample for analysis for the June 2020 sample was $n=398$, and for September 2020 ($n=198$).

The majority of women in our sample were in a monogamous relationship (60%) followed by those reporting as single (25%). The majority of participants had completed some form of higher vocational or tertiary education such as diploma (25%), university graduate (31%) or postgraduate (14%). Close to half of the population (46%) reported having responsibility for dependents. Of those that did, (25%) have responsibility for at least two children.

Sample Characteristics – June 2020

The age range for the first study is 22 – 66 years old and with a mean age of 46 years old ($SD=11.42$) the sample, being female only, produces a comparatively higher mean to the national average of 36 years old (Australian Bureau of Statistics, 2020 (2)).

In time one, self-reported likelihood of contracting Covid-19 is low ($Mean=37$, $SD=28.3$) and knowledge regarding the disease is above average ($Mean=71.7$, $SD=19.7$). The

score for willingness to take risks is slightly below average ($Mean=46$, $SD=23.7$). Participants, on average, self-reported their general health as being well ($Mean=64.42$, $SD=21.24$) on average mental health for the sample ($Mean=65.11$, $SD=25.16$) and life satisfaction ($Mean=66.94$, $SD=20.68$).

Sample Characteristics - September 2020

Of the 398 initial respondents, the repeated measures survey retained 207 return participants. Participants were identified through a response ID number associated with Qualtrics records. The mean age was 47 years old ($SD= 11.34$) with an age range of 25 – 66 years old. Again, the bimodal age distribution was evident in the second capture.

The likelihood of contracting Covid-19 remained low ($Mean=34$, $SD=25.4$), Covid-19 knowledge above average ($Mean=71.4$, $SD=20.2$) and there is marginal change across the sample found in risk willingness ($Mean=47$, $SD=24.9$) in capture two. There is no significant change general health ($Mean=64.53$, $SD=23.45$), however, mental health decreased ($Mean=64$, $SD=25.58$) as did life satisfaction ($Mean=63.89$, $SD=22.4$). All coping response and mini-marker Big 5 personality traits mean scores are provided in Table 2.

Table 1 OLS regression scores of Australian women's coping responses June 2020

	Self-Distractio	Active Coping	Denial	Substance Use	Emotional Support	Instrumental Support	Behavioural Disengagement	Venting	Positive Reframing	Planning	Humour	Acceptance	Religion	Self-Blame
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Variable	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Age	-.022*** (-3.61)	-.021*** (-3.28)	-.016*** (-2.95)	-.016** (-2.65)	-.021*** (-3.42)	-.033*** (-5.74)	-.018*** (-3.52)	-.014** (-2.73)	-.015* (-2.42)	-.019*** (-3.14)	-.021*** (-3.32)	.001 (0.23)	-.016* (-2.17)	-.027*** (-4.75)
Risk	.003** (0.94)	.008* (2.23)	.004 (1.21)	.009* (2.39)	.007* (1.95)	.008* (2.43)	.007* (2.369)	.007* (2.12)	.010* (2.49)	.009* (2.28)	.009* (2.38)	-.000 (0.23)	.008 (1.78)	.006 (1.82)
Covid Knowledge	-.002 (-0.48)	.005 (1.07)	-.004 (-1.08)	-.004 (-0.92)	-.004 (-0.99)	-.008 (-1.83)	.004 (1.02)	-.003 (0.72)	-.004 (-0.93)	-.007 (-1.47)	-.015*** (-2.93)	.000 (0.05)	-.003 (-0.61)	-.008 (-1.84)
Education Level	.116 (1.78)	.076 (1.15)	.040 (0.68)	.122 (1.91)	.134* (2.08)	.029 (0.48)	.124* (2.25)	.037 (0.65)	.122 (1.79)	.116 (1.76)	.088 (1.30)	.046 (0.68)	.252*** (3.26)	.014 (0.24)
Married	-.300 (-1.62)	.026 (0.14)	-.657*** (-3.90)	-.225 (-1.25)	-.176 (-0.97)	-.219 (-1.27)	-.068 (-0.44)	-.213 (-1.33)	-.010 (-0.06)	-.046 (-0.25)	-.150 (-0.78)	-.178 (-0.93)	-.479* (2.23)	-.211 (-1.22)
Children	.179 (0.92)	.148 (0.74)	.317 (1.78)	.077 (0.41)	.247 (1.29)	.338 (1.85)	.0892 (0.55)	.149 (0.88)	.255 (1.26)	.153 (0.78)	-.118 (-0.58)	.030 (0.15)	.654*** (2.88)	.257 (1.41)
Income	.001 (0.13)	.001 (0.14)	-.014 (-1.46)	.008 (0.75)	.001 (0.16)	.005 (0.54)	.004 (0.53)	.004 (0.48)	-.004 (-0.42)	-.004 (-0.40)	.007 (0.65)	.006 (0.57)	-.012 (-0.98)	.000 (0.00)
General Health	-.001 (-0.22)	-.002 (-0.41)	-.001 (-0.29)	.004 (0.83)	.002 (0.59)	-.001 (-0.39)	-.001 (-0.29)	.001 (0.46)	.004 (0.79)	.001 (0.25)	.003 (0.66)	-.002 (-0.46)	-.010 (-1.74)	.004 (0.91)
Life Satisfaction	-.012* (-1.98)	.005 (0.91)	-.004 (-0.88)	-.003 (-0.56)	.003 (0.56)	-.014** (2.62)	-.008 (-1.67)	.000 (0.17)	.008 (1.32)	-.005 (-0.91)	.007 (1.17)	.008 (1.27)	.0128 (1.80)	-.019*** (-3.49)
Mental Health	-.015*** (-3.19)	-.010* (-2.08)	-.005 (-1.25)	-.000 (-0.10)	-.008 (-1.73)	-.015*** (-3.28)	-.019*** (-4.74)	-.015*** (-3.68)	-.008 (-1.67)	-.017*** (-3.58)	.003 (0.75)	-.009 (-1.94)	-.001 (-0.32)	-.016*** (-3.65)
Extraversion	.293* (2.43)	.022 (0.18)	.192 (1.75)	.051 (0.43)	.253* (2.13)	.255* (2.26)	.096 (0.96)	.178 (1.70)	.150 (1.20)	.066 (0.54)	.288* (2.30)	.206 (1.63)	.340* (2.42)	.064 (0.57)
Agreeableness	.208 (1.21)	.168 (0.96)	.288 (1.84)	-.177 (-1.07)	.219 (1.30)	.241 (1.50)	-.021 (-0.15)	-.067 (0.46)	.030 (0.17)	.142 (0.82)	-.277 (-1.56)	-.033 (-0.19)	.169 (0.84)	-.162 (-1.02)
Conscientiousness	.117 (0.69)	.110 (0.63)	.394** (2.52)	.206 (1.24)	-.063 (-0.38)	.054 (0.34)	-.012 (-0.09)	.325* (2.19)	-.089 (-0.51)	.179 (1.04)	.078 (0.44)	-.090 (-0.51)	.299 (0.80)	.186 (1.86)
Emotional Stability	-.005 (-0.06)	-.036 (-0.39)	-.300*** (-3.63)	-.253*** (-2.88)	-.292*** (-3.26)	-.265*** (-3.12)	-.234*** (-3.10)	-.394*** (-5.01)	-.134 (-1.43)	-.162 (-1.76)	-.387*** (-4.12)	.038 (0.40)	-.038 (-0.37)	-.246*** (-2.90)
Openness	.195 (1.88)	.358*** (3.37)	.057 (0.61)	.136 (1.35)	.372*** (3.64)	.254** (2.62)	.161*** (6.26)	.275*** (3.06)	.331*** (3.07)	.388*** (3.71)	.262* (2.44)	.403*** (3.73)	.340*** (2.81)	.155 (1.60)
	N 359 Prob>F 0.000 R2= 24.52	N 367 Prob>F0.000 R2 = 8.75	N 362 Prob>F0.000 R2= 27.80	N 363 Prob>F0.000 R2= 18.77	N 365 Prob>F0.000 R2= 28.00	N 365 Prob>F 0.000 R2= 34.38	N 363 Prob>F 0.000 R2= 35.45	N 365 Prob>F 0.000 R2= 34.54	N 364 Prob>F0.000 R2= 17.95	N 366 Prob>F0.000 R2= 29.76	N 364 Prob>F0.000 R2= 24.55	N 362 Prob>F 0.024 R2= 07.66	N 361 Prob>F 0.000 R2= 21.73	N 366 Prob>F 0.000 R2= 38.83

*, **, *** represent statistical sig. at 10, 5 and 1% respectively

Table 2: Coping Responses descriptive statistics Wilks' Lambda (Time)

	June N	Sept N	June Mean	Sept Mean	June SD	Sept SD	Min	Max	Wilks' Lambda	Sig.
Self-Distractio	186	186	2.45	2.38	.896	.888	1	4	.999	.630
Active Coping	188	188	2.56	2.49	.867	0.892	1	4	.997	.449
Denial	188	188	1.75	1.73	.881	.900	1	4	.999	.744
Substance Use	188	188	1.60	1.56	.897	.850	1	4	1.000	.874
Emotional Support	186	186	2.14	2.13	.893	.920	1	4	1.000	.867
Instrumental Support	187	187	1.97	2.01	.901	.935	1	4	.997	.444
Behavioural Disengagement	190	190	2.31	2.24	.845	.834	1	4	.998	.498
Venting	189	189	2.06	2.12	.862	.852	1	4	.994	.309
Positive Reframing	189	189	2.68	2.53	.879	.922	1	4	.989	.156
Planning	189	189	2.50	2.44	.950	.944	1	4	.998	.528
Humour	187	187	1.90	1.93	.921	.955	1	4	.997	.479
Acceptance	188	188	2.96	2.94	.852	.915	1	4	.998	.551
Religion	187	187	1.98	1.93	1.06	1.00	1	4	1.000	.928
Self-Blame	189	189	1.91	1.908	.942	.939	1	4	.997	.491
Risk Willingness	198	198	47.23	46.91	23.54	24.67	0	100	1.000	.787
General Health	197	197	66.30	64.91	21.36	23.21	1	100	.998	.503
Mental Health	194	194	65.31	63.93	24.90	25.72	0	100	.997	.451
Life Satisfaction	198	198	66.99	63.75	20.62	22.45	1	98	.987	.116
Openness	197	197	4.37	4.48	.966	.949	1	4	.992	.198
Conscientiousness	196	196	4.02	5.37	.615	1.01	1	4	.441	.000
Extroversion	194	194	4.16	4.16	.801	.899	1	4	1.000	.908
Agreeableness	196	196	4.67	5.59	.528	.940	1	4	.569	.000
Emotional Stability	191	191	4.80	4.81	1.15	1.17	1	4	1.000	.856

Table 3: Coping responses descriptive statistics Wilks' Lambda (time and age interaction)

	June N	Sept N	June 18-40 Mean	SD	June 41-70 Mean	SD	Sept 18-40 Mean	SD	Sept 41-70 Mean	SD	Min	Max	Wilks' Lambda	Sig.
Self-Distraction	186	186	2.46	.920	2.44	.877	2.52	.816	2.28	9.29	1	4	.993	.250
Active Coping	188	188	2.65	.959	2.49	.789	2.63	.892	2.39	.883	1	4	.999	.647
Denial	188	188	1.67	.837	1.80	.911	2.00	.911	1.55	.848	1	4	.951	.002
Substance Use	188	188	1.45	.861	1.70	.912	1.80	.946	1.39	.730	1	4	.935	.000
Emotional Support	197	196	2.17	.846	2.12	.893	2.35	.927	1.96	.884	1	4	.982	.069
Instrumental Support	187	187	1.97	.885	1.96	.917	2.25	.920	1.83	.910	1	4	.975	.032
Behavioural Disengagement	190	190	2.35	.880	2.28	.822	2.35	.904	2.15	.780	1	4	.997	.453
Venting	189	189	1.98	.860	2.12	.863	2.29	.870	1.99	.820	1	4	.968	.013
Positive Reframing	189	189	2.68	.883	2.68	.881	2.62	.866	2.47	.960	1	4	.997	.447
Planning	189	189	2.51	.972	2.50	.937	2.49	.887	2.40	.987	1	4	.999	.711
Humour	187	187	1.89	.904	1.90	.937	2.17	.964	1.75	.913	1	4	.973	.026
Acceptance	188	188	3.045	.838	2.91	.861	2.80	.954	3.04	.876	1	4	.979	.046
Religion	187	187	1.87	1.07	2.06	1.05	2.16	1.03	1.75	.958	1	4	.958	.042
Self-Blame	189	189	1.75	.915	2.01	.950	2.20	.935	1.69	.885	1	4	.914	.000
Risk Willingness	198	198	44.19	25.06	49.46	22.19	51.27	23.54	43.71	25.15	0	100	.966	.010
General Health	197	197	64.31	24.98	67.75	18.21	64.00	21.58	65.07	24.41	1	100	.999	.596
Mental Health	194	194	65.29	24.51	65.33	25.30	60.20	24.62	66.72	26.28	0	100	.991	.188
Life Satisfaction	198	198	65.50	22.76	68.09	18.92	61.13	23.48	65.68	21.56	1	98	.999	.647
Openness	197	197	4.05	.819	4.25	.778	3.56	1.91	3.24	1.93	1	4	.984	.082
Conscientiousness	196	196	4.31	1.09	4.41	.858	4.53	.913	4.45	.977	1	4	.996	.382
Extroversion	194	194	4.05	.819	4.25	.778	4.14	.918	4.17	.889	1	4	.994	.290
Agreeableness	196	196	3.95	.594	4.06	.628	5.14	1.14	5.53	.878	1	4	.985	.092
Emotional Stability	191	191	4.68	.475	4.67	.565	5.48	.912	5.67	.955	1	4	.990	.166

Table 4: Pairwise correlation between ages over time
(18 – 40 years old as reference group)

	Mean Diff. T1	Sig.	Mean Diff. T2	Sig.
Self-Distraction	-.018	.892	-.236	.074
Active Coping	-.161	.210	-.238	.071
Denial	-.130	.322	-.450	.001
Substance Use	-.252	.057	-.406	.001
Emotional Support	-.051	.133	-.387	.004
Instrumental Support	-.008	.954	-.414	.003
Behavioural Disengagement	-.068	.585	-.197	.110
Venting	.136	.284	-.298	.017
Positive Reframing	-.004	.975	-.148	.277
Planning	-.019	.894	-.090	.519
Humour	.015	.913	-.418	.003
Acceptance	-.131	.299	.244	.135
Religion	.196	.213	-.405	.006
Self-Blame	.259	.138	-.513	.001
Risk Willingness	5.27	.119	-7.56	.033
General Health	3.43	.266	1.07	.750
Mental Health	.044	.990	6.51	.081
Life Satisfaction	2.58	.384	4.55	.159
Openness	.098	.485	-.076	.580
Conscientiousness	.108	.225	.395	.007
Extroversion	.202	.084	.024	.855
Agreeableness	-.013	.861	.193	.157
Emotional Stability	0.14	.935	.384	.026

Results

Predictors of coping

Limited sociodemographic independent variables of interest were statistically significant factors across the 14 coping responses. Those who were married (compared to single women) were less likely to employ denial as a coping response ($B=-.657, p<.005$), women with higher levels of education and those with children (as opposed to without) were more likely to use religion as a coping response ($B=.252, p<.05$). And those with higher self-assessed Covid-19 knowledge were less likely to use humour to deal with their situation ($B=.015, p<.05$). Overwhelmingly younger participants showed a greater likelihood of engaging in a (avoidance or approach) response.

Interestingly women’s income and self-rated general health showed no relationship with any of the fourteen strategies in the BriefCope scale. While the two factors are unrelated

for the purpose of the study higher income certainly provides greater opportunity for access to health and related socio-economic services during the pandemic. Further, it would be reasonable to assume that during such a health crisis, there would be some correlation between an individual's self-reported health and the strategies they employed to psychologically cope with a nationwide health shock the level of the current pandemic, and yet there is not.

We also see that those who report a higher life satisfaction are more likely to report an instrumental support strategy ($B = .014, p < 0.10$), and less like to employ a self-blame strategy ($B = .019, p < 0.05$). Further, women with higher (more positive) self-rated mental health scores are less likely to employ self-distraction ($B = -.012, p < 0.05$), instrumental support ($B = -.015, p < 0.05$), behavioural disengagement ($B = -.019, p < 0.05$), venting ($B = -.015, p < 0.05$), planning ($B = -.017, p < 0.05$) or self-blame strategies ($B = -.016, p < 0.05$).

Our personality trait analysis centres primarily on the statistically significant results for respondent's emotional stability and openness. Women in our sample who are higher in emotional stability are less likely to engage in avoidant strategies such as denial ($B = -.300, p < 0.05$), substance abuse ($B = -.253, p < 0.05$), behavioural disengagement ($B = -.234, p < 0.05$), venting ($B = -.394, p < 0.05$), or self-blame ($B = -.246, p < 0.05$). Interestingly they are also less likely to engage in approach strategies, such as emotional support ($B = -.292, p < 0.05$), instrumental support ($B = -.265, p < 0.05$), and humour ($B = -.387, p < 0.05$). Finally, women in our sample higher in openness are more likely to engage in 10 of the 14 coping strategy styles, with the exceptions being the four avoidant strategies of self-distraction, denial, substance abuse, and self-blame.

Coping response change over time

Using the Wilks' Lambda (λ) as an omnibus to test the main effect of time revealed a statistically significant change for two personality dimensions, those being, agreeableness $\lambda =$

0.569, $F(1, 194) = 146.824$, $p < .000$; and conscientiousness $\lambda = 0.441$, $F(1, 194) = 245.741$, $p < .000$. But no statistically significant coping responses (Table 2).

The time and age interactions show statistically significant effects for avoidant responses: Denial, $\lambda = 0.951$, $F(1, 186) = 9.510$, $p < .005$. Venting, $\lambda = 0.968$, $F(1, 187) = 6.224$, $p < .020$; Self-Blame, $\lambda = 0.914$, $F(1, 187) = 17.669$, $p < .001$. And approach coping responses: instrumental Support, $\lambda = 0.975$, $F(1, 185) = 4.663$, $p < .050$; acceptance, $\lambda = 0.979$, $F(1, 186) = 4.032$, $p < .050$. There is also a change in use of religion, $\lambda = 0.958$, $F(1, 185) = 8.092$, $p < .010$ and, humour, $\lambda = 0.973$, $F(1, 185) = 5.039$, $p < .050$. Finally, we find a statistically significant age and time interaction for willingness to take risks, $\lambda = .966$, $F(1, 196) = 6.816$, $p < .010$ (table 3).

