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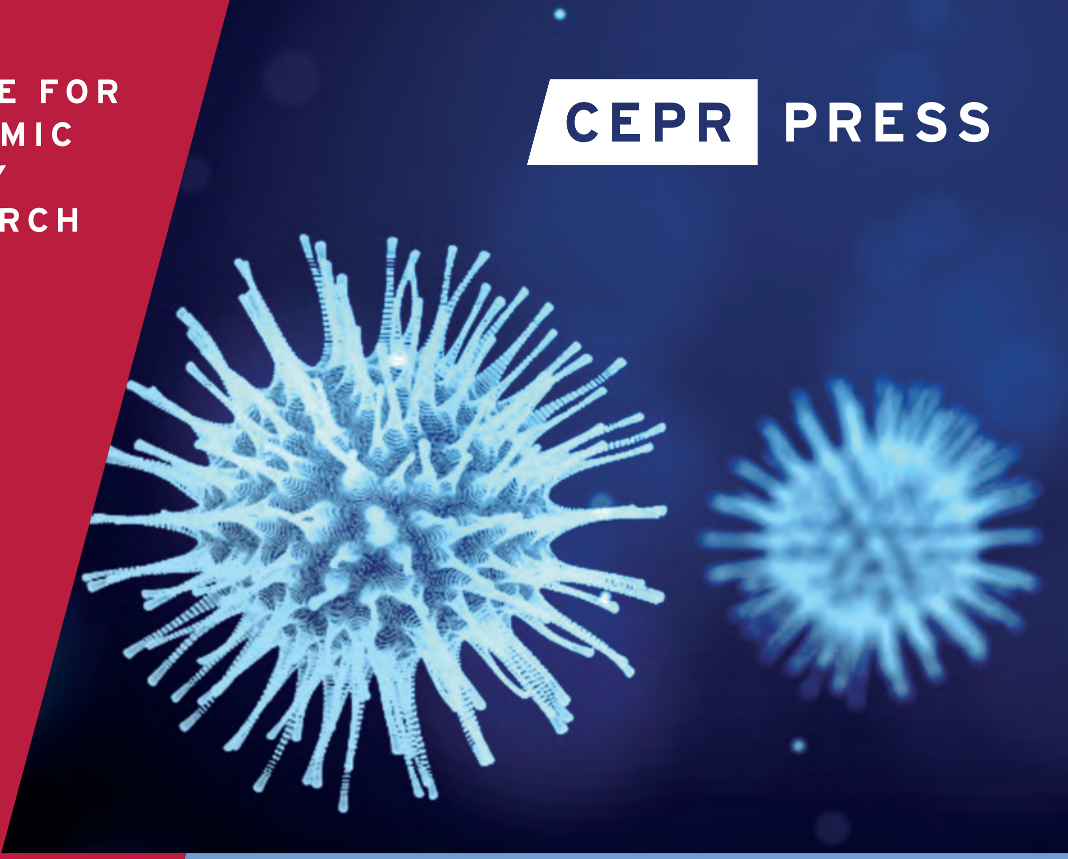

COVID ECONOMICS

VETTED AND REAL-TIME PAPERS

ISSUE 20
20 MAY 2020

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Covid Economics
Vetted and Real-Time Papers

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

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

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

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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.

American Economic Review

American Economic Review, Applied Economics

American Economic Review, Insights

American Economic Review, Economic Policy

American Economic Review, Macroeconomics

American Economic Review, Microeconomics

American Journal of Health Economics

Economic Journal

Economics of Disasters and Climate Change

International Economic Review

Journal of Development Economics

*Journal of Econometrics**

Journal of Economic Growth

Journal of Economic Theory

*Journal of the European Economic Association**

Journal of Finance

Journal of Financial Economics

Journal of International Economics

*Journal of Labor Economics**

Journal of Monetary Economics

Journal of Public Economics

Journal of Political Economy

Journal of Population Economics

*Quarterly Journal of Economics**

Review of Economics and Statistics

*Review of Economic Studies**

Review of Financial Studies

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

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The cost of the COVID-19 crisis: Lockdowns, macroeconomic expectations, and consumer spending[1]

Olivier Coibion,[2] Yuriy Gorodnichenko[3] and Michael Weber[4]

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Date submitted: 16 May 2020; **Date accepted:** 17 May 2020