Based on these findings subsequent pairwise comparisons were used to assess direction of the interaction effect (Table 4). The pairwise comparisons show that a range of coping mechanisms become more apparent for the younger cohort as time passes. The findings show no changes between ages in the first data capture (T1), however, across the two time periods, we see the younger cohort report an increase of using coping responses. The analysis highlights increased use of avoidant responses: denial, mean difference of 0.450, $p = 0.001$; substance use, mean difference of 0.406, $p = .001$; venting, mean difference 0.418, $p = .017$ and, self-blame, mean difference of 0.513, $p = .001$. Interestingly, the younger cohort also increased use in approach coping responses, emotional support mean difference 0.387, $p = 0.004$ and, instrumental support mean difference .414, $p = 0.003$. Finally, the findings show the younger cohort's propensity for risk willingness increased .756, $p = 0.033$. And, in self-report of personality dimension conscientiousness, mean difference -.395, $p = .007$ and emotional stability mean difference -.384, $p = .026$ (table 4) played a greater role for the older cohort across time periods.

Discussion

Our key finding that younger women (compared to older women) are more likely to enact a coping strategy – be it positive or negative – and that across time are more likely to specifically engage in avoidant (denial, substance use, venting and self-blame) and approach (emotional and instrumental support) strategies speaks to the current Covid-19’s psychological impact disproportionately affecting younger women relative to the rest of the Australian population.

Such findings, namely the variance in choice to engage a coping strategy as a function of age, may in some part be due to the significant and pronounced diversity of issues faced by younger Australian women, particularly across their 30’s (Lucke & Johnstone, 2020). Our sample population aligns with the general view of women with multiple roles, for example, increased financial commitments, child rearing, marital & inter-personal conflict, parental care needs, labour & education commitments, disproportionate household labour toil, etc. Further, women (particularly younger adults) often dominate employment in frontline ‘essential services’ such as nursing, teaching and hospitality labour roles (Workplace Gender Equality Agency, 2020) which then translate to higher potential risk in relation to both transmission and the psychological stressors that is the current pandemic. Based on such, it may be that for younger women, the uncontrollable stochastic shock of Covid-19 has resulted in a disproportionate use of avoidant responses. This may be because uncontrollable situations are more associated with emotional, avoidant strategies (Troy, Shallcross and Mauss, 2013). Emotion focused, avoidant strategies consist of an individual focusing their stress on the feelings caused by the stressful situation (Afshar et al., 2015). That said, our findings also indicate younger women in our cohort seeking to adapt and cope in a practical and communal way, through increased engagement in emotional and instrumental support. Such coping responses rely on an individual’s inter and intra personal resources and abilities – emotional

intelligence and social support – to buffer or navigate them through a period of uncertainty (Zysberg & Zisberg, 2020). Further highlighting the importance of the association between social support and connectedness for women’s management of stress, resilience and overall wellbeing.

Cautiously it is important not to overstate key age difference findings for the cohort engaged in our current study. Successfully mitigating stressful environments and events is certainly in some part a learned behaviour, a skill that develops with age. Research has shown that older adults (who may have experience dealing with previous encounters of infectious disease or particular personal health issues were found to be able to evaluate the current pandemic as more controllable) relative to younger cohorts (Chew et al. 2020). This is because older adults generally have “superior” coping strategies to regulate emotion (Charles, 2010). Even when using emotional strategies, they favour those low in negative responses like anger and instead are more adaptive to the environment (Yeung and Fung, 2007; Meléndez, Satorres and Delhom, 2020).

Whilst our study does not specifically find a link between wellbeing and knowledge (Wanberg, Csillag, Douglass, Zhou and Pollard, 2020; Wang et al. 2020), our analysis did show a relationship between low knowledge and humour as a coping response, and that for the younger cohort the use of humour remains an important component in their coping. This may raise wider concerns, in the context that younger women are reporting a preference towards avoidance strategies. When humour is served negatively, such as self-defeating or as aggressive behaviours, negative social implications may result particularly societal costs associated with risky behaviours (Kennison & Messer, 2018). Thus, our study’s findings relating to increased risk willingness in our younger cohort and across time (in the context of the current pandemic) prompts further investigation.

Our findings that key socio-economic factors such as level of education, income, marital status and general health showed little to no association with women's reporting to engage a coping response may suggest that biological factors such as age and personality play far greater roles in women's assessments of stress and the decision to employ or not employ a coping response. Our analysis shows components of a positive change in personality in the dimensions: conscientiousness and emotional stability. Literature reports that longstanding change continuity generally occurs over years rather than months, so our findings most likely reflect beginnings of change, or a temporary state (Roberts et al., 2017). However, it maybe that these changes indicate the beginnings of one's adaptive coping, as personality traits can condition coping responses to manifest a strategies to stress (Meléndez et al., 2020). Regardless of cause in the context of this study, these proximate changes to conscientiousness and emotional stability have been found to be linked to increased self and social responsibility (Sutin et al., 2020). They are important signals of change in an individual's intrapersonal perspective because conscientiousness and emotionally stable people are more aware of cushioning themselves from perceived stressful situations and avoiding impulse reactions (Weller et al., 2018). This is because both of these traits involve practical qualities related to planning and persistence (Caspi et al., 2005).

The current behavioural study is not without limitations. Firstly, the age range of our sample population is not normally distributed, rather it is bimodal, with a stronger representation by older Australian women. This naturally provides an over-representation above the mean & median Australian women's age. Secondly, all measures were self-evaluated & submitted online, and thus may not have been uniform in setting collection for all participants. Unfortunately, due to the ongoing community Covid-19 restrictions across June to September 2020, online survey was the only practical method of data collection approved by university ethics protocols.

As Covid-19 continues to re-appear in domestic populations even where it is thought to have been eradicated, future research would do well to further assess commonalities in socio-demographic and or personality traits associated with both approach and avoidant coping choices to form greater empirical understanding of at-risk individuals. Further, the current study collates no data on the transmission of Covid-19 related information (news, social media, health care providers, etc) across the pandemic and how this may exacerbate stress and coping behaviours. Future research would do well to incorporate some measure of level and frequency of pandemic related information across time, and its relationship with coping decisions.

Conclusion

This study contributes to the emerging literature studying approach and avoidant responses during the current Covid-19 pandemic (Volk et al, 2020) using a large sample of Australian women across time. Our research identifies certain approach and avoidant responses and acknowledges the behavioural and cognitive trends of Australian women during this pandemic. Our findings that younger Australian women are so far more likely to enact a coping strategy that is avoidant, compared to older women even across time, warrants further research not just into the strategies that they employ, but also the drivers of such a generational difference.

References

- Australian Bureau of Statistics (1), (2021, Feb 3) Household Impacts of COVID-19 Survey, November 2020. Retrieved from: <https://www.abs.gov.au/statistics/people/people-and-communities/household-impacts-covid-19-survey/latest-release#data-download>
- Almlund, M., Duckworth, A. L., Heckman, J., & Kautz, T. (2011). Personality psychology and economics. In *Handbook of the Economics of Education* (Vol. 4, pp. 1-181). Elsevier.
- Barber, S.J., & Hyunji, K., (2020). Covid-19 Worries and Behavior Changes in Older and Younger Men and Women. The Gerontological Society of America,
- Baumann, N., Kaschel, R., & Kuhl, J. (2005). Striving for unwanted goals: Stress-dependent discrepancies between explicit and implicit achievement motives reduce subjective well-being and increase psychosomatic symptoms. *Journal of Personality and Social Psychology*, 89(5), 781–799.
- BehaviourWorks Australia, (2020). *Survey of COVID-19 Responses to Understand Behaviour*, Monash University. Retrieved from: <https://www.behaviourworksaustralia.org/survey-of-covid-19-responses-to-understand-behaviour-scrub-project/> Last accessed on 2 Feb, 2021
- Biddle, N., Edwards, B., Gray, M., & Sollis, K. (2020). Hardship, distress, and resilience: The initial impacts of COVID-19 in Australia. ANU Centre for Social Research and Methods, 33(April), 1–43. doi.org/10.26193/HLMZNW
- Bolger, N. (1990). Coping as a personality process: A prospective study. *Journal of personality and social psychology*, 59(3), 525.
- Booth-Butterfield, M. and Wanzer, M. (2017). Humour, Stress and Coping, in Robert, C. (2017). *The Psychology of Humor at Work: A Psychological Perspective*
- Burki, T. (2020). The indirect impact of COVID-19 on women. *The Lancet. Infectious Diseases*, 20(8), 904–905. [https://doi.org/10.1016/S1473-3099\(20\)30568-5](https://doi.org/10.1016/S1473-3099(20)30568-5).
- Carver, C. S., & Connor-Smith, J. (2010). Personality and Coping. *Annual Review of Psychology*, 61(1), 679–704.
- Carver, C. S., & Scheier, M. F. (1994). Situational coping and coping dispositions in a stressful transaction. *Journal of Personality and Social Psychology*, 66(1), 184–195. <https://doi.org/10.1037/0022-3514.66.1.184>
- Chan, H. F., Moon, J. W., Savage, D. A., Skali, A., Torgler, B., & Whyte, S. (2020). Can psychological traits explain mobility behavior during the COVID-19 pandemic? *Social Psychological & Personality Science*.
- Chew, Q. H., Wei, K. C., Vasoo, S., Chua, H. C., & Sim, K. (2020). Narrative synthesis of psychological and coping responses towards emerging infectious disease outbreaks in the general population: practical considerations for the COVID-19 pandemic. *Tropical Journal of Pharmaceutical Research*, 61(7).

- Connor-Smith, J. K., & Flachsbart, C. (2007). Relations between personality and coping: a meta-analysis. *Journal of personality and social psychology*, 93(6), 1080.
- Gausman, J. & Langer, A., (2020). Sex and Gender Disparities in COVID-19 Pandemic. *Journal of Women's Health*, 29(4), 465-466.
- Gillett, J. E., & Crisp, D. A. (2017). Examining coping style and the relationship between stress and subjective well-being in Australia's 'sandwich generation.' *Australasian Journal on Ageing*, 36(3), 222–227.
- Goubet, K. E., & Chryssikou, E. G. (2019). Emotion Regulation Flexibility: Gender Differences in Context Sensitivity and Repertoire. *Frontiers in psychology*, 10, 935. <https://doi.org/10.3389/fpsyg.2019.00935>
- Gurvich, C., Thomas, N., Thomas, E. H., Hudaib, A. R., Sood, L., Fabiatis, K., ... & Kulkarni, J. (2020). Coping styles and mental health in response to societal changes during the COVID-19 pandemic. *International Journal of Social Psychiatry*, 0020764020961790.
- Hirani, S., Lasiuk, G., & Hedadoren, K. (2016). The intersection of gender and resilience. *Journal of Psychiatric and Mental Health Nursing*, 23, 455–467. [doi.org/doi/epdf/10.1111/jpm.12313](https://doi.org/10.1111/jpm.12313)
- Hobfoll, S.E., Dunahoo, C.L., Ben-Porath, Y. *et al.* (1994). Gender and coping: The dual-axis model of coping. *Am J Commun Psychol* 22, 49–82. doi.org/10.1007/BF02506817
- Jang, K. L., Livesley, W. J., & Vernon, P. A. (1996). Heritability of the big five personality dimensions and their facets: a twin study. *Journal of personality*, 64(3), 577-592.
- Jang, K. L., Thordarson, D. S., Stein, M. B., Cohan, S. L., & Taylor, S. (2007). Coping styles and personality: a biometric analysis. *Anxiety, Stress, & Coping*, 20(1), 17-24.
- Kahneman, D., & Krueger, A. B. (2010). Developments in the Measurement of Subjective Well-Being, *Journal of Economic Perspectives*, 20(1), 3-24. [doi/pdfplus/10.1257/089533006776526030](https://doi.org/10.1257/089533006776526030)
- Kelly, M. M., Tyrka, A. R., Price, L. P., & Carpenter, L. L. (2008). Sex Differences in the Use of Coping Strategies : *Depression Anxiety*, 25(10), 839–846
- Kennison, S. M., & Messer, R. H. (2019). Humor as social risk-taking: The relationships among humor styles, sensation-seeking, and use of curse words. *Humor*, 32(1), 1–21. doi.org/10.1515/humor-2017-0032
- Krentz, M., Kos, E., Green, A. & Garcia-Alonso, J. (2020). Easing the COVID-19 Burden on Working Parents, Boston Consulting Group. Retrieved from: <https://www.bcg.com/en-gb/publications/2020/helping-working-parents-ease-the-burden-of-covid-19>. Last accessed on: 2 Feb, 2021.
- Lazarus, R.S. & Folkman, S. (1984). *Stress, Appraisal, and Coping*, Springer Publishing Company, New York, NY.
- Leipold, B., & Greve, W. (2009). A conceptual bridge between coping and development. *European Psychologist*, 14(1), 40–50. <https://doi.org/10.1027/1016-9040.14.1.40>

- López, L., & Rodó, X. (2020). The end of social confinement and COVID-19 re-emergence risk. *Nature Human Behaviour*, 4(7), 746–755. <https://doi.org/10.1038/s41562-020-0908-8>
- Lucke, J., & Johnstone, M. (2020). “It’s Been a Bit of a Rollercoaster”: Australian Women’s Difficulties and Coping Strategies. *Issues in Mental Health Nursing*, 1-11.
- Matud, M. P. (2004). Gender differences in stress and coping styles. *Personality and Individual Differences*, 37(7), 1401–1415. <https://doi.org/10.1016/j.paid.2004.01.010>
- McLaren, H. J., Wong, K. R., Nguyen, K. N., & Mahamadachchi, K. N. D. (2020). Covid-19 and women’s triple burden: Vignettes from Sri Lanka, Malaysia, Vietnam and Australia. *Social Sciences*, 9(5). doi.org/10.3390/SOCSCI9050087
- Madgavka, A., White, O., Krishnan, M., Mahajan, D. & Azcue, X., (2020). What is good for gender equality is good for the economy and society as well. The COVID 19 pandemic puts that truth into stark relief and raises critically important choices. 1–19.
Retrieved from: <https://www.mckinsey.com/featured-insights/future-of-work/covid-19-and-gender-equality-countering-the-regressive-effects>
- Mahmoud, J. S. R., Staten, R. T., Hall, L. A., & Lennie, T. A. (2012). The relationship among young adult college students’ depression, anxiety, stress, demographics, life satisfaction, and coping styles. *Issues in mental health nursing*, 33(3), 149-156.
- McBride, H., & Ireland, C. (2016). The impact of coping style, self-efficacy, emotional reaction and resilience on trauma related intrusive thoughts. *Journal of Forensic Practice*, 18(3), 229–239.
- McCrae, R. R., & Costa Jr, P. T. (1986). Personality, coping, and coping effectiveness in an adult sample. *Journal of personality*, 54(2), 385-404.
- Meléndez, J. C., Satorres, E., & Delhom, I. (2020). Personality and coping. What traits predict adaptive strategies? *Anales de Psicología*, 36(1), 39–45.
<https://doi.org/10.6018/analesps.349591>
- Miller, C. C. (2020). Nearly Half of Men Say They Do Most of the Home Schooling . 3 Percent of Women Agree . *New York Times*, 1–12.
<https://www.nytimes.com/2020/05/06/upshot/pandemic-chores-homeschooling-gender.html>
- Meyer, B. (2001). Coping with severe mental illness: Relations of the brief COPE with symptoms, functioning, and well-being. *Journal of Psychopathology and Behavioral Assessment*, 23(4), 265–277. <https://doi.org/10.1023/A:1012731520781>
- Ortiz-Ospina, E., & Roser, M. (2019). Happiness and Life Satisfaction - Our World in Data. *OurWorldInData.Org*. Retrieved from <https://ourworldindatahttps://ourworldindata.org/happiness-and-life-satisfaction>
- Pearlin, L. I., & Schooler, C. (1978). The structure of coping. *Journal of Health and Social Behavior*, 19(1), 2–21. <https://doi.org/10.2307/2136319>

- Porcelli, A. J., & Delgado, M. R. (2017). Stress and decision making: effects on valuation, learning, and risk-taking. *Current Opinion in Behavioral Sciences*, 14, 33–39. <https://doi.org/10.1016/j.cobeha.2016.11.015>
- Prentice, C., Zeidan, S., & Wang, X. (2020). Personality, trait EI and coping with COVID 19 measures. *International Journal of Disaster Risk Reduction*, 51(August), 101789. <https://doi.org/10.1016/j.ijdrr.2020.101789>
- Rafnsson, F. D., Jonsson, F. H., & Windle, M. (2006). Coping strategies, stressful life events, problem behaviors, and depressed affect. *Anxiety, Stress and Coping*, 19(3), 241–257. <https://doi.org/10.1080/10615800600679111>
- Rodriguez, L. M., Litt, D. M., & Stewart, S. H. (2020). Drinking to Cope with the Pandemic: The Unique Associations of COVID-19-Related Perceived Threat and Psychological Distress to Drinking Behaviors in American Men and Women. *Addictive Behaviors*, 110(June), 106532.
- Roberts, B. W., Luo, J., Briley, D. A., Chow, P. I., Su, R., & Hill, P. L. (2017). A Systematic Review of Personality Trait Change. *Psychological Bulletin*, 143(2), 117–141. <http://dx.doi.org/10.1037/bul0000088>
- Roser, M., Ritchie, H., Ortiz-Ospina, E., & Hasell, J. (2020). Coronavirus Pandemic (COVID-19) - Statistics and Research - Our World in Data. *Our World in Data*. Retrieved from <https://ourworldindata.org/coronavirus>
- Roth, S., & Cohen, L. J. (1986). Approach, Avoidance, and Coping With Stress. *American Psychologist*, 41(7), 813–819. <https://doi.org/10.1037/0003-066X.41.7.813>
- Saucier, G. (1994). Mini-Markers: A brief version of Goldberg's unipolar Big-Five markers. *Journal of personality assessment*, 63(3), 506-516.
- Seegerstrom, S. C., & Smith, G. T. (2019). Personality and coping: Individual differences in responses to emotion. *Annual review of psychology*, 70, 651-671.
- Skinner, E. A., Edge, K., Altman, J., & Sherwood, H. (2003). Searching for the Structure of Coping: A Review and Critique of Category Systems for Classifying Ways of Coping. *Psychological Bulletin*, 129(2), 216–269.
- Specht, J., Egloff, B., & Schmukle, S. C. (2011). Stability and Change of Personality Across the Life Course: The Impact of Age and Major Life Events on Mean-Level and Rank-Order Stability of the Big Five. *Journal of Personality and Social Psychology*, 101(4), 862–882. <https://doi.org/10.1037/a0024950>
- Sutin, A. R., Luchetti, M., Aschwanden, D., Lee, J. H., Sesker, A. A., Strickhouser, J. E., Stephan, Y., & Terracciano, A. (2020). Change in five-factor model personality traits during the acute phase of the coronavirus pandemic. *PLoS ONE*, 15(8 August), 1–13. <https://doi.org/10.1371/journal.pone.0237056>
- Trivers, R. (1972). Parental investment and sexual selection. *Sexual Selection & the Descent of Man, Aldine de Gruyter, New York*, 136-179.