We study how the differential timing of local lockdowns due to COVID-19 causally affects households' spending and macroeconomic expectations at the local level using several waves of a customized survey with more than 10,000 respondents. About 50% of survey participants report income and wealth losses due to the corona virus, with the average losses being $5,293 and $33,482 respectively. Aggregate consumer spending dropped by 31 log percentage points with the largest drops in travel and clothing. We find that households living in counties that went into lockdown earlier expect the unemployment rate over the next twelve months to be 13 percentage points higher and continue to expect higher unemployment at horizons of three to five years. They also expect lower future inflation, report higher uncertainty, expect lower mortgage rates for up to 10 years, and have moved out of foreign stocks into liquid forms of savings. The imposition of lockdowns can account for much of the decline in employment in recent months as well as declines in

1 We thank the National Science Foundation for financial support in conducting the surveys. We also thank Shannon Hazlett and Victoria Stevens at Nielsen for their assistance with the collection of the PanelViews Survey. Results in this article are calculated based on data from The Nielsen Company (US), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. Information on availability and access to the data is available at http://research.chicagobooth.edu/nielsen. We thank Peter McCrory for sharing data on the timing of lockdowns.

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consumer spending. While lockdowns have pronounced effects on local economic conditions and households' expectations, they have little impact on approval ratings of Congress, the Fed, or the Treasury but lead to declines in the approval of the President.

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Business cycles are rarely a matter of life and death in advanced economies, but the COVID19 crisis is a grim reminder that economics is a dismal science and that, quite literally, policymakers face a painful tradeoff between saving lives and saving the economy. Apart from a myriad of excruciating ethical choices, making a policy decision is particularly difficult in the current environment because policymakers and the public have only limited information on the scale of the economic calamity as well as the economic cost of lockdowns.

To provide these crucial inputs for policy, we fielded several waves of a customized survey on all households participating in the Kilts Nielsen Consumer Panel (KNCP) to elicit beliefs, employment status, spending, and portfolio allocations both before and during the COVID19 crisis. In short, we paint a very bleak state and outlook for the U.S. economy. We also use differential timing of imposing lockdowns at the local level to quantify the effect of lockdowns on households' economic outlook and their spending responses. We find that the cost of lockdowns is very large.

We first report aggregate statistics across survey waves to study how the arrival COVID19 affected spending patterns and expectations on average between the pre-crisis wave in January 2020 and April 2020. Consistent with earlier work (Coibion, Gorodnichenko and Weber, 2020, Bick and Blandin, 2020), we find a massive decline in the employment rate: the rate fell by 5 percentage points which is larger than the cumulative drop in the employment-to-population ratio during and after the Great Recession. Overall spending drops by $1,000 per month between January and April which corresponds to a 31% drop in spending with heterogeneous responses across granular categories. Specifically, we find one of the largest drops in debt payments including mortgages, student, and auto loans. This result highlights the possibility of a wave of defaults in the next few months, indicating a slower economic recovery and possibly explaining the increase in loan provisions by major US banks in recent weeks. Households also spend substantially less on discretionary expenses such as transportation, travel, recreation, entertainment, clothing, and housing-related expenses. Medical expenses, utilities, education-related expenses, and food expenses also decrease but to a lesser extent. We also document large decreases in planned spending on durables during the crisis. On average, survey participants are 5 percentage points less likely to purchase durables during the crisis wave relative to the pre-crisis wave which translates into an average drop in spending on durables of almost $1,000.

In line with these negative outcomes at the individual level, households' macroeconomic expectations have become far more pessimistic. Average perceptions of the current unemployment rate increased by 11 percentage points with similar magnitudes for expectations of unemployment in one year. Unemployment expectations over the next three to five years also increased by an average of 1.2 percentage points, indicating that households expect the downturn to have persistently negative effects on the labor market. Consistent with this view, inflation expectations over the next twelve months on average dropped by 0.5 percentage points but uncertainty increased by 0.3 percentage points. Current mortgage rate perceptions as well as expectations for the end of 2020 and 2021 dropped on average by about 0.4

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percentage points with even larger drops in average expectations over the next five to ten years. These changes from before to during the COVID19 pandemic document dramatic shifts in spending, income and wealth losses, and expectations and allow us to benchmark our cross-sectional findings to these aggregate statistics. The increased uncertainty at the household level as well the large drop in planned spending indicate the potential role for some form of liquidity insurance to curb the desire for precautionary spending and stimulate demand once local lockdowns are lifted (D'Acunto et al. 2020).