- United Nations Conference on Trade Development (UNCTAD). (2020). Impact of the COVID-19 pandemic on trade and development. United Nations, 1–112. Retrieved from: <https://unctad.org/webflyer/impact-covid-19-pandemic-trade-and-development-transitioning-new-normal>. Last accessed 2 Feb, 2021.
- Volk, A. A., Brazil, K. J., Franklin-Luther, P., Dane, A. V., & Vaillancourt, T. (2021). The influence of demographics and personality on COVID-19 coping in young adults. *Personality and Individual Differences*, 168(September 2020), 110398. <https://doi.org/10.1016/j.paid.2020.110398>
- Whyte, S., Brooks, R. C., & Torgler, B. (2018). Man, woman, “other”: Factors associated with nonbinary gender identification. *Archives of sexual behavior*, 47(8), 2397-2406.
- Whyte, S., Chan, H. F., & Torgler, B. (2018). Do men and women know what they want? Sex differences in online daters’ educational preferences. *Psychological science*, 29(8), 1370-1375.
- Whyte, S., & Torgler, B. (2020). Evolutionary Psychology and Reproduction. *The Sage Handbook of Evolutionary Psychology: Applications of Evolutionary Psychology*, 477.
- Workplace Gender Equality Agency, (2020). Gendered impact of COVID-19, retrieved from: <https://www.wgea.gov.au/topics/gendered-impact-of-covid-19>
- The World Bank. (2020). Global Action Urgently Needed to Halt Historic Threats to Poverty Reduction. Retrieved from: <https://www.worldbank.org/en/news/feature/2020/10/07/global-action-urgently-needed-to-halt-historic-threats-to-poverty-reduction>. Last accessed on 2 Feb, 2021.
- Yeung, D. Y. L., & Fung, H. H. (2007). Age differences in coping and emotional responses toward SARS: A longitudinal study of Hong Kong Chinese. *Aging and Mental Health*, 11(5), 579-587.
- Zysberg, L., & Zisberg, A. (2020). Days of worry: Emotional intelligence and social support mediate worry in the COVID-19 pandemic. *Journal of Health Psychology*. <https://doi.org/10.1177/1359105320949935>

Thinning out spectators: Did football matches contribute to the second COVID-19 wave in Germany?¹

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This paper provides an ex-post analysis of football matches' contribution to the spread of COVID-19 during Germany's second infection wave in summer and autumn 2020. We find slightly positive effects from occurring professional football matches on newly registered cases of the virus in the respective counties. An upper boundary gives us that an additional match in a county on average raises the number of daily registered cases by up to between 0.52 and 0.91 cases per 100,000 inhabitants after three weeks. Hence, this on average implies an increase in the seven-day incidence per 100,000 inhabitants by up to between 3.6 and 6.4. We do not find qualitatively different results in a subsample of German top league matches which were associated to have the strictest hygiene regulations. Most importantly, the found effect is mediated by the incidence level at the day of the match with very few infections for matches at a seven-day incidence below 25. As an underlying mechanism, we identify increases in the local mobility. Further, infections are not explicitly driven by higher occupancy levels. We finally show that the ban of away fans successfully restricts the spread of COVID-19 beyond county borders and also find indication for a reduced effect from football matches in the presence of the 'lockdown light' which Germany launched in early November.

1 I am thankful for very helpful comments by Andreas Lichter, Benedikt Schmal and Simon Schulten. All remaining errors are my own.

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1 Introduction

Since early 2020, countries all over the world fight COVID-19 and its impact on their economy and public health. Even with vaccines as glimmer of hope, the pandemic's end remains uncertain. Hence, a persistent concern of businesses and policy makers is to find ways to adapt to the new circumstances and to reorganize public life. One of which could be to restart and allow events and activities in public but under additional, preemptive measures in place (McCloskey et al., 2020; Memish et al., 2020; Nunan and Brassey, 2020; Parnell et al., 2020), for example stricter hygiene regulations. Up to now, there unfortunately is only little evidence on the functioning and the limitations of such tools in most economic sectors. In particular, there is a lack of analyses on the importance of the prevailing infection level or the number of participants. This paper contributes to partly closing this gap for mass gatherings in evaluating German football matches in summer and autumn 2020 which took place in front of a thinned-out audience. The German top division, the Bundesliga, for example is renowned for typically being the football league with the highest average attendance worldwide with on average more than 40,000 fans per match. In the running 2020/2021 season, attendance has been limited so that the average number of fans in the stadium has been approximately 4,800 fans per match when fans were allowed.

Football is known for its enthusiastic supporters, packed stadiums and loud fan chants - factors which potentially boost the spread of COVID-19. While the transmission could be mitigated by the fact that matches are open-air, there nevertheless is robust evidence on football matches and similar sports events to have accelerated the first wave in early 2020 (Ahammer et al., 2020; Olczak et al., 2020; Wing et al., 2020). Still, to our knowledge, there is no analysis on the reopening of stadiums under stricter conditions such as a prohibition of alcohol, lower occupancy levels, no away team fans or partially no fan chants. This missing knowledge may also be a reason why stadium reopenings have been handled very differently across the European top leagues. While Spain does not allow any fans into the top leagues' stadiums, Italy allowed up to 1,000 spectators. France reopened its stadiums for up to more than 5,000 visitors at the beginning of the 2020/2021 season. England started the reopening of stadiums for up to 4,000 fans in early December 2020 but reclosed stadiums in response to the detection of a virus mutation.¹ In Germany, counties, starting in early August 2020, individually and independently reallocated spectators to attend matches. The federal government later on September 15, 2020, set a general rule for sports events to allow an occupancy of up to 20% or at least 1,000 spectators. These reopenings were bounded to harsher restrictions in the presence of higher local case numbers of more than 35 cases per seven days per 100,000 inhabitants in a county (Hartmann, 2020). Some federal states with very low case numbers even relaxed these rules, for example

¹Depending on the local incidence, the number of spectators allowed was reduced to 2,000 or zero in England.

Schleswig-Holstein allowed 25% occupancy.² With the introduction of stricter rules on the national level ('lockdown light') on November 2, 2020, in response to rapidly rising case rates from mid-October onwards, stadiums were closed again.

With regard to the sharp increase in cases in autumn 2020 and a current debate on reopening stadiums or event halls again (s., e.g., Altenburg et al. (2021)), the question whether football matches contributed to the acceleration of the second wave in Germany arises.³ To take account of the timing of matches, geographical variation, and delayed repercussions, we analyze the German matches in an event study setup as already applied in the context of COVID-19 by for example Dave et al. (2021), Dave et al. (2020b), DeFilippis et al. (2020), Gupta et al. (2020), Ispording et al. (2021), Lange and Monscheuer (2021), and Mangeum and Niekamp (2021).

We find some but - with regard to the significance of parts of our regressions - limited evidence for football matches contributing to the transmission of COVID-19 in the respective counties. This effect is especially mediated by the prevailing incidence of COVID-19 cases as we find the risk of infections for incidence levels below 25 cases per 100,000 inhabitants over seven days at the matchday to be humble. As a main mechanism, we determine that mobility increases in counties where football matches take place. We could not carve out an effect of short-term transmission to neighbouring counties or away team counties. We also show that most cases are mainly related to the age groups of 15-34 and 35-59 years with limited, short-term spillovers to the vulnerable, elderly population. Finally, we observe insignificant effects when including the time periods from the lockdown phase after early November and show that the lockdown and related behavioral changes effectively reduced transmissions in response to football matches. From these results, it seems to be likely that the applied policy, to reduce spectators in stadiums if a county's seven-day incidence exceeds 35, was at least necessary.

2 Literature

Among others, due to the high frequency of contacts, research has identified mass gatherings and highly occupied event locations as one driver of the COVID-19 crisis. While Dave et al. (2020a) do not find regional inclines in COVID-19 cases to be related to a single rally in the US election campaign⁴, Bernheim et al. (2020) provide evidence for eighteen rallies to have raised local case numbers.⁵ Similarly, Cotti et al. (2020)

²Also in Saxony and Mecklenburg-Western Pomerania, higher occupancy levels were allowed, for example at matches of the clubs Dynamo Dresden (Saxony) up to 35% and Hansa Rostock (Mecklenburg-Western Pomerania) up to 26%.

³For a detailed description of the course of the COVID-19 crises in Germany throughout 2020, see for example Lange and Monscheuer (2021).

⁴Dave et al. (2020b) also do not find the US 'Black Lives Matter' protests to increase COVID-19 case rates. They conclude that these protests decreased social distancing but simultaneously reduced mobility of non-involved people.

⁵In general, locations of higher contact frequency experience higher case numbers. Dave et al. (2021) detect a motorcycle rally with 500,000 participants to have increased local case numbers but to also have caused transmission across the country

find long queues on election day in Wisconsin's primary election to foster the positive test rate in counties with higher attendance in-person at polling locations.

For Germany, Felbermayr et al. (2020) show that tourism to and from crowded Apres-Ski parties in Ischgl, Austria, has been a main driver of COVID-19. Fetzer (2020) hints at the relevance of restaurants for the spread of COVID-19 in the UK. By making use of spatial variation in the exposure to a governmental program subsidizing restaurant meals during certain times of the week, he finds this policy to have caused eight to seventeen percent of all cases in the respective time period. This finds support in Chang et al. (2021). They argue that especially restaurants and shopping are risky locations or activities by using US cell phone mobility data.

With regard to sports events, research especially focussed on the contribution of events to the first wave in early 2020 (Ahammer et al., 2020; Olczak et al., 2020; Wing et al., 2020). These studies mainly investigate cross-sectional, time-invariant differences on the county level, only weakly control for timing issues of matches, and also cannot refer to more recently introduced hygiene and occupancy restrictions. Still, they contribute very important benchmark findings: Ahammer et al. (2020) analyze indoor events and find an additional NBA (professional basketball) or NHL (professional ice hockey) match to raise COVID-19 cases in the respective US county and its neighbouring counties by nine percent. They also estimate the effect's development over time but do not account for the specific timing of matches. Their findings are in line with Wing et al. (2020) who determine an NHL/NBA match to be related to almost 800 additional cases. They argue that college matches less strongly drive infections. Their results indicate the necessity to account for the relevance and engagement of matches and league differences. Probably, closest to our examination is Olczak et al. (2020) who analyse the impact of amateur and professional football matches especially in March 2020 in the UK. They estimate six additional cases per 100,000 inhabitants to be related to every single football match. As they mainly find an increasing number of cases as a consequence of sports events, the hope that less occupied stadiums and adapted hygiene regulations can guide a way back for supporters has to be tested carefully.

To our knowledge, there is almost no research on sports events' influence on COVID-19 in Europe's second wave and hence in the presence of social distancing measures yet. One exception is a paper by Parshakov (2021) who studies the significant effect of football matches on COVID-19 cases in Belarus. He finds an additional spectator in a football match to equal 0.15 to 0.5 additional COVID-19 cases throughout the next two months. As the matches analysed there have not experienced stricter hygiene regulations and as the analysis is based on quite vague, privately collected data from Belarus which is also aggregated on the monthly level, we again cannot draw a conclusion for matches conducted under additional rules.

due to travelling. Lange and Monscheuer (2021) show that two anti-COVID demonstrations in Germany sharply increased case rates. They underline the connection between "COVID-19 deniers" and the spread of the disease. In terms of population density, complementary results are shown in Ahammer et al. (2020), Felbermayr et al. (2020), and Wing et al. (2020).

Note that there is also research on the spread of influenza at sport events by Cardazzi et al. (2020) and Stoecker et al. (2016). The former find that influenza mortality increases in US cities where new top league teams are introduced. The authors conclude that this makes sport events a hotspot for the transmission of viruses. Similar results are presented in Stoecker et al. (2016) who present inclining influenza transmission in the presence of the Super Bowl. Finally, also note that it is likely that people's behavior has not only changed outside of the stadium, see for example Mendolia et al. (2021) for voluntary changes in mobility, but that sports spectators also adapt due to the higher exposure to risk related to the pandemic. In fact, Gitter (2017) for the H1N1 virus in Mexico and Reade and Singleton (2020) for COVID-19 in Europe show that less people voluntarily attend matches due to higher case rates. Reade et al. (2020) specifically analyse stadium demand in Belarus where football matches have been continued without any regulatory changes in response to COVID-19. They find that attendance dropped in early 2020 due to high uncertainty but recovered throughout the season.

3 Data and Empirical Strategy

To quantify potential effects of football matches on COVID-19 case rates in Germany, we construct a dataset mainly consisting of three components.

First of all, we collect data on daily COVID-19 cases on the German "Kreis" (county) level⁶ which is provided by Germany's main health monitoring institution, the Robert-Koch-Institut (RKI).⁷ This data also includes information on the age group of an infected person and whether he or she recovered, died or still is infectious. In our analysis, we primarily focus on data ranging from August 10, 2020 to November 08, 2020 which we downloaded on December 13, 2020. This time frame covers all professional football matches in the season 2020/2021 which were played in front of fans as they were banned from stadiums again from November 02, 2020, onwards due to rising COVID-19 cases.⁸ Hence, our sample across 401 counties over 91 days forms a balanced panel of 36,491 observations.

Secondly, we create a list of all ($\approx 1,200$) professional football matches which took place during this time in Germany. We include matches from the top four German men's divisions ("Bundesliga", "2. Bundesliga", "3. Liga", "Regionalligen"⁹), the women's top league ("Bundesliga"), cup matches and friendly or test matches. Moreover, there are a few matches from international competitions ("Champions League", "Eu-

⁶German counties can either be independent cities or a conglomerate of several municipalities. The mean population is about 200,000 inhabitants.

⁷<https://www.arcgis.com/home/item.html?id=f10774f1c63e40168479a1feb6c7ca74>

⁸We first abstract from using data beyond November 08, 2020, due to potentially reduced transmission related to the semi-lockdown afterwards. Still, we later on report findings on an extended time period with regard to the effectiveness of the lockdown in our robustness checks.

⁹There are five "Regionalligen" whereas there is only one "Bundesliga", "2. Bundesliga", and "3. Liga" each.

ropa League”) and from the national teams, too. To obtain precise information on the crowd’s size relative to the stadium capacity - which is likely to be a relevant measure for the spread of the virus - we collect information on attendance and capacity, as well.¹⁰ Descriptive statistics on the matches by leagues can be found in Table A1. We exploit substantial variation in the timing of the matches throughout summer and autumn 2020, as well as heterogeneity in the hygiene and spectator restrictions between counties and over time. Figures 1 and 2 present the number of matches played at a specific day and document the variation in observed attendance and occupancy across matches. Overall, we observe matches in 127 of 401 German counties. In how far treated counties differ from untreated regions will be examined later on.

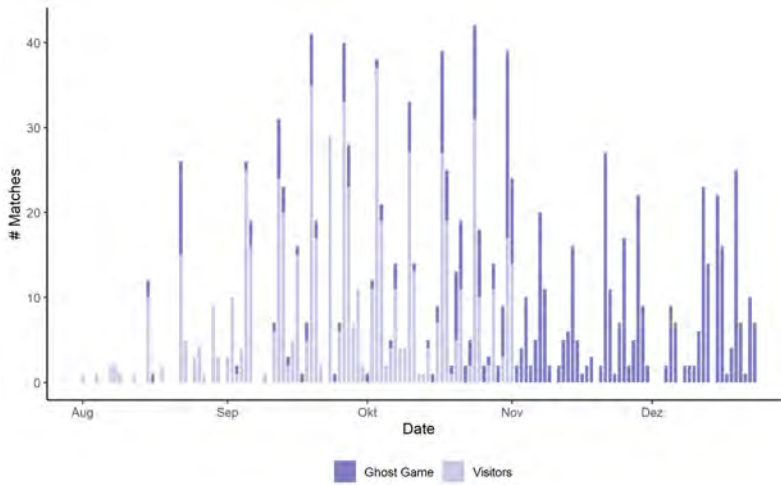


Figure 1: Played Matches With Visitors Over Time

Finally, we complement the dataset with Google Mobility Data¹¹ to track behavioral changes in the population on the state and day level which could affect case rates. Match occurrence highly varies across counties and over time. Also, several counties experience a repeated treatment (e.g., several home matches of a team). Therefore, it is important to assess the effect of a match independently and to disentangle the forces of individual matches. Moreover, the delayed effect of matches - as cases related to a match will be registered several days after the match date - demands for a fine-grained method to evaluate the role for the spread of COVID-19. To tackle these issues, we apply a two-way fixed effects model with staggered treatment - an

¹⁰Exact attendance data is extracted from kicker.de and fussball.de.

¹¹<https://www.google.com/covid19/mobility/>

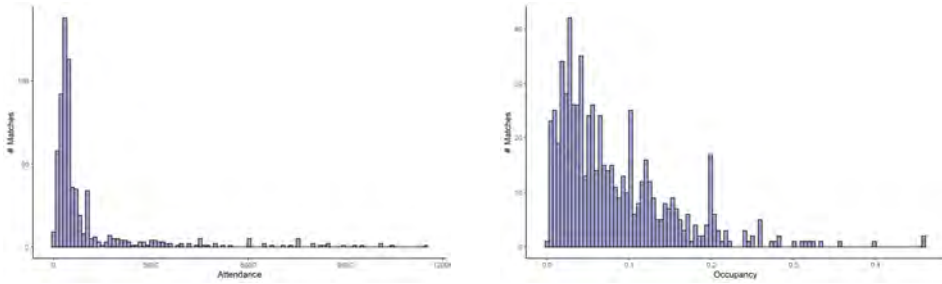


Figure 2: Visitor and Occupancy Distribution for Matches with Visitors Allowed

Note: The left plot is a histogram which mirrors the number of matches which have been played in front of a respective number of spectators (attendance). The right plot is a histogram on the number of matches which were played in the presence of specific occupancy levels. The y-axis gives the number of matches. The x-axis is a continuum of possible attendance or occupancy levels.

event study - as it especially considers the timing of matches and their effects' development over time. In doing so, we use the following approach as baseline:

$$COVID_{it} = \sum_{d=-15, d \neq 0}^{22} \beta_d Match_{it-d} + X'_{st} \zeta + \theta_i + \lambda_t + \eta_{sw} + \epsilon_{it} \tag{1}$$

where $COVID_{it}$ is a measure of COVID-19 transmission in county i at time t . We mainly refer to the daily number of newly registered cases per 100,000 inhabitants here as there has been little variation in the number of deaths in Germany throughout the summer months until late October (s. Figure A3).¹² $Match_{it}$ is an indicator for county i 's exposure to football matches - which can be the number of matches per 100,000 inhabitants or the number of visitors/spectators per 100,000 inhabitants - on day t . Hence, we control for the relative impact with respect to the population size of counties. d gives the number of lags and leads of the treatment in days in the effect window. Therefore, we do not exploit a dichotomous event dummy here. Note that both treatment indicators named contain different factors. While the match variable does not account for the exact number of fans in the stadium, it also considers effects outside of the stadium such as private gatherings or infections on the way to the match (e.g., public transportation). The number of visitors on the other hand gives a better impression of the relevance of the actual number of people in the stadiums. As an effect window, we observe the two weeks before and the three weeks after a county is treated.¹³ Matches typically are exogenous treatments as the weekend on which they take place are set in advance before the start of the season (s., e.g., Lichter et al. (2017)).¹⁴ Moreover, we control for changes in the mobility of people which we capture by X_{st} which includes time-variant Google mobility data.¹⁵ Further,

¹²Still, we provide an analysis on the number of deaths in our discussion later on. Note that the RKI does not document death dates but lists the registration date of the case as time stamp.

¹³Our results are also robust to an extension of the post-effect window to four weeks (s., e.g., Figure A21 later on).

¹⁴The exact date and time is then fixed a few weeks in advance.

¹⁵As changes in mobility have a delayed impact on cases, we match the 7-day lag of the data to the cases. The RKI data show that - on average - it takes more than five days from infection to a positive test result. Moreover, we abstract from

we consider day and county fixed effects θ_i and λ_t which control for factors implying incidence heterogeneity in the cross-section or over time. This could for example include differences in the population density or age distribution of counties and weekday effects or trends in case numbers across entire Germany. Finally, as we observe treatments on the county level, we can include fixed effects for state s and week w combinations to control for underlying regional trends in our data - similar to Gupta et al. (2020) who include state fixed effects on the daily level. These fixed effects should especially consider the rapid development in COVID-19 cases in October which started in federal states such as Bavaria or Berlin and took place with delay in some, mostly Eastern and Northern federal states. This would neither be suitably absorbed by county or day fixed effects. All regressions are estimated with standard errors clustered on the county level.

Note that professional football teams mostly come from urban regions. As this could have resulted in significant disparities between treated and untreated counties, we provide probit regression estimates on the socio-demographic and economic characteristics of the counties in Table A2.¹⁶ Indeed, we find that a county's number of inhabitants is a main determinant of hosting a football match from our sample which fits to the hypothesis of matches taking place in especially large cities. Still, we can control for this difference in our regressions as we observe the relative treatment effect per 100,000 inhabitants and weight the treatment impact by match of visitors per 100,000 inhabitants. Moreover, we identify treated counties to have a lower share of inhabitants above 65 years which, if at all, could bias the number of registered cases and deaths downwards (Felbermayr et al., 2020). This makes it more difficult to find clear effects and hence can be interpreted as a hurdle which has to be overcome. Moreover, county fixed effects should account for this difference. Finally, note that the available income seems to be lower in treated counties. But this factor has not been found to robustly be associated with heterogeneity in German case numbers (Felbermayr et al., 2020; Krenz and Strulik, 2021). Population density does not differ between both groups of states which e.g. correlates with accessibility via road which has been found to be a relevant driver of COVID-19 cases in Germany (Krenz and Strulik, 2021). Other crucial measures for the fight against COVID-19 such as the hospital (bed) density do not differ between treated and untreated counties.

4 Results

In the following, we present general findings for the effect of football matches on the transmission of COVID-19 in Germany across counties and over time. To better understand the forces which drive potential effects,

including data on the frequency of tests. The RKI collects weekly data on the state level but laboratories only report these voluntarily. This also results into a substantial share of tests which are not matched to the correct federal state. We therefore follow Ispording et al. (2021) who state that date fixed effects pick up changes in testing.

¹⁶All data included in the regression are extracted from the German Regionalstatistik (<https://www.regionalstatistik.de/genesis/online/logon>) or the German Regionalatlas (<https://www-genesis.destatis.de/gis/genView?GenMLURL=https://www-genesis.destatis.de/regatlas/AI008-1.xml&CONTEXT=REGATLAS01>). We use the most recent data available.

we also conduct narrower analyses on for example specific age groups, spatial transmission, or the role of the prevailing incidence of infections.

General Findings: First of all, we analyse the effect of all football matches in the sample, which took place in front of spectators, in the simplest setup. For that, we weight the number of matches per county with the inverse population size.¹⁷ We then regress the number of daily cases per 100,000 inhabitants on the number of matches per 100,000 inhabitants and its leads and lags. Plotting the coefficients of the event study framework as explained in Section 3 gives us Figure 3.¹⁸

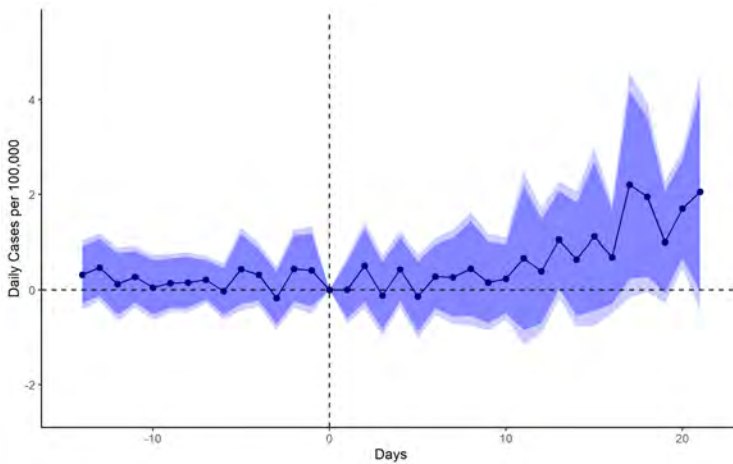


Figure 3: Effect of Matches per 100,000 Inhabitants

Note: The plot shows the coefficients of $Match_{it-d}$ from the regression in equation (1). The x-axis "Days" gives the respective value for d . On the y-axis, the number of daily registered COVID-19 cases per 100,000 inhabitants on the county-level is given. The shaded areas give the 95% and 90%-confidence intervals of the related coefficients. The sample includes all matches in the dataset with an audience of above zero.

The same regression with the number of spectators per 100,000 inhabitants as treatment indicator is shown in Figure 4. Unsurprisingly, we do not find an effect in the first week after a match in both plots. This is due to the fact that potential infections will be symptomatic with delay and hence be registered several days after the match.¹⁹ This is robust for both treatment indicators used.²⁰ We find an increasing trend in the number of cases in both plots over the three weeks post-treatment with only slightly insignificant coefficients from the match per 100,000 inhabitants treatment indicator and significant effects from the spectator treatment

¹⁷Note that we at this stage only include matches which were not played behind closed door (visitors > 0) as ghost games cannot be distinguished from no games in terms of visitors. Later, we analyse the effect of matches without visitors to find out whether gatherings outside the stadiums also contributed to case numbers.

¹⁸As we deal with an unbalanced exposure to the treatment across counties, we do not plot the binned endpoint coefficients as for example neither done in Fuest et al. (2018).

¹⁹If available, the RKI also reports the date of infection of a case. For such cases, the average duration between infection and registration of the case - which is much right-skewed - lies above five days. Hence, we do not expect a clear trend throughout the first post-treatment week and an upward-trending slope of the event study coefficients after approximately one week.

²⁰Also note that both plots show that there is no significant pre-trend, i.e., treated and untreated counties do not differ in the development of COVID-19 cases before the treatment.

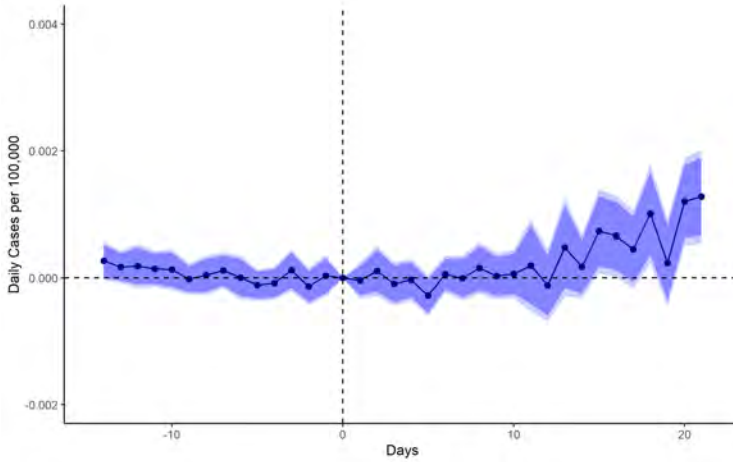


Figure 4: Effect of Visitors per 100,000 Inhabitants

Note: The plot shows the coefficients of $Match_{it-d}$ from the regression in equation (1). The x-axis "Days" gives the respective value for d . On the y-axis, the number of daily registered COVID-19 cases per 100,000 inhabitants on the county-level is given. The shaded areas give the 95% and 90%-confidence intervals of the related coefficients. The sample includes all matches in the dataset with an audience of above zero.

indicator.²¹ That we find significant effects from visitors but not from matches in general could be an indicator that the number of visitors tends to be the more crucial measure for infections. This would imply infections to mainly be related to in-stadium contacts. If there was one more match per 100,000 inhabitants, this would result in an increase of 2.05 daily cases per 100,000 inhabitants - or 0.23 standard deviations respectively - after three weeks. Similarly, an increase in the number of visitors per 100,000 inhabitants by one raises the number of daily cases per 100,000 inhabitants by 0.0013 after three weeks. Considering a county of about 100,000 inhabitants, this implies that 1000 additional spectators at a match increase the daily number of cases after three weeks by 1.3. Put differently, a one standard deviation increase causes additional 0.13 daily cases per 100,000 inhabitants. Still, these baseline findings may be sensitive to different factors which then mitigate the actual implications for future matches.

Age Distribution: One of these factors is the age distribution among affected people. A main objective during the pandemic has been the protection of vulnerable groups such as elderly people. As shown in Figure A4, up to 40% of all COVID-19 cases in spring came from the age group of 60+ which largely contributed to the number of COVID-19 deaths throughout the first wave. Starting from August onwards, the share of COVID-19 cases among this age group has been increasing again. If and to what extent football matches could have contributed to the growth in cases among different ages is shown in Figure A5. We intuitively find

²¹Note that we only find significant effects for late post-treatment periods (e.g., two and a half weeks after the respective match). This suggests that infection transfers and transmission also take place throughout the days after a match. Moreover, the delayed upward trend is in line with the time it takes to observe symptoms and to test. Following information provided by the RKI (2020), it usually takes 5 to 6 days between infection and symptoms but it can also last up to 14 days (95th percentile of incubation time).

most cases to belong to the age groups of 15-34 and 35-59 year-olds. Children and elderly people seem to be less affected by football matches in the short-run. Similar patterns are found for the alternative treatment indicator visitors per 100,000 inhabitants of the respective age group (s. Figure A6). Young adults' case rate increases by 0.0005 cases per additional visitors per 100,000 inhabitants. Admittedly, we now also see slightly positive estimates for the age group of 60 years and older but there is not a robust upward trend. When considering that the age group 35-59 years is the one with the highest absolute share of the German population (approx. 35%), we find that most football-related infections are associated with this age group. This seems to be likely with regard to potentially fewer old people attending matches in the presence of the pandemic.

Gender: There is no doubt that the majority of fans at football matches is male. Hence, we test for gender patterns. When choosing matches as treatment indicator (s. Figure A7), we indeed find female case numbers to start increasing later. Still, the coefficient of the effect after three weeks is only partially higher for males (at about two additional daily cases per 100,000 inhabitants for both genders). When considering visitors as treatment variable (s. Figure A8), we find highly significant effects for both genders and no virtual differences between men and women. Whereas the heterogeneity across age groups indicated limited short-term transmission across socio-demographic groups, one can opposingly understand the gender outcomes as a hint for a quick and pervasive transmission of the virus. Still, the development over time indicates that men seem to experience an implied trend earlier.

Incidence Level: Especially relevant for policy makers and at the heart of this study is the question whether stricter regulations for spectators also work out in the presence of rising infections or whether their functioning is not secured beyond a certain threshold. Also, recent research has shown that contact tracing - which becomes more challenging with increasing infection numbers - is crucial (Fetzer and Graeber, 2020). To understand the (in)sensitivity of such measures in football stadiums, we estimate the effect of matches at different incidence levels at the matchday. In particular, we calculate the 7-day case incidence per 100,000 inhabitants on the county level at each matchday and divide matches up in groups into incidences below 15, 15-25, 25-35, and above 35. Results of the regressions referring to this dispersion are provided in Figures 5 and A9. When using matches as the treatment indicator, we find very few relations between football matches and COVID-19 cases for 7-day incidence levels below 25 cases per 100,000 inhabitants. But especially for matches at an incidence level above the mark of 25 or even 35, we find much more fluctuation and partly higher intermediate effects of up to more than 10 daily cases per 100,000 inhabitants for an increase in matches per 100,000 inhabitants by one. This impression becomes even clearer for visitors per 100,000 inhabitants as treatment indicator. Here, we see strong increases for seven-day incidence levels above 25.

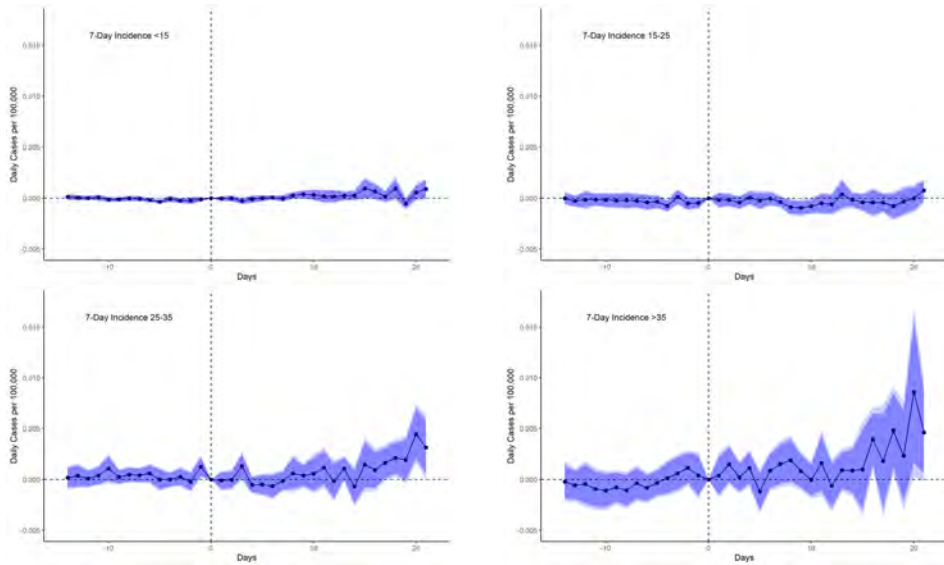


Figure 5: Effect of Visitors per 100,000 Inhabitants Under Different Incidence Levels

Note: The plots show the coefficients of $Match_{it-d}$ from the regression in equation (1). The x-axis "Days" gives the respective value for d . On the y-axis, the number of daily registered COVID-19 cases per 100,000 inhabitants of the respective age group on the county-level is given. The shaded areas give the 95% and 90%-confidence intervals of the related coefficients. The sample includes all matches in the dataset with an audience of above zero. The information in the top left corner gives the respective incidence level category.

While it is not surprising that higher incidence levels provoke more infections, it is striking that we partly observe substantial increases for infection levels already above 25. Hence, these findings are to some extent in line with the administrative decision to limit higher occupancy levels to at least an incidence level such as 35.²²

Away Teams: An important question with regard to the spread of COVID-19 is the spatial transmission across county borders via e.g. travel (Adda, 2016; Chinazzi et al., 2020; Coven et al., 2020). In early stages of the pandemic, this issue was addressed by closing borders or restricting holiday travel within Germany. With regards to football, away fans were excluded from German football matches in professional leagues.²³ Therefore, we will analyze the effect of matches on the number of newly registered cases in the county where the away team comes from. This on the one hand contributes to the discussion on the spread of COVID-19 throughout the country in relation to a match - even though away fans are not allowed in professionals' stadiums and hence should avoid travelling. More importantly, it also provides insights to infections outside

²²Finally, note that when analyzing these outcomes, it has to be considered that matches with a seven-day incidence of above 35 were played in front of a much reduced audience. Also see Figure A10 for the relation between incidence level and spectators at matches. This simultaneous relation between visitors and COVID-19 cases at the incidence margin of 35 is avoided by using the match treatment indicator.