To assess the economic damage that households attribute to the virus, we elicit information on the perceived financial situation of the survey participants and possible losses due to the corona virus, both in income and wealth. We measure households' concerns about their financial situation on a ten-point Likert scale with higher levels indicating being more concerned. The average (median) response is 7 (8) indicating that many households are highly concerned about their personal financial situation. We also find large declines both in their income and wealth. Forty-two percent of employed respondents report having lost earnings due to the virus with the average loss being more than $5,000. More than 50% of households with significant financial wealth report having lost wealth due to the virus and the average wealth lost is at $33,000. Given the important role of wealth effects for consumption, the drop in wealth puts further downward pressure on future consumption (Lettau and Ludvigson, 2004).

What are the economic costs of lockdowns? To answer this question, we compare economic outcomes for households in counties with lockdowns to households in counties without lockdowns. We instrument lockdowns with a dummy variable that equals one if the county has any confirmed COVID cases. Our identification exploits the heterogeneous timing of when the first COVID cases were identified in different counties. As we argue below, most lockdowns occur when only a handful of COVID cases are reported in a location, which is largely random. By themselves, these few cases are unlikely to change economic behavior of households (we provide external evidence to support this identifying assumption). We also control for share of confirmed cases at the county level which proxies for direct health effects on the economy. While our analysis is not a randomized controlled trial, we have taken a number of steps to interpret the effect of lockdowns on beliefs and choices causally.

In our first set of tests, we study the labor market response to local lockdowns. Individuals living in counties currently under lockdown are 2.8 percentage points less likely to be employed, have a 1.9 percentage points lower labor-force participation, and are 2.4 percentage points more likely to be unemployed. This degree of variation introduced by lockdowns is large. For example, these results imply that lockdowns account for close to sixty percent of the decline in the employment to population ratio. Furthermore, since we can only estimate the short-run effects of lockdowns on labor markets, these numbers are likely to be a lower bound on the total effects of lockdowns on labor markets, as continued lockdowns are likely to lead to business failures and further job loss.

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To analyze the degree to which disruptions in labor markets translate into changes in aggregate demand, we study the spending patterns of survey participants using survey answers on dollar spending in narrowly defined categories during the months from January to April. We find that households under lockdown spend on average 31 log percentage points less than other households, indicating a large drop in aggregate demand due to mobility restrictions and the effect of the pandemic on income and economic expectations. However, the magnitudes of the decline vary dramatically across spending categories. To better understand the effect of the pandemic on future aggregate demand conditions, we analyze spending plans of households. We first document that lockdowns are not a significant determinant of current financial constraints and durable purchases in the months pre-crisis, thereby ruling out possible concerns that any result we document might be driven by financial constraints or past purchases because purchases of many durable goods are lumpy. At the extensive margin, survey participants under lockdown are 3.5 percentage points less likely to purchases larger ticket items in the next 12 months. At the intensive margin, these survey participants plan to spend almost 26 log percentage points less. Taken together, these results indicate a persistent drop in future aggregate demand, possibly due to a mix of lower expected income, heightened uncertainty, and supply restrictions. To the extent that part of the drop in planned spending reflects precautionary savings, our results indicate that tax rebates or other forms of direct transfers to households might be less effective than during normal recessions (Johnson et al. 2006, Parker et al. 2013).

Higher uncertainty should not only result in lower spending due to precautionary motives but might also result in portfolio reallocations out of risky assets and into safe assets. Conditional on having savings totaling more than one-month of income, participants under lockdown have a 1.7 percentage point higher portfolio share in checking accounts and a 0.7 percentage point lower share in foreign stocks, consistent with a flight to safety. We do not find a significant reaction for the share of savings held in US equity, possibly because US equity markets already had partially bounced back by the time we fielded the survey in early April of 2020.

We then move on to study the effect of lockdowns on subjective expectations, which can shed light on the speed and shape of the recovery. First, survey participants that are under lockdown expect 0.5 percentage points lower inflation over the next 12 months, which might in part explain the depressed spending response of households. Consistent with the idea that the impact of the pandemic on inflation is not clear, we find that the individual-level uncertainty about future expected inflation increases by more than 0.6 percentage points. Second, we analyze the effect on the expected unemployment rate at different horizons. The pandemic increases current unemployment estimates by staggering 13.8 percentage points, expectations for the unemployment rate in one year increase by 13 percentage points, and long-run expectations over the next three to five years are on average still 2.4 percentage points higher. These results indicate, at least through the lens of household expectations, that a V-shaped recovery might be unlikely. Moreover, given the length of

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heightened unemployment according to household expectations, these results could warrant an extension of unemployment insurance benefits to ensure no sharp drop in demand once claims expire. Third, we look at the effect on mortgage rate expectations, which are a central transmission mechanism for monetary policy to household consumption. The COVID-19 pandemic results in current mortgage rate perceptions that are 0.7 percentage points lower, with similar effects for a forecast horizon until the end of 2020, 2021 but even larger effects at the long run over the next five to ten years. Hence, the pandemic results in a level shift of the term structure of mortgage rates. The negative effect on expectations in the long run suggests that the lower bound on nominal interest rates might be a binding constraint for monetary policy makers for the foreseeable future.