²³Recent research by Lange and Monscheuer (2021) shows that packed bus tours to anti-COVID demonstrations could have contributed to infection numbers. This may indicate that trips of away fans - which often are centrally planned bus trips by the football clubs - could be of an additional risk as well.

the stadiums - assuming that away fans cannot attend the matches in the stadiums, and hence could watch those (possibly some in groups) at home or in pubs which were opened at this time. In Figure A11, we present the effect of an additional match per 100,000 inhabitants of the away county on the spread of COVID-19 there. We neither identify a significant effect of football matches on daily case numbers three weeks after the match nor a systematic pattern.²⁴ Hence, we suggest that this implies infections outside of the stadiums to be limited and below the numbers observed in home counties. To ensure that the smaller to non-existing effect in away counties is not driven by an on average too low interest for the match in away counties or e.g. no possibility to follow matches in the away county as no TV stream is available, we also run the regressions for only matches with a subsample of Bundesliga, 2. Bundesliga and 3. Liga (top league) matches which are all streamed. Here, we do not identify an effect either which supports the overall findings.

Note that we can also interpret these results as a quasi-placebo test for the general effect of football matches from above.

Finally, we also provide additional evidence on the non-existence of COVID-19 transmission across county borders as an extension in the appendix. We discuss potential spreading to neighbouring counties and throughout commuting networks there.

Occupancy: To further investigate the relevance of spectator density on the number of cases, we also estimate the effect of different levels of occupancy. Olczak et al. (2020) show that already low levels of stadium occupancy (e.g. below 20%) raise COVID-19 deaths. Still, this finding covers matches where people were free to densely gather together. Hence, new distancing measures might be effective here. Moreover, note that for example Chang et al. (2021) suggest that there is a non-linear relation between occupancy and infections as already a small reduction in case numbers can have a high impact on the reduction of cases in several public locations such as restaurants. In our analysis - to avoid an endogeneity problem in our regressions due to simultaneity between the daily case numbers and the occupancy - we only include matches in the regression sample which were played at an incidence level of up to 35. Above this mark, increasing cases cause a reduction in allowed visitors and hence occupancy. We present the results on different occupancy levels (0-5%, 5-10%, 10-15%, 15%+) in Figures A12 and A13. We find that there is no clear relation between a higher occupancy level and caused infections. It seems that the allowed occupancy levels are below a critical threshold so that social distancing measures similarly remain effectively - given the incidence level cap. At all occupancy levels, we see slight increases in cases to the end of the effect window. Moreover, by the fact that occupancy on this level does not drastically drive infections, we support suggestions by Olczak et al. (2020) that transmission typically does not take place at the seat but probably on crowded ways or

²⁴Note that we include all matches in the regressions on away team counties including ghost matches as those rules do not matter for e.g. watching a match on TV.

queues in the stadium.

Ghost Matches: Facing an increase in case numbers over time in the sample, almost one half of the matches in the data were played behind closed doors. We make use of these matches to cross-check our results on infections inside and outside the stadiums. Figure A14 presents the event study coefficients of ghost matches. We do not find an increasing pattern in a county's COVID-19 cases in response to a ghost match. This impression results in two conclusions: Firstly, we find evidence for ghost matches to fulfill their purpose to not additionally drive infections. Secondly, ghost matches would only allow for infections outside of the stadiums. As all fans are banned, private gatherings could even increase for the subsample of ghost games. Still, we cannot find any evidence for such infections. This underlines our claim from above that detected infections mainly originate from spectators on their trip to the arena or the ways in the stadium.

Top Leagues: In addition, we shed light on the question whether top league matches better mitigated potential effects on case numbers. Especially after politics announced the exclusion of football fans starting from November 2, 2020, many clubs complained that there is no evidence that top league football matches accelerated COVID-19 transmission.²⁵ To test this hypothesis, we run regressions of equation (1) for a subsample of top league matches - including Bundesliga, 2. Bundesliga, and 3. Liga matches. We present these results in Figure A15. We identify an increase in the case numbers with a rising number of visitors or matches relative to the county's population. Hence, we argue that also top league matches with the potentially best hygiene regulations cannot avoid slight increases in the case numbers. After three weeks, the found effect of above 0.001 additional daily cases per 100,000 inhabitants for an additional visitor per 100,000 inhabitants is similar to the estimates in the overall sample in Figure 3.

Deaths: Besides registered cases, the number of related deaths is an important indicator to determine the downsides of reopening football stadiums. As we saw that the age group 60+ did not experience a clear, short-run increase in cases, the question arises whether there is a fatality effect at all. We present event study findings on the effect of all matches and visitors in our sample on the respective counties' number of deaths in Figure A16. Note as the RKI does not document the date of death but the registration date for a deceased case, we would expect to already see effects as soon as for cases. Interestingly and in line with the age distribution of football-related cases²⁶, we cannot find a significant increase for both treatment indicators - matches and visitors. This could also hint at a self-selection effect that especially vulnerable fans do not attend matches anymore. Still, this explanation does not hold for infections after the match (for example a person who got infected in the stadium and infects another one a few days later).

Lockdown Effects: For our analyses above, we relied on data until November 08, 2020, which is just

²⁵For example in the light of the semi-lockdown, Axel Hellmann, board member of the Bundesliga club Eintracht Frankfurt, emphasized that there has not been a single COVID-19 case which was retraced to a Bundesliga match (Hess, 2020).

²⁶Since the beginning of the crisis in Germany, more than 95% of all deaths belong to the population of 60 years and older.

until one week after the the beginning of the German 'lockdown light' to ensure that our results are not biased by potentially less transmission opportunities. That the lockdown led to a reduction of the growth in COVID-19 infections can be easily seen in Figure A3. To assess whether the lockdown also reduced the infections originating from the latest football matches, we extend our observation period of COVID-19 cases to December 06, 2020 and reestimate our main regressions. As can be seen in Figure A17, the overall effect of an additional match per 100,000 inhabitants is corrected downwards and now turns out to be clearly insignificant while still showing a positive but less steep upward trend. This indicates that the transmission from more recent matches could have been decelerated partly through the additional measures - even in the presence of higher infection levels. Note that the effect from an additional visitor per 100,000 inhabitants is still significant after three weeks. Still, the insignificance of the match effect after including lockdown COVID-19 cases indicates that the effect's robustness is much weaker than for effects from mass gatherings during the first COVID-19 wave with less hygiene regulations (Ahammer et al., 2020; Olczak et al., 2020; Wing et al., 2020).

5 Mechanism

While we cannot clearly determine where infections related to football matches happen, there should still be a way to identify additional, football-induced mobility patterns which result in the observed increase in cases. Hence, we subsequently provide evidence for increased mobility in counties and on days which were exposed to football matches. For that, we apply mobile phone mobility data provided by the RKI (for a detailed discussion of the data, s. Schlosser et al. (2020)²⁷) which gives daily information on mobility of people in a specific county.²⁸ In particular, the data represents the relative change in mobility in a county on a 2020 day compared to the average of all days in the same month of the preceding year which have been the same weekday. To be precise, i.e., the mobility on a saturday, August 01, 2020, is for example compared to the average mobility on all saturdays in August 2019.

If football matches caused an influx in the mobility, we should therefore find an increase in the mobility - or mobility change compared to 2019 - for matches on a certain date in a county where a football match took place. We investigate this by estimating a simple differences-in-differences model following the equation:

$$Mobility_{it} = \gamma_0 + \gamma_1 Match_{it} + X_{it} + \zeta + \epsilon_{it}$$

²⁷<https://osf.io/n53cz/>

²⁸Note that the Google Mobility Data are not suitable for this analysis because the data is only available on the state level.

where $Mobility_{it}$ gives county i 's mobility change on day t in comparison to the previous year in percentage points. γ_1 is the coefficient of interest as it gives us the marginal effect of the match or visitor indicator on the mobility in county i at day t . X_{it} encompasses county-level covariates on the daily level such as the prevailing incidence level. Finally, ζ is a set of county and date fixed effects which are intended to capture heterogeneity in e.g. mobility shocks due to COVID-19 policies or weather fluctuations. Further, we again add interactions of the state and week to control for regional, temporary patterns and also introduce county linear time trends. All regressions are presented in Table 1. We use data for all counties between the dates in the sample on which the first and last match with visitors took place - August 01, 2020 and November 01, 2020.

Table 1: Effects of Football Matches on Mobility Changes

	<i>Mobility_{it}</i>							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Matches per 100,000 Inh.	1.157** (0.574)	1.226** (0.494)	1.239** (0.505)	1.179** (0.492)				
Visitors per 100 Inh.					1.117*** (0.375)	1.189*** (0.258)	1.179*** (0.282)	1.113*** (0.251)
Matches per 100,000 Inh. (Away County)	0.398 (0.478)	0.717* (0.423)	0.608 (0.412)	0.774* (0.416)	0.394 (0.474)	0.710* (0.421)	0.600 (0.409)	0.767* (0.415)
7-Day Incidence (1-Day-Lag)				-0.051*** (0.014)				-0.051*** (0.014)
7-Day Incidence ∈ [35,50)				-0.024 (0.328)				-0.025 (0.328)
7-Day Incidence ∈ [50,∞)				-0.241 (0.658)				-0.235 (0.658)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Week FE	No	Yes	No	Yes	No	Yes	No	Yes
Lin. County Trend	No	No	Yes	No	No	No	Yes	No
Observations	37,293	37,293	37,293	37,293	37,293	37,293	37,293	37,293
R ²	0.823	0.871	0.868	0.873	0.823	0.871	0.868	0.873
Adjusted R ²	0.821	0.869	0.865	0.871	0.821	0.869	0.865	0.871

Note:

*p<0.1; **p<0.05; ***p<0.01. Standard errors clustered on the county level.

We find that an additional match per 100,000 inhabitants increases mobility by about 1.2 percentage points which is equivalent to an incline of 0.065 standard deviations of the mobility change. This demonstrates a potential mechanism of infection effects from football matches. Increased mobility could cause additional COVID-19 cases. Similarly, more visitors of a football match raise mobility. In particular one visitor per 100 inhabitants increases the mobility 2020 in relation to 2019 by about 1.1 percentage point or 0.06 standard

deviations. This is very much in line with our findings from above. Moreover, the similar size of the effects fits the fact that an average match has about 1,000 spectators.

We also checked whether we find significant effects on the away county. Results show that there is an unrobust and much smaller effect of football matches in the away counties. Only when inserting state-week interactions, we observe a significant effect. We interpret these results as support for our findings from above that there are none to much smaller effects of football matches in away counties which could be caused by the channel of a smaller reaction in the mobility.

Note that these findings are robust to a variation in the used fixed effects and the inclusion of variables indicating the current incidence level. The latter should account for behavioural changes in response to the dynamic of the virus and potential changes in the measures against the virus.²⁹

6 Discussion

Our results show that there indeed is a relation between mass gatherings and COVID-19 transmission. This also holds in the presence of additional hygiene measures. Our general findings show an increase of about 2.05 daily cases per 100,000 inhabitants for an additional match per 100,000 inhabitants and 0.0013 daily case per 100,000 inhabitants for an additional visitor per 100,000 inhabitants. When performing a simple back-of-the-envelope calculation, we end with the following estimated effects and magnitudes: As the average match with audience in our sample implied 0.444 matches per 100,000 inhabitants and welcomed 1,045 spectators which translates to 407 spectators per 100,000 inhabitants, this equals an average increase of about 0.91 daily case per 100,000 inhabitants for the match treatment indicator and 0.52 daily cases per 100,000 inhabitants for the spectator treatment indicator after three weeks.³⁰ In general, we interpret the finding from the match treatment indicator as an upper boundary as this treatment is more likely to pick up effects from out-of-stadiums events. These could be even unrelated to professional football (e.g. amateur football matches or other sports events at the same days). The visitor treatment indicator should reveal a smaller upward bias. This variable mostly just considers variation in the attendance in the stadium and not activity outside of the stadium. Hence, we argue that on average a match seems to increase the seven-day incidence per 100,000 inhabitants by up to between 3.6 and 6.4 - keeping in mind that these numbers strongly vary with outer circumstances.

²⁹Note that we do not include the RKI Mobility Data in the event studies above as this control variable would incorporate mobility changes originating from football. Lastly, at the first glance it may be surprising that there is no clear, additional reduction in mobility for higher incidence levels which were typically related to stricter measures against the spread of the virus. This is also due to the day day fixed effects. When leaving out the linear incidence variable, we get that a prevailing incidence of 35 to 50 (over 50) significantly reduces the mobility by about 0.6 (2.4) percentage points.

³⁰Again note that these numbers should be interpreted carefully. The reason is that there are several mitigating factors which impact the actual effect of a single match (e.g., incidence level, number of spectators).

Further note that our findings suggest to continue keeping away fans out of the stadiums as this contributes to the spatial transmission of COVID-19. Moreover, our results suggest increasing sensitivity to the inclusion of visitors at rising incidence levels. Policy makers should consider the non-linear relation between incidence levels and cases.

Also recapitulate that the effects found here are hardly comparable to findings from the earlier phase of the pandemic as in Ahammer et al. (2020) or Olczak et al. (2020). Besides the general rules in the stadium, also people's behavior has changed endogenously. To disentangle the effect of behavioral adaptations and exogenous impacts in the presence of sport events (like in Reade et al. (2020) or Reade and Singleton (2020)) is an interesting question which should be tackled in additional research. Still, our results indicate that a match with limited attendance does not have such devastating consequences in the short-run - especially in the presence of low incidence levels - as prior in Ahammer et al. (2020) where one sports event is related to up to 30 registered infections and 1.5 deaths per 100,000 inhabitants or in Wing et al. (2020) who find an NHL/NBA match to cause 783 COVID-19 registered infections. Interestingly, our short-run effects on registered infections do not seem to be much lower than the results for football matches in Olczak et al. (2020) as we find a match per 100,000 inhabitants to increase cases by about 0.55 to 0.95 per 100,000 inhabitants per day after three weeks where the respective study only finds a match to increase cases by six per 100,000 inhabitants overall. This can be caused by the generally lower number of registered cases in their sample or a more granular analysis of matches in lower leagues. Opposingly, we do not find strong effects on deaths while they identify two additional deaths per 100,000 inhabitants per match. Other findings by Parshakov (2021), that every spectator causes 0.15 to 0.5 infections throughout the next two months in Belarus, exceed our results by far. When comparing our estimates to recent results by for example Fetzer (2020) who finds an UK policy subsidizing restaurants to account for eight to seventeen percent of all infections or Lange and Monscheuer (2021) who find anti-COVID demonstrations to increase infection rates by more than 35 percent in treated counties, the effect of football matches seems to be rather small. We observe that treated counties on average document 10.97 daily infections per 100,000 inhabitants after three weeks. Relating this to the found effect from football matches, we can relate up to 5-8.5% of infections and only in the respective counties after 21 days to a football match as an upper boundary.

Nevertheless, while being able to account for time-variant and regional trends, the event study approach suffers minor issues which should be kept in mind: First, event studies account for matches as additive treatments whose effects are insensitive of each other and are cumulatively summed up to get the overall effect. As a previous match which increased the infection level could cause the effect of a subsequent match to increase, this could slightly underestimate the effect of earlier matches while overestimating the effect of later matches. Secondly, the model assumes a parallel trend in the infections after a match across treated

counties. Nevertheless, this could be violated by the heterogeneous registration velocity of new cases as e.g. test results take longer in rural areas. Similarly, the asymmetric treatment timing across counties could bias results due to unidentical comparisons of newly treated and formerly treated counties (Sun and Abraham, 2020). Finally, we cannot completely control for the mechanism behind infections. Whereas top league matches could cause infections outside of the stadium as well (e.g. people following the match together on TV), this is unlikely for lower league matches such as in the Regionalliga. Here, less strict hygiene rules on the other hand could cause proportionally more cases in the stadium.³¹ Moreover, note that our results are based on a still limited sample size of 1203 matches of which 660 were played in front of spectators. Especially the small sample size for top league matches due to the early decision to exclude spectators again should be considered when generalizing this paper's results.

For purposes of robustness, we also changed the regional time fixed effects from the weekly to daily level on the state level and also implemented time trends/fixed effects on the more granular NUTS2 (38 administrative regions) or county level (s. Figure A18 and A19)³². We moreover tested for different suitable clusters of standard errors (s. Figure A20). We also modified the post-treatment effect to exemplarily four weeks (s. Figure A21). These adaptations did not change our results qualitatively - neither in the overall sample nor in the reduced top league sample.

Lastly, we checked whether additionally controlling for fluctuation in the population's risk perception over time changes our findings. For that, we include state-level data on four measures of risk perception from the (mostly) bi-weekly data of the COSMO study (Betsch et al., 2020). In fact, we included variables which capture the perceived risk of infection, the perceived severity of an infection, the perceived ease of avoiding an infection, and the perceived affective risk perception across time and counties. Again, this does not change our results.

7 Conclusion and Future Research

Sports is at the heart of most societies. In the presence of a pandemic, a trade-off between this welfare contribution and potential impacts on society's health might arise. To align both of these interests, policy makers introduced stricter hygiene regulations to reallow fans back into the stadiums. At the example of German professional football, we show that these hygiene concepts cannot fully avoid infections related to matches. The number of infections caused is mediated by the actual infection level at the day of the match in the respective county. In particular, only few infections emerge at a seven-day incidence below 25.

³¹Due to stricter hygiene rules in the top leagues and also in the DFB-Pokal (German cup competition), a lot of teams from lower leagues for example switched the location of the cup match to the top team's stadium.

³²Varying the time trends used shows that regressions without trends are revealed to have upward-biased coefficients.

Our results cannot account for the exact infection dynamics (e.g. insufficient distance between fans, public transport to match) and are based on quite roughly defined treatment indicators. Still, we are confident to contribute relevant findings to optimizing living with the virus. Policy makers should take note of these results in embellishing hygiene regulations more efficiently, as we highlight the limitation of reopenings in the presence of too high infection levels. Nevertheless, as highlighted in a recent note by Singleton et al. (2021), "[p]olicy makers need more evidence on if, when and how it is safe to open sports stadiums as Covid-19 rages" - especially in the presence of a mutating virus. We are looking forward to more contributions on this issue.