Finally, to assess the political consequences of lockdowns, we ask respondents to rate several government bodies on a 0 (poor) to 10 (excellent) scale. We find that being under lockdown results in a 6.2 point lower rating for the President but a 3.1 point higher rating for the U.S. Center for Disease Control. Taken together, our findings help us understand the drivers of heterogeneous consumer expectations and spending patterns which is crucial to design policy interventions in an effective way.

Jointly, these findings provide new real-time evidence on the economic consequences of the COVID-19 pandemic. Our repeated surveys are able to provide unprecedented detail on how the COVID crisis has affected labor markets, household spending decisions and expectations, and even portfolio reallocations in recent months. Strikingly, we find that much of the declines in employment and spending can be attributed to lockdowns rather than to the share of the population infected by the coronavirus. While we cannot speak to the welfare effects of these policies in the absence of knowing to what extent they are successful in slowing the spread of the disease, our results do indicate a direct and large role for the preventative lockdown measures in accounting for the size of the resulting downturn.

I Related Literature

We relate to the fast-growing literature studying the economic consequences of the COVID19 pandemic. Binder (2020) shows that 30% - 40% of Americans are very concerned about the corona crisis, postponed travel and delayed purchases of larger ticket items as early as March 2020 but became more optimistic about the unemployment situation and revised downward their inflation expectations once being told about the cut in the federal funds target rate on March 3rd. Fetzer et al. (2020) show the arrival of the corona virus in a country leads to a large increase in internet searches around the world. In a survey experiment on a US population, they find survey participants vastly overestimate the mortality rate and the contagiousness of the virus. Hanspal et al. (2020) study the income and wealth loss in a survey and the impact on expectations about the economic recovery. Barrios and Hochberg (2020) and Allcott et al. (2020) use internet searches, survey data, and travel data from smartphones to document that political partisanship determines the perception of risk associated with COVID19 and non-essential travel activity. Bursztyn et al. (2020) study

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the effect of media consumption on the perception of the corona virus. Dingel and Neiman (2020) use data from responses to two Occupational Information Network surveys and estimate that about 37% of jobs can be performed from home, whereas Mongey (2020) documents that employees that are less likely to be able to work from home are mainly non-white and without a college degree. Using initial unemployment insurance claims, Baek et al. (2020) study the effect of lockdowns on employment at the state-level. Andersen et al. (2020), Chen et al. (2020), and Baker et al. (2020) study the consumption response to the COVID19 pandemic. On the quantitative side, a growing literature jointly models the dynamics of the pandemic and the economy to quantify the economic costs and benefits of different policies (see Atkeson (2020), Barro et al. (2020), Eichenbaum et al. (2020), Farboodi et al. (2020), Jones et al. (2020), Kaplan et al. (2020), Krueger et al. (2020), Guerrieri et al. (2020), Alvarez et al. (2020), and Dietrich et al. (2020)). Finally, our Nielsen survey builds on previous work using the Nielsen panelists to study the formation and updating of economic expectations (Coibion et al. (2019, 2020) and D'Acunto et al (2020a, b)). Coibion et al. (2020) also use Nielsen surveys to study the effect of the pandemic on labor markets and find large drops in labor-force participation due to a wave of early retirements.

II Data and Survey Design

This section describes the survey design we use to elicit expectations, plans, and past spending decisions. We first detail the Nielsen Homescan panel on which we run the survey and then provide more information on the structure of the survey.

A. Nielsen Panel

Since June 2018, we have been fielding customized surveys inviting participation by all household members in the KNCP on a quarterly frequency. The KNCP represents a panel of approximately 60,000 households that report to AC Nielsen (i) their static demographic characteristics, such as household size, income, ZIP code of residence, and marital status, and (ii) the dynamic characteristics of their purchases, that is, which products they purchase, at which outlets, and at which prices. Panelists update their demographic information at an annual frequency to reflect changes in household composition or marital status.