References

- Adda, J. (2016). Economic Activity and the Spread of Viral Diseases: Evidence From High Frequency Data. *Quarterly Journal of Economics*, 131(2):891–941.
- Ahammer, A., Halla, M., and Lackner, M. (2020). Mass Gatherings Contributed to Early COVID-19 Spread: Evidence from US Sports. *COVID Economics*, 30:44–62.
- Altenburg, M., Eils, R., Gaertner, B., Gastmeier, P., Harzer, O., Heppner, F., Kainzinger, F., Kriegel, M., Kruell, M., Lassahn, C., Meyer, T., Raue, P., Schade, W., Spoerr, W., Wilhelm, K., Wodarz, K., Wolfrath, B., and Zinn, G.-C. (2021). Schrittweise Rückkehr von Zuschauern und Gästen: Ein integrierter Ansatz für Kultur und Sport.
- Bernheim, B. D., Buchmann, N., Freitas-Groff, Z., and Otero, S. (2020). The Effects of Large Group Meetings on the Spread of COVID-19: The Case of Trump Rallies. *Working Paper*.
- Betsch, C., Wieler, L. H., and Habersaat, K. (2020). Monitoring Behavioural Insights Related to COVID-19. *Lancet*, 395(10232):1255–1256.
- Cardazzi, A., Humphreys, B., Ruseski, J. E., Soebbing, B. P., and Watanabe, N. (2020). Professional Sporting Events Increase Seasonal Influenza Mortality in US Cities. *West Virginia University Economics Faculty Working Paper Series 6-2020*.
- Chang, S., Pierson, E., Koh, P. W., Geradin, J., Redbird, B., Grusky, D., and Leskovec, J. (2021). Mobility Network Models of COVID-19 Explain Inequalities and Inform Reopening. *Nature*, 589:82–87.
- Chinazzi, M., Davis, J. T., Ajelli, M., Gioannini, C., Litvinova, M., Merler, S., Pionotti, A. P. y., Mu, K., Rossi, L., Sun, K., Viboud, C., Xiong, X., Yu, H., Halloran, M. E., Longini Jr., I. M., and Vespignani, A. (2020). The Effect of Travel Restrictions on the Spread of the 2019 Novel Coronavirus (COVID-19) Outbreak. *Science*, 368:395–400.
- Cotti, C. D., Engelhardt, B., Foster, J., Nesson, E. T., and Niekamp, P. S. (2020). The Relationship Between In-Person Voting and COVID-19: Evidence from the Wisconsin Primary. *NBER Working Paper 27187*.
- Coven, J., Gupta, A., and Yao, I. (2020). Urban Flight Seeded the COVID-19 Pandemic Across the United States. *COVID Economics*, 54(4):121–157.
- Dave, D., McNichols, D., and Sabia, J. J. (2021). The Contagion Externality of a Superspreading Event: The Sturgis Motorcycle Rally and COVID-19. *Southern Economic Journal*, 87(3):769–807.
- Dave, D. M., Friedson, A. I., Matsuzawa, K., McNichols, D., Redpath, C., and Sabia, J. J. (2020a). Risk Aversion, Offsetting Community Effects, and COVID-19: Evidence from an Indoor Political Rally. *NBER Working Paper 27522*.
- Dave, D. M., Friedson, A. I., Matsuzawa, K., Sabia, J. J., and Safford, S. (2020b). Black Lives Matter Protests, Social Distancing, and COVID-19. *NBER Working Paper 27408*.
- DeFilippis, E., Impink, S. M., Singell, M., Plozer, J. T., and Sadun, R. (2020). Collaborating During Coronavirus: The Impact of COVID-19 on the Nature of Work. *NBER Working Paper 27612*.
- Felbermayr, G., Hinz, J., and Chowdhry, S. (2020). Apres-ski: The Spread of Coronavirus from Ischgl through Germany. *COVID Economics*, 22:177–204.
- Fetzer, T. (2020). Subsidizing the Spread of COVID19: Evidence from the UKs Eat-Out to-Help-Out Scheme. *CAGE Discussion Paper 517*.
- Fetzer, T. and Graeber, T. (2020). Does Contact Tracing Work? Quasi-Experimental Evidence from an Excel Error in England. *CAGE Discussion Paper 521*.
- Fuest, C., Peichl, A., and Siegloch, S. (2018). Do Higher Corporate Taxes Reduce Wages? Micro Evidence from Germany. *American Economic Review*, 108(2):393–418.
- Gitter, S. R. (2017). The H1N1 Virus and Mexican Baseball Attendance. *Athens Journal of Sports*, 4(4):263–275.
- Gupta, S., Nguyen, T. D., Lozano Rojas, F., Raman, S., Lee, B., Bento, A., Simon, K. I., and Wing, C. (2020). Tracking Public and Private Responses to the COVID-19 Epidemic: Evidence from State and Local Government Actions. *NBER Working Paper 27027*.
- Hartmann, U. (2020). "Das soll jetzt erst einmal eine Art Experiment werden". *Sueddeutsche Zeitung*.
- Hess, P. (2020). Eintracht-Vorstand Hellmann spricht von Symbolpolitik. *Frankfurter Allgemeine Zeitung*.

- Isphording, I. E., Lipfert, M., and Pestel, N. (2021). Does Re-Opening Schools Contribute to the Spread of Sars-Cov-2? From Staggered Summer Breaks in Germany. *IZA Discussion Paper No. 13790*.
- Krenz, A. and Strulik, H. (2021). The Benefits of Remoteness - Digital Mobility Data, Regional Road Infrastructure, and COVID-19 Infections. *German Economic Review*. forthcoming.
- Lange, M. and Monscheuer, O. (2021). Spreading the Disease: Protest in Times of Pandemics. *Working Paper*.
- Lichter, A., Pestel, N., and Sommer, E. (2017). Productivity Effects of Air Pollution: Evidence From Professional Soccer. *Labour Economics*, 48:54–66.
- Mangeum, D. and Niekamp, P. (2021). JUE Insight: College Student Travel Contributed to Local COVID-19 Spread. *Journal of Urban Economics*. forthcoming.
- McCloskey, B., Zumla, A., Ippolito, G., Blumberg, L., Arbon, P., Cicero, A., Endericks, T., Lim, P. L., and Borodina, M. (2020). Mass Gathering Events and Reducing Further Global Spread of COVID-19: A Political and Public Health Dilemma. *Lancet*, 395(10230):1096–1099.
- Memish, Z. A., Steffen, R., White, P., Dar, O., Azhar, E. I., Sharma, A., and Zumla, A. (2020). Mass Gatherings Medicine: Public Health Issues Arising From Mass Gathering Religious and Sporting Events. *Lancet*, 393(10185):2073–2084.
- Mendolia, S., Stavrunova, O., and Yerokhin, O. (2021). Determinants of the Community Mobility During the COVID-19 Epidemic: The Role of Government Regulations and Information. *Journal of Economic Behavior and Organization*, 184:199–231.
- Mense, A. and Michelsen, C. (2020). Rumliche Ausbreitung von COVID-19 durch interregionale Verflechtungen. *Wirtschaftsdienst*, 100(6):416–421.
- Nunan, D. and Brassey, J. (2020). What is the Evidence For Mass Gatherings During Global Pandemics? A Rapid Summary of Best-Available Evidence. *Oxford COVID-19 Evidence Service*.
- Olczak, M., Reade, J. J., and Yeo, M. (2020). Mass Outdoor Events and the Spread of an Airborne Virus: English Football and COVID-19. *COVID Economics*, 47:162–183.
- Parnell, D., Widdop, P., Bond, A., and Wilson, R. (2020). COVID-19, Networks and Sport. *Managing Sport and Leisure*. forthcoming.
- Parshakov, P. (2021). The Spread of COVID-19 and Attending Football Matches: Lesson from Belarus. *Working Paper*.
- Reade, J. J., Schreyer, D., and Singleton, C. (2020). Stadium Attendance Demand During the COVID-19 Crisis: Early Empirical Evidence From Belarus. *Applied Economics Letters*. forthcoming.
- Reade, J. J. and Singleton, C. (2020). Demand for Public Events in the COVID-19 Pandemic: A Case Study of European Football. *European Sport Management Quarterly*. forthcoming.
- RKI (2020). Epidemiologischer Steckbrief zu SARS-CoV-2 und COVID-19. https://www.rki.de/DE/Content/InfAZ/N/Neuartiges_Coronavirus/Steckbrief.html. Accessed: 2020-12-14.
- Schlosser, F., Maier, B. F., Hinrichs, D., Zachariae, A., and Brockmann, D. (2020). COVID-19 Lockdown Induces Disease-Mitigating Structural Changes in Mobility Networks. *Proceedings of the National Academy of Sciences*, 117(52):32883–32890.
- Singleton, C., Bryson, A., Dolton, P., Reade, J. J., and Schreyer, D. (2021). What Can We Learn About Economics from Sport during Covid-19. *Working Paper*.
- Stoecker, C., Sanders, N. J., and Barreca, A. (2016). Success Is Something to Sneeze At: Influenza Mortality in Cities that Participate in the Super Bowl. *American Journal of Health Economics*, 2(1).
- Sun, L. and Abraham, S. (2020). Estimating Dynamic Treatment Effects in Event Studies with Heterogeneous Treatment Effects. *Journal of Econometrics*. forthcoming.
- Wing, C., Simon, D. H., and Carlin, P. (2020). Effects of Large Gatherings on the COVID-19 Epidemic: Evidence From Professional and College Sports. *Working Paper*.

A Appendix

A.1 Extension: Transmission Across County Borders

We subsequently especially discuss the spatial transmission of potential infections from football matches across counties. For that, we firstly examine neighbouring counties of treated regions (comparable to Ahammer et al. (2020)). Moreover, we then make use of commuter data provided by the German Employment Agency (Agentur für Arbeit).³³ The data includes information on the interrelation of counties with respect to commuting for work. We use this as proxy of general commuting behavior between counties and network interconnections. The advantage of this data is that the general reduction in mobility during the pandemic cannot totally be reduced in the world of work. Thus, this data should make up a relevant part of the remaining mobility and can also account for spreading beyond close regional borders to for example far distant federal states. Mense and Michelsen (2020) use the same data to investigate interregional interdependences as an infection mitigator in the first wave 2020. They find commuter networks to significantly explain changes in infection rates. While the effect decreased during the first lockdown, it nevertheless remained robustly existent.

To make use of the data, we follow a similar weighting strategy as Mense and Michelsen (2020) and create a treatment variable in the form of

$$Transmission_{it} = \sum_{j=1, j \neq i}^{401} [Match_{jt} \times \frac{Incommuter_{ij} + Outcommuter_{ij}}{Population_i}]$$

which equals the sum of the match or visitor indicator (as used above) weighted with the exposure to commuting over all counties. In detail, we calculate the share of people who travel between county i and any other county j of the 401 counties relative to county i 's population which is $\frac{Incommuter_{ij} + Outcommuter_{ij}}{Population_i}$. This commuter density is the weight for the exposure to the treatment in county j . Summing this new treatment indicators up over all states gives the respective transmission indicator. As we include the exposure to the treatment in the treated counties j and the commuting behavior, we ensure that higher exposure to risk gives a higher value for $Transmission_{it}$. The variable can be interpreted as a likelihood or probability of infection spillover in case that football matches contribute to COVID-19 spreading. In comparison to the approach to use neighbouring counties, this procedure will account for example for the bias that the counties' population is not suitably given by the number of border counties or geographical distance only.

To measure the potential effect of matches on counties which directly border treated counties, potential spillovers will be analyzed here. We plot the estimated coefficients for the effect of matches in a neighbouring county in Figure A1. We do not find any significant effects of a match in the neighbouring county. This on the one hand underlines the trustworthiness of the detected patterns - as we hence do not only cover fractions of the development of cases over time - but it also indicates the limited spatial spreading due to less people in the stadiums.³⁴ Only in the right plot (where the relative number of visitors is the treatment indicator), we see a slight - though insignificant - increase in the cases after two and a half weeks.³⁵

Here we now also provide results on our findings with respect to commuting. Applying the created transmission indicator as a treatment indicator in our event study setup should hint at the role of football matches

³³<https://statistik.arbeitsagentur.de/DE/Navigation/Statistiken/Interaktive-Angebote/Pendleratlas/Pendleratlas-Nav.html>

³⁴Ahammer et al. (2020) documents that spreading to neighbouring counties has taken place for NBA and NHL matches in early 2020.

³⁵When extending the ex-post time horizon, we neither find any significant effects.

for spatial transmission and can be seen as a robustness check to our findings on the limited transmission to neighbouring counties which are most likely to be locations to which commuting takes place. As can be seen in Figure A2, we cannot find a systematic effect of the transmission indicator on the infection numbers in states with a higher exposure to travel from and to counties with matches with visitors.

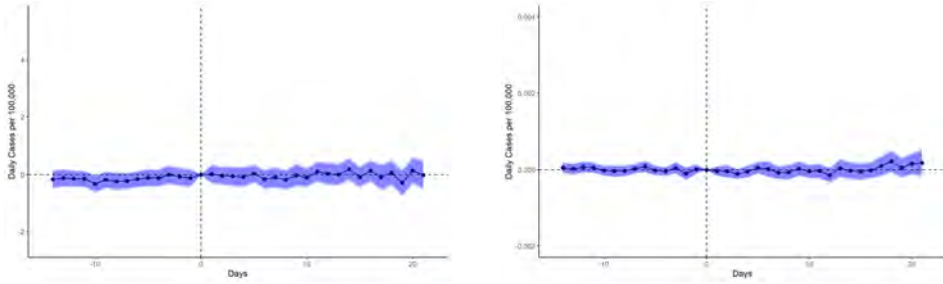


Figure A1: Effect of Matches and Visitors per 100,000 Inhabitants on Neighbouring Counties

Note: The plots show the coefficients of $Match_{it-d}$ from the regression in equation (1). The left plot uses the number of matches per 100,000 inhabitants in a neighbouring county on the county level as treatment indicator, the right plot the number of visitors per 100,000 inhabitants in a neighbouring county on the county level. The x-axis "Days" gives the respective value for d . On the y-axis, the number of daily registered COVID-19 cases per 100,000 inhabitants of the respective gender on the county-level is given. The shaded areas give the 95% and 90%-confidence intervals of the related coefficients. The sample includes all matches in the dataset with an audience of above zero.

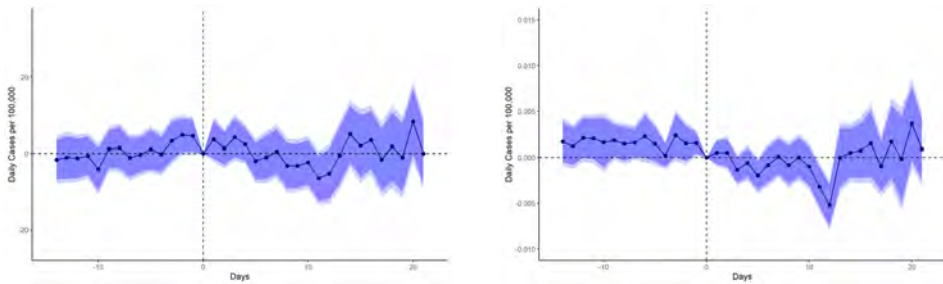


Figure A2: Effect of Matches and Visitors per 100,000 Inhabitants on Commuter-Exposed Counties

Note: The plots show the coefficients of $Match_{it-d}$ from the regression in equation (1). The left plot uses the commuter index based on the interaction with the number of matches per 100,000 inhabitants on the county level as treatment indicator, the right plot the commuter index based on the interaction with the number of visitors per 100,000 inhabitants on the county level. The x-axis "Days" gives the respective value for d . On the y-axis, the number of daily registered COVID-19 cases per 100,000 inhabitants of the respective gender on the county-level is given. The shaded areas give the 95% and 90%-confidence intervals of the related coefficients. The sample includes all matches in the dataset with an audience of above zero.

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A.2 Figures and Tables

Table A1: Descriptive Statistics on Included (Semi-)Professional Football Matches

Competition	# Matches	...of which no Ghost Games	Mean # Visitors	Mean Occupancy
Bundesliga	108	33	4809.3	11.97%
2. Bundesliga	108	41	2515.3	10.41%
3. Liga	149	44	2777.4	13.47%
Regionalliga West	194	100	437.8	5.62%
Regionalliga Suedwest	137	109	481.4	5.55%
Regionalliga Nordost	121	116	751.4	9.73%
Regionalliga Nord	98	71	431.9	10.23%
Regionalliga Bayern	27	21	283.0	7.31%
DFB-Pokal	46	21	1640.1	8.90%
Others	110	52	695.0	6.31%
Women's Bundesliga	65	28	377.6	5.50%
Women's DFB-Pokal	40	24	189.6	6.87%
Σ	1203	660	1045.1	8.26%

Note: "Others" include matches from the following competitions: Champions League, Europa League, State Cup finals ("Landespokal"), national team matches and friendlies. "Average # Visitors" and "Average Occupancy" give the respective values for the subsample of matches which were played in front of spectators. Match dates range from 2020-08-01 and 2020-12-23.

Table A2: Socio-Demographic and Economic Differences Between Treated and Untreated Counties

	(1 = Treated, 0 = Untreated)	
	(1)	(2)
<i>N</i> = 401 counties 127 treated, 274 untreated		
ln(Inhabitants)	0.322*** (0.052)	0.356*** (0.068)
Share Age \geq 65	-4.096** (1.667)	-4.873** (2.100)
Population Density	0.015 (0.010)	0.016 (0.010)
Share Foreigners	-1.454* (0.865)	-0.760 (1.232)
ln(Available Income)	-0.594** (0.296)	-0.634* (0.373)
Share Protestants	-0.013 (0.216)	0.341 (0.572)
Share Catholics	0.087 (0.195)	0.406 (0.508)
Share Households with Children	-0.017 (0.023)	-0.022 (0.026)
Average Household Size	0.071 (0.709)	0.173 (0.779)
Hospital Density	-1.256 (2.507)	-2.098 (2.681)
Hospital Bed Density	0.019 (0.012)	0.020 (0.013)
State FE	No	Yes
Observations	401	401
McFadden (Pseudo-)R ²	0.294	0.315

Note: The table gives marginal effects at the variables' means of socio-demographic and economic differences between the treated and untreated counties estimated in probit regressions with heteroskedasticity-robust standard errors. Treated counties are all counties in which at least one match took place which is included in the sample. There are only three out of the 127 counties which did not have a match where visitors were allowed to attend but only ghost games.