Nielsen attempts to balance the panel on nine dimensions: household size, income, age of household head, education of female household head, education of male household head, presence of children, race/ethnicity, and occupation of the household head. Panelists are recruited online, but the panel is balanced using Nielsen's traditional mailing methodology. Nielsen checks the sample characteristics on a weekly basis and performs adjustments when necessary.

Nielsen provides households with various incentives to guarantee the accuracy and completeness of the information households report. They organize monthly prize drawings, provide points for each

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instance of data submission, and engage in ongoing communication with households. Panelists can use points to purchase gifts from a Nielsen-specific award catalog. Nielsen structures the incentives to not bias the shopping behavior of their panelists. The KNCP has a retention rate of more than 80% at the annual frequency. Nielsen validates the reported consumer spending with the scanner data of retailers on a quarterly frequency to ensure high data quality. The KNCP filters households that do not report a minimum amount of spending over the previous 12 months. Information on consumer spending is available only with a pronounced lag however, so we are not yet able to combine information from our survey responses with underlying spending decisions on the part of households.

B. Survey

Nielsen runs surveys on a monthly frequency on a subset of panelists in the KNCP, the online panel, but also offers customized solutions for longer surveys. Retailers and fast-moving consumer-goods producers purchase this information and other services from Nielsen for product design and target-group marketing. At no point of the survey did Nielsen tell their panelists that the survey they fielded was part of academic research which minimizes the concerns of survey demand effects.

In January and April of 2020, we fielded the two waves of the survey that we exploit in the current paper. Our survey design builds on the Michigan Survey of Consumers, the New York Fed Survey of Consumer Expectations, the Panel on Household Finances at the Deutsche Bundesbank as well as D'Acunto et al. (2020). The January wave was fielded to 63,732 households. 18,344 individuals responded for a response rate of 26.80% and an average response time of 16 minutes 47 seconds. The response rate compares favorably to the average response rates of surveys on Qualtrics that estimates a response rate between 5% to 10%. The April wave had 13,771 unique respondents and a sample of 50,870. Nielsen provides weights to ensure representativeness of the households participating in the survey. We report descriptive statistics for participating households in Appendix Table 1. The average household income is $68,000 and the average household size 2.6. On average, survey participants are 50 years old and 73% of survey participants are white These statistics are similar to other studies using the Nielsen panel, such as Coibion at al. (2019).

The online appendix contains the detailed questions we use in the current paper. We collect information on spending (per month) in the last three months in detailed categories such as debt payments including mortgages, auto loans, and student loans, housing expenses, utilities, food, clothing, gas, medical expenses, transportation costs, travel and entertainment, education and child care, furniture and other small durables, as well as a catch-all category including charitable giving. We also ask participants about purchases of larger durables such as cars or houses over the last 6 months as well as plans to buy these items over the next 12 months. We then elicit financial constraints, and financial portfolios conditional on any savings larger than one month of income.

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Subsequently, we elicit inflation expectations. We follow the design in the New York Fed Survey of Consumer Expectations (SCE) and ask specifically about inflation, because asking about prices might induce individuals to think about specific items whose prices they recall rather than about overall inflation (see Crump et al. (2015) for a paper describing and using the SCE data). We elicit a full probability distribution of expectations by asking participants to assign probabilities to different possible levels of the inflation rate. In addition, we also ask about the perception of the current unemployment rate and the expected unemployment rate in twelve months, and the next three to five years and the current rate on a fixed-rate 30-year mortgage as well as the expected rate at the end of 2020, 2021, and in the next five to ten years. Mortgages with a 30-year fixation period represent the most popular mortgage product in the U.S., accounting for more than 70% of mortgages originated over the period 2013-2016.[1]

To measure labor market conditions, we first ask respondents on whether they have a paid job and if they say no, whether they are actively looking for a job. If they answer no, we classify them as out of the labor force. In case survey participants have a paid job, we ask them whether they have lost any earnings due to the virus and if so, ask them to provide an estimate. Similarly, if respondents have savings of more than one month of income, we also ask them whether they have lost any wealth and if so, how much.

Regarding the corona virus, we ask participants if they have heard any news about it and if so, how concerned they are about their financial situation with a qualitative scale from 0 to 10. Moreover, we ask them whether they are currently under lockdown (we also observe their zipcodes), and ask to evaluate how different government bodies are handling the crisis. Finally, we ask households to estimate expected duration of lockdowns and time before conditions return to normal.