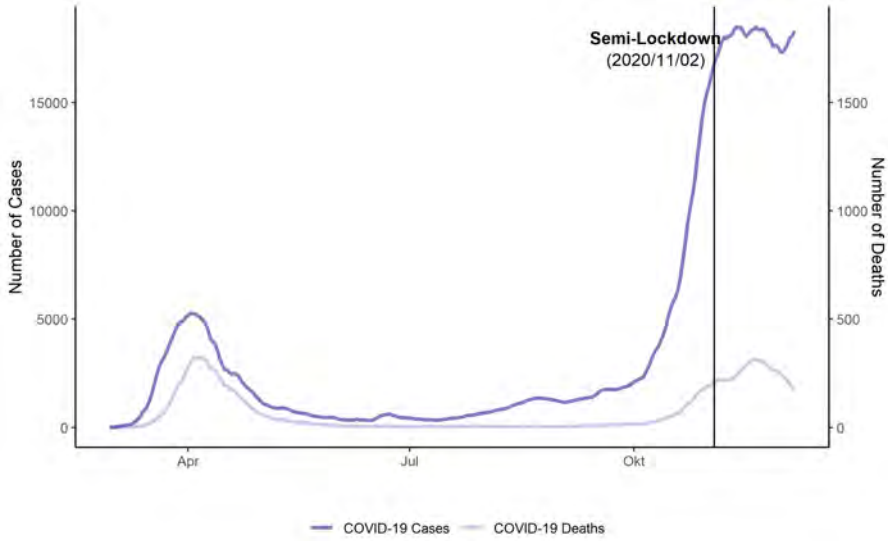


Figure A3: Registered COVID-19 Cases and Deaths as of Registration Day in Germany

Note: The plot shows the development of the seven-day moving average of daily registered COVID-19 cases and deaths from March 01, 2020 to December 06, 2020 for overall Germany. Note that deaths are related to the cases' registration date as well and not the date of death.

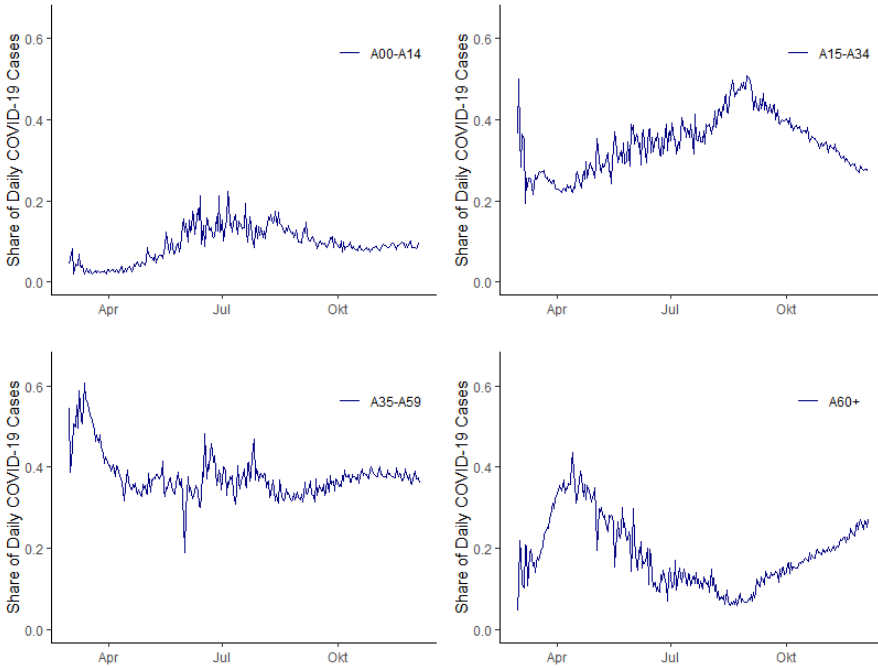


Figure A4: Distribution of Cases Across Age Groups and Over Time

Note: The plot shows the share of daily COVID-19 cases per age group of the total number of registered cases. The sample ranges from March 01, 2020 to December 06, 2020.

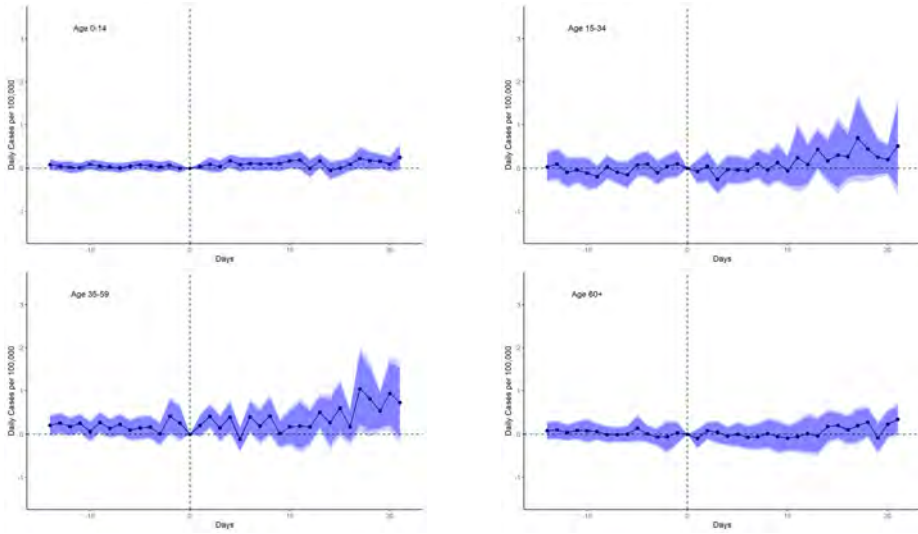


Figure A5: Effect of Football Matches per 100,000 Inhabitants of Respective Age Groups

Note: The plots show the coefficients of $Match_{it-d}$ from the regression in equation (1) estimated separately for each age group. The x-axis "Days" gives the respective value for d . On the y-axis, the number of daily registered COVID-19 cases per 100,000 inhabitants of the respective age group on the county-level is given. The shaded areas give the 95% and 90%-confidence intervals of the related coefficients. The sample includes all matches in the dataset with an audience of above zero. The information in the top left corner gives the respective age group.

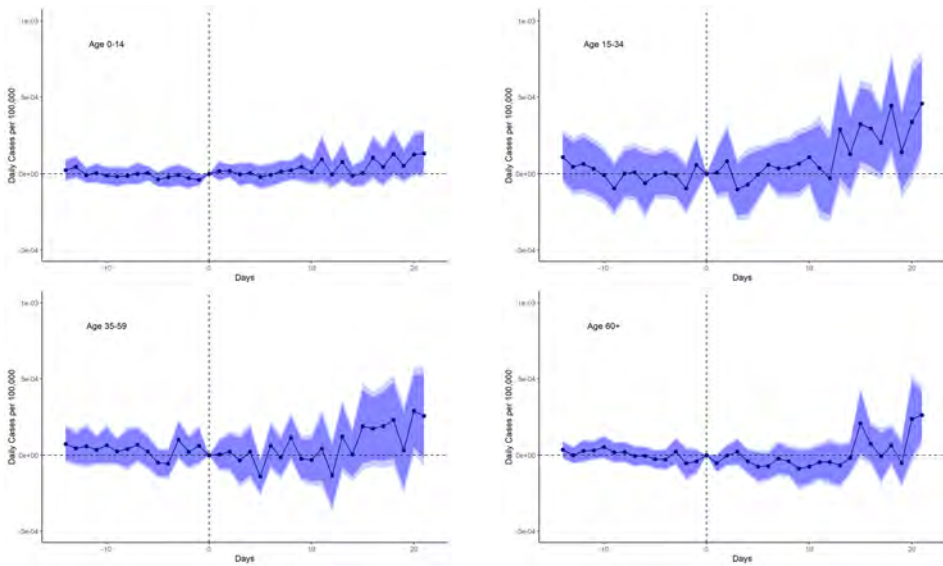


Figure A6: Effect of Visitors per 100,000 Inhabitants of Respective Age Groups

Note: The plots show the coefficients of $Match_{it-d}$ from the regression in equation (1) estimated separately for each age group. The x-axis "Days" gives the respective value for d . On the y-axis, the number of daily registered COVID-19 cases per 100,000 inhabitants of the respective age group on the county-level is given. The shaded areas give the 95% and 90%-confidence intervals of the related coefficients. The sample includes all matches in the dataset with an audience of above zero. The information in the top left corner gives the respective age group.

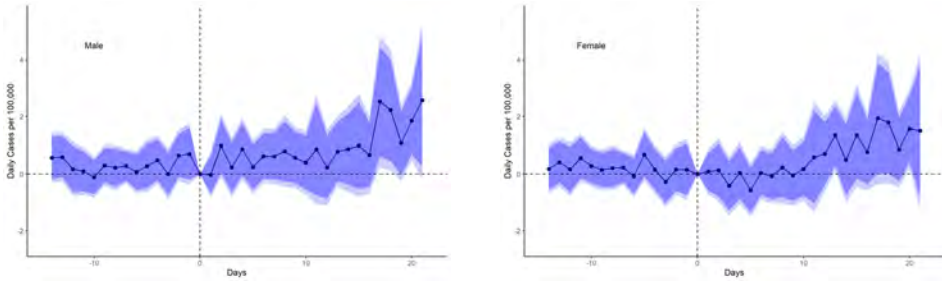


Figure A7: Effect of Matches per 100,000 Inhabitants on Gender

Note: The plots show the coefficients of $Match_{it-d}$ from the regression in equation (1) estimated separately for each gender. The x-axis "Days" gives the respective value for d . On the y-axis, the number of daily registered COVID-19 cases per 100,000 inhabitants of the respective gender on the county-level is given. The shaded areas give the 95% and 90%-confidence intervals of the related coefficients. The sample includes all matches in the dataset with an audience of above zero. The information in the top left corner gives the respective gender.

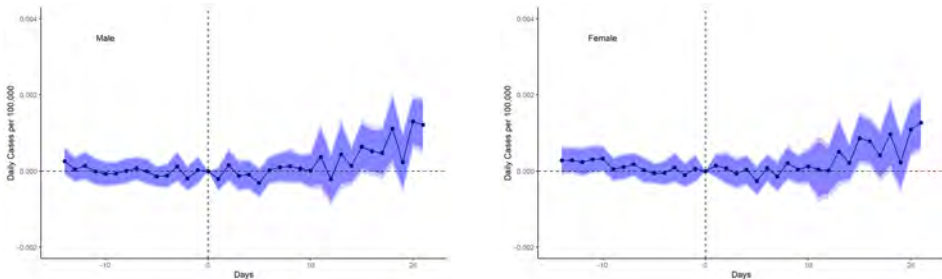


Figure A8: Effect of Visitors per 100,000 Inhabitants on Gender

Note: The plots show the coefficients of $Match_{it-d}$ from the regression in equation (1) estimated separately for each gender. The x-axis "Days" gives the respective value for d . On the y-axis, the number of daily registered COVID-19 cases per 100,000 inhabitants of the respective gender on the county-level is given. The shaded areas give the 95% and 90%-confidence intervals of the related coefficients. The sample includes all matches in the dataset with an audience of above zero. The information in the top left corner gives the respective gender.

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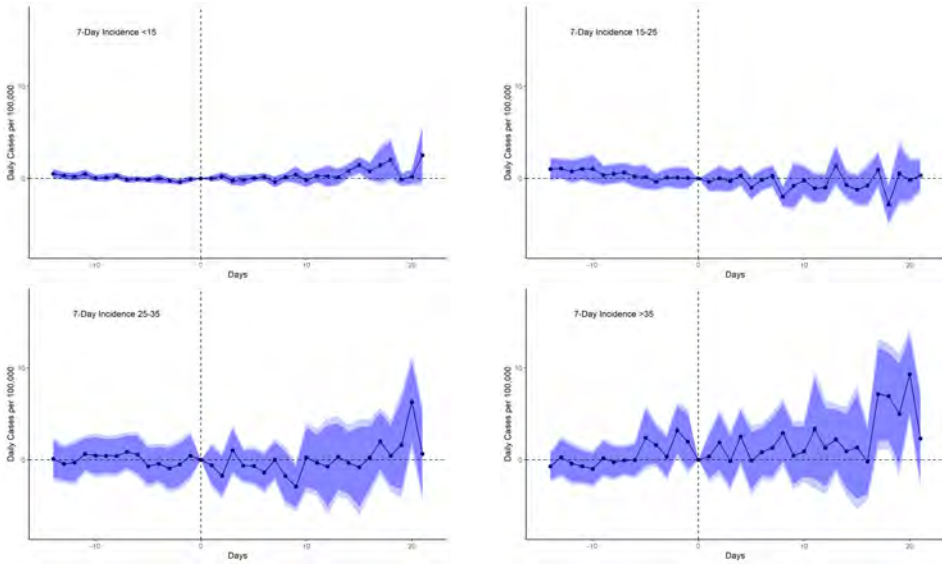


Figure A9: Effect of Matches per 100,000 Inhabitants Under Different Incidence Levels

Note: The plots show the coefficients of $Match_{it-d}$ from the regression in equation (1). The x-axis "Days" gives the respective value for d . On the y-axis, the number of daily registered COVID-19 cases per 100,000 inhabitants of the respective age group on the county-level is given. The shaded areas give the 95% and 90%-confidence intervals of the related coefficients. The sample includes all matches in the dataset with an audience of above zero. The information in the top left corner gives the respective incidence level category.

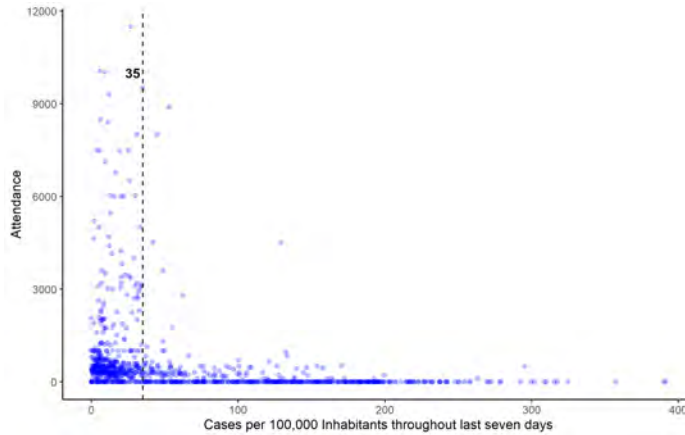


Figure A10: Attendance Depending on Incidence Level on Match Day

Note: The plot gives the number of visitors attending matches. Every dot represents a match in the sample. The x-axis gives the number of COVID-19 cases per 100,000 inhabitants throughout the last seven days in the county ("Kreis") where the match took place. The y-axis gives the respective number of visitors. The dashed vertical line represents the 35 incidence level which served German counties as benchmarks to strengthen non-pharmaceutical interventions. The single outlier at 4000 attendance at an incidence level of above 100 is a match in Berlin where the individual district's incidence level is the central measure for additional measures against COVID-19.

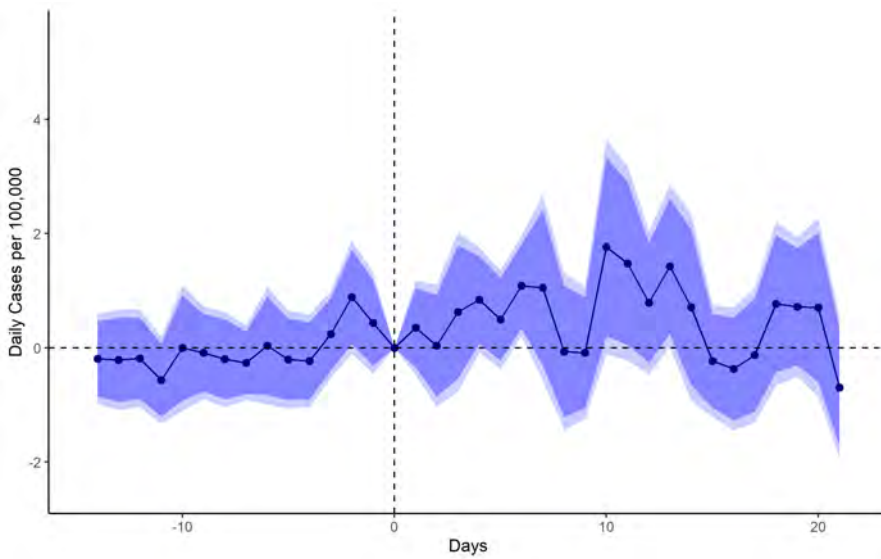


Figure A11: Effect of Matches per 100,000 Inhabitants on Away Team Counties

Note: The plot shows the coefficients of $Match_{it-d}$ from the regression in equation (1). The x-axis "Days" gives the respective value for d . On the y-axis, the number of daily registered COVID-19 cases per 100,000 inhabitants on the away county-level is given. The shaded areas give the 95% and 90%-confidence intervals of the related coefficients. The sample includes all matches in the dataset.

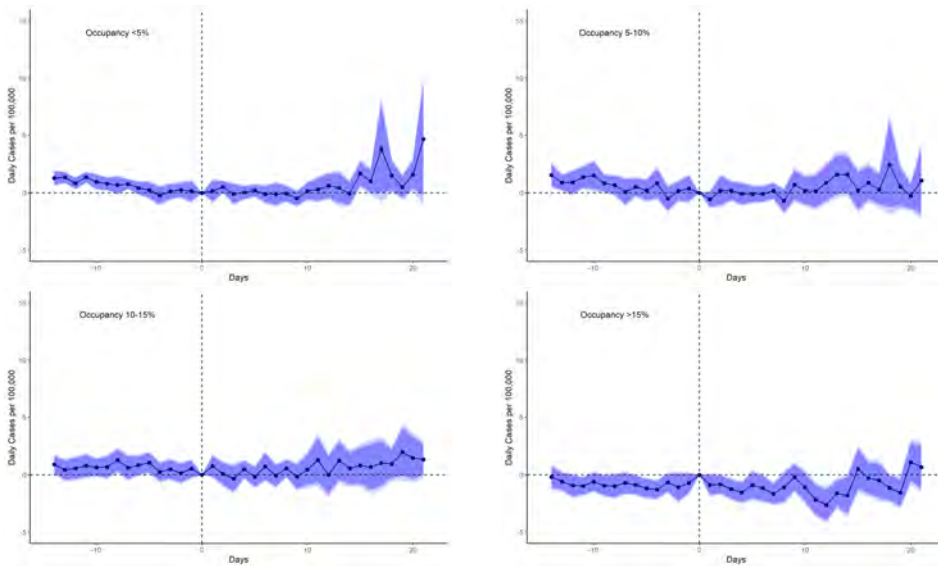


Figure A12: Effect of Matches per 100,000 Inhabitants (Occupancy Level)

Note: The plots show the coefficients of $Match_{it-d}$ from the regression in equation (1). The x-axis "Days" gives the respective value for d . On the y-axis, the number of daily registered COVID-19 cases per 100,000 inhabitants of the respective age group on the county-level is given. The shaded areas give the 95% and 90%-confidence intervals of the related coefficients. The information in the top left corner gives the respective occupancy level.

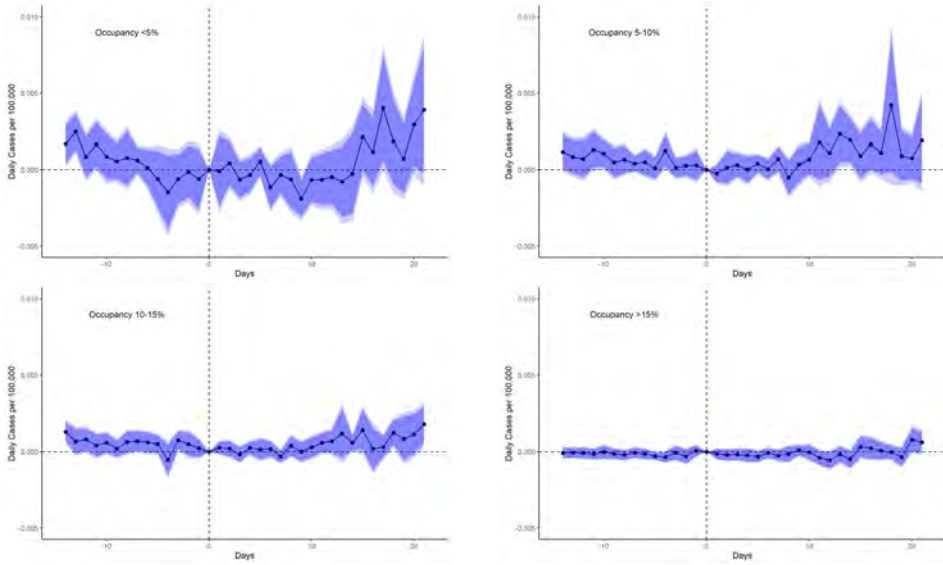


Figure A13: Effect of Visitors per 100,000 Inhabitants (Occupancy Level)

Note: The plots show the coefficients of $Match_{it-d}$ from the regression in equation (1). The x-axis "Days" gives the respective value for d . On the y-axis, the number of daily registered COVID-19 cases per 100,000 inhabitants of the respective age group on the county-level is given. The shaded areas give the 95% and 90%-confidence intervals of the related coefficients. The sample includes all matches in the dataset with an audience of above zero. The information in the top left corner gives the respective occupancy level.

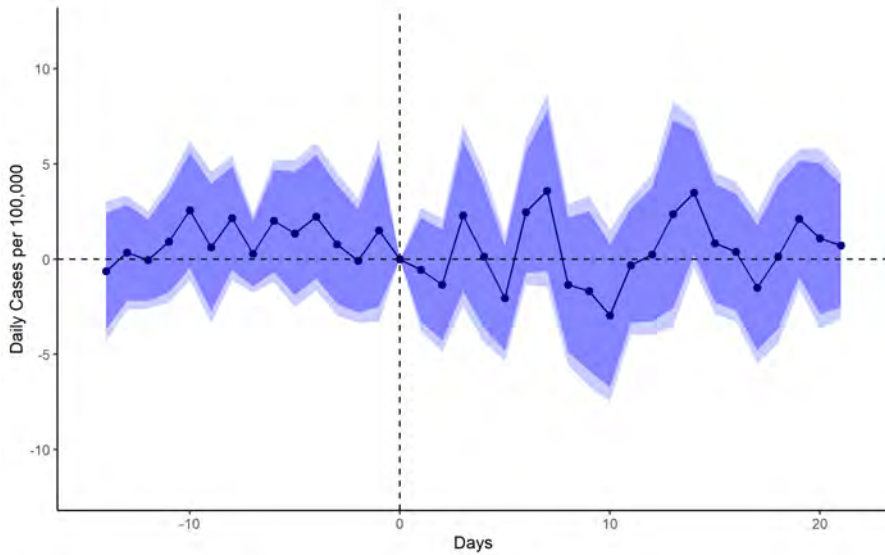


Figure A14: Effect of Ghost Matches per 100,000 Inhabitants

Note: The plot shows the coefficients of $Match_{it-d}$ from the regression in equation (1). The plot uses the number of ghost matches per 100,000 inhabitants on the county level as treatment indicator. The x-axis "Days" gives the respective value for d . On the y-axis, the number of daily registered COVID-19 deaths per 100,000 inhabitants on the county-level is given. The shaded areas give the 95% and 90%-confidence intervals of the related coefficients. The sample includes all ghost matches in the dataset.

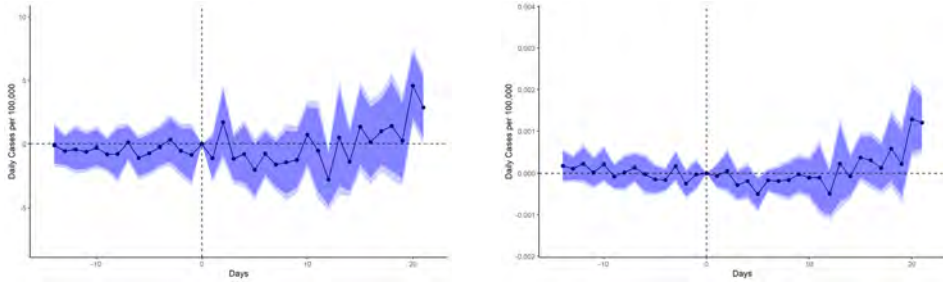


Figure A15: Effect of Matches and Visitors per 100,000 Inhabitants (Top Leagues)

Note: The plots show the coefficients of $Match_{it-d}$ from the regression in equation (1). The left plot uses the number of matches per 100,000 inhabitants on the county level as treatment indicator, the right plot the number of visitors per 100,000 inhabitants on the county-level is given. The x-axis "Days" gives the respective value for d . On the y-axis, the number of daily registered COVID-19 cases per 100,000 inhabitants on the county-level is given. The shaded areas give the 95% and 90%-confidence intervals of the related coefficients. The sample includes all matches in the dataset with an audience of above zero.

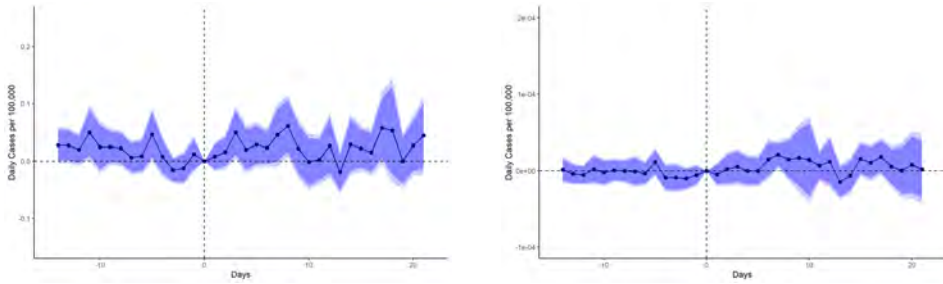


Figure A16: Effect of Matches and Visitors per 100,000 Inhabitants on Deaths

Note: The plots show the coefficients of $Match_{it-d}$ from the regression in equation (1). The left plot uses the number of matches per 100,000 inhabitants on the county level as treatment indicator, the right plot the number of visitors per 100,000 inhabitants on the county-level is given. The x-axis "Days" gives the respective value for d . On the y-axis, the number of daily registered COVID-19 deaths per 100,000 inhabitants on the county-level is given. The shaded areas give the 95% and 90%-confidence intervals of the related coefficients. The sample includes all matches in the dataset with an audience of above zero.

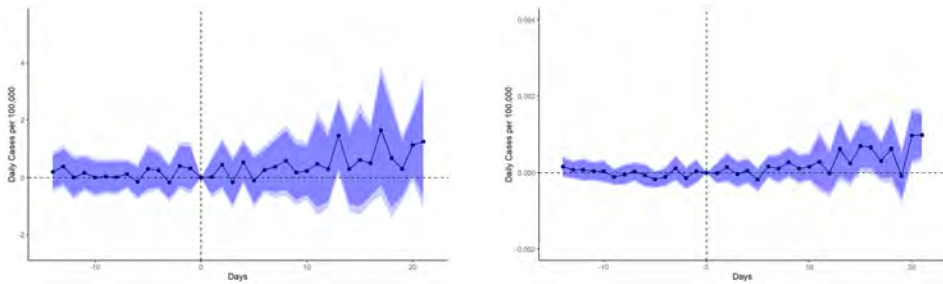


Figure A17: Effect of Matches and Visitors per 100,000 Inhabitants on COVID-19 Cases (Extended Observation Period)

Note: The plots show the coefficients of $Match_{it-d}$ from the regression in equation (1). The left plot uses the number of matches per 100,000 inhabitants on the county level as treatment indicator, the right plot the number of visitors per 100,000 inhabitants on the county-level is given. The x-axis "Days" gives the respective value for d . On the y-axis, the number of daily registered COVID-19 cases per 100,000 inhabitants on the county-level is given. The shaded areas give the 95% and 90%-confidence intervals of the related coefficients. The sample includes all matches in the dataset with an audience of above zero. The observation period for these plots is extended to December 06, 2020.

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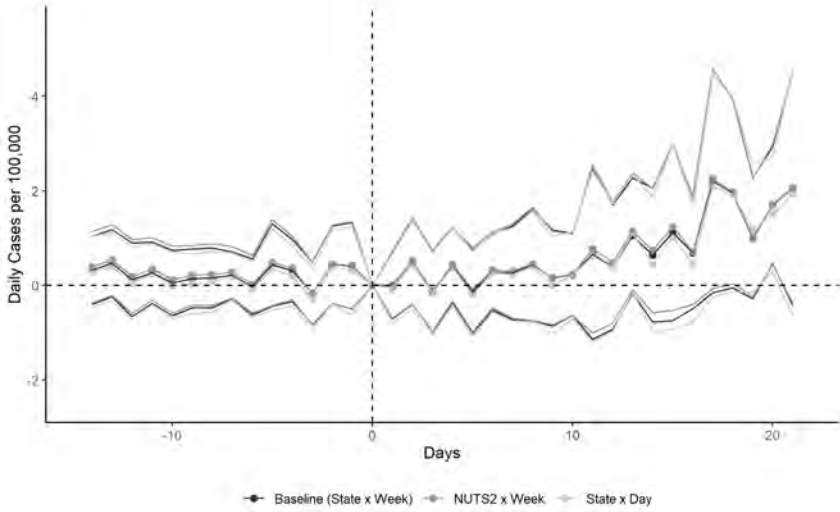


Figure A18: Effect of Matches per 100,000 Inhabitants (Different Regional Inference Approach I)

Note: The plot shows the coefficients of $Match_{it-d}$ from the regression in equation (1) or slightly adapted regressions. The plot uses the number of matches per 100,000 inhabitants on the county level as treatment indicator. The x-axis "Days" gives the respective value for d . On the y-axis, the number of daily registered COVID-19 deaths per 100,000 inhabitants on the county-level is given. The additional lines give the 95%-confidence intervals of the related coefficients. The sample includes all matches in the dataset with an audience of above zero. The differently colored event study estimates and confidence intervals represent different regression models estimated with varying regional trends.

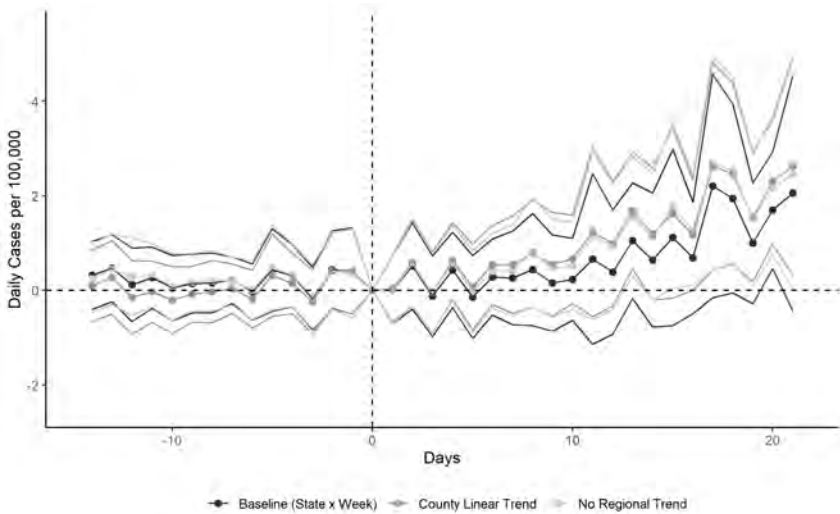


Figure A19: Effect of Matches per 100,000 Inhabitants (Different Regional Inference Approach II)

Note: The plot shows the coefficients of $Match_{it-d}$ from the regression in equation (1) or slightly adapted regressions. The plot uses the number of matches per 100,000 inhabitants on the county level as treatment indicator. The x-axis "Days" gives the respective value for d . On the y-axis, the number of daily registered COVID-19 deaths per 100,000 inhabitants on the county-level is given. The additional lines give the 95%-confidence intervals of the related coefficients. The sample includes all matches in the dataset with an audience of above zero. The differently colored event study estimates and confidence intervals represent different regression models estimated with varying regional trends.

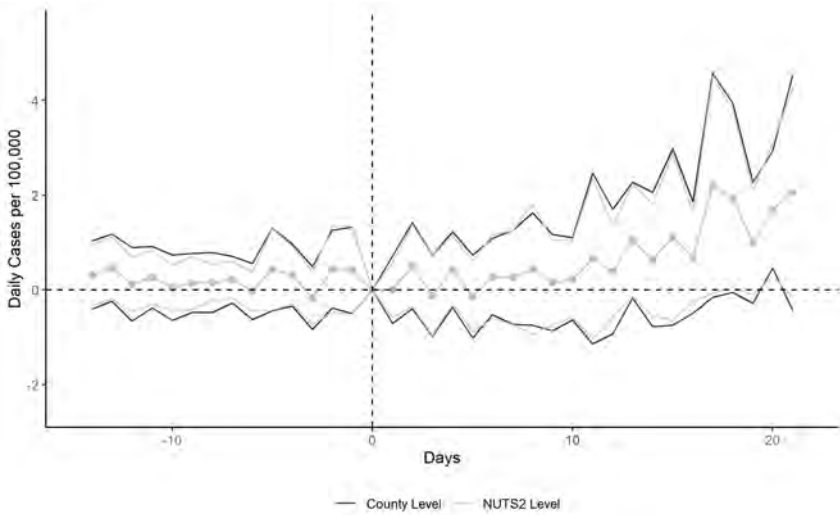


Figure A20: Effect of Matches per 100,000 Inhabitants (Different Clusters for Standard Errors)

Note: The plot shows the coefficients of $Match_{it-d}$ from the regression in equation (1). The plot uses the number of matches per 100,000 inhabitants on the county level as treatment indicator. The x-axis "Days" gives the respective value for d . On the y-axis, the number of daily registered COVID-19 deaths per 100,000 inhabitants on the county-level is given. The shaded areas give the 95% and 90%-confidence intervals of the related coefficients. The sample includes all matches in the dataset with an audience of above zero. The differently colored confidence intervals represent different clusters used for standard error correction.

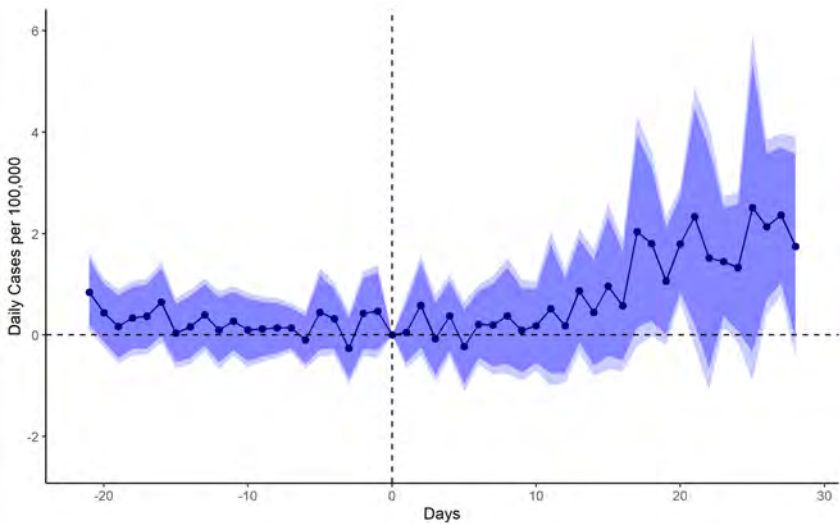


Figure A21: Effect of Matches per 100,000 Inhabitants (4 Week Post-Treatment Effect Window)

Note: The plot shows the coefficients of $Match_{it-d}$ from the regression in equation (1). The plot uses the number of matches per 100,000 inhabitants on the county level as treatment indicator. The x-axis "Days" gives the respective value for d . On the y-axis, the number of daily registered COVID-19 deaths per 100,000 inhabitants on the county-level is given. The shaded areas give the 95% and 90%-confidence intervals of the related coefficients. The sample includes all matches in the dataset with an audience of above zero.