III The COVID19 Crisis in the Survey Data

A major contribution of our study to the growing literature on the effects of COVID19 on expectations and spending is the panel dimension of our survey. Hence, we can study in detail how spending, perceptions, and expectations changed over time pre and during the pandemic and also benchmark our cross-sectional estimates to the movements in these aggregates over time.

A. Pre-crisis vs. Crisis Statistics

Tables 1 and 2 provide average statistics of all the variables we analyze in the paper for the pre-crisis wave in January, the crisis wave in April, as well as the difference. Panel A of Table 1 first documents the labor market statistics. Consistent with Coibion, Gorodnichenko and Weber (2020), we find a dramatic (5 percentage point) drop in employment which is larger than the cumulative decrease in the employment-to-

[1] According to data from the National Mortgage Database program, jointly managed by the Federal Housing Finance Agency (FHFA) and the Consumer Financial Protection Bureau (CFPB).

population ratio during and after the Great Recession. The unemployment rate only increased by 2 percentage points because more than 4 percent of our survey population dropped out of the labor force which is even larger than the cumulative drop in labor-force participation between 2008 and 2016 of 3 percentage points.[2]

Panel B of Table 1 studies differences in liquidity and financial constraints across survey waves. Surprisingly, the fraction of survey participants that is able to cover an unexpected expense equal to one month of income slightly increases.[3] In a similar spirit, the fraction of households reporting significant financial wealth (more than one month of income) increases slightly.[4] Given the collapse of employment and financial markets, one may have expected that households should have less liquidity and access to credit. However, there is an offsetting factor. Because consumer spending declines dramatically, household could have greater (precautionary) savings and hence, on balance, there is little change in liquidity and access to credit.[5]

Panel C focuses on portfolio reallocations for the subsample of survey participants that have savings larger than one months of income. In the aggregate, we find small decreases in portfolio shares for cash, foreign assets, and gold but increases in US bonds and stocks. Overall, the portfolio reallocations are, however, small consistent with many savers not trading frequently (Giglio et al., 2019).

Finally, Panels D to G report average statistics for inflation expectations and uncertainty, unemployment and mortgage rates, both current, over the near future, as well as in the longer run. Inflation expectations on average dropped by 0.5 percentage points but uncertainty increased by 0.3 percentage points. Average perceptions of current unemployment rates increased by 11 percentage points with similar magnitudes for expectations in one year. Unemployment expectations over the next three to five years also increased by an average of 1.2 percentage points. These results are qualitatively similar (i.e., a large, short-run increase in unemployment with unemployment rates elevated by one percentage point in 3-5 years) when we drop observations for unemployment rates larger than 40% but economic magnitudes of the average differences across waves are about half the size. Current mortgage rate perceptions as well as expectations for the end of 2020 and 2021 also dropped on average by about 0.4 percentage points with even larger drops in average expectations over the next five to ten years. The change in average

[2] Unemployment is defined as the ratio of those respondents that currently do not have a paid job but are looking for one. We define labor-force participation as the fraction of the overall survey population that is either employed or looking for work.

[3] The survey question is "Suppose that you had to make an unexpected payment equal to one month of your after-tax income, would you have sufficient financial resources (access to credit, savings, loans from relatives or friends, etc.) to pay for the entire amount?"

[4] The survey question is "Does your household have total financial investments (excluding housing) worth more than one month of combined household income?"

[5] Another possibility is that income declined so much that more households can find credit to cover this correspondingly reduced amount of spending.

expectations show some dramatic differences across waves pre and during the crisis and allow us to benchmark our cross-sectional estimates below to movements in the aggregate.

We now move on to study the change in average monthly spending in the three months before the two survey waves. One concern with survey data is that participants might only partially recall their past expenditure. To benchmark our survey data, we first compare the reported average monthly spending in the January wave to the monthly spending in the 2018 Consumer Expenditure Survey (CEX). To do so, we take the annual data from the CEX, divide it by 12 to get monthly averages, and match the survey categories to the categories in the CEX. Some differences are expected for at least two reasons. First, no one-to-one mapping exists between categories in the different datasets. Second, consumer spending is seasonal and the CEX survey is a monthly average over a year, while the Nielsen survey covers a specific part of a year. Despite these inconsistencies, consumer spending in the Nielsen survey is reasonably close to consumer spending in the CEX (Appendix Table 2). Overall monthly spending in our survey is $3,999 which is smaller than the average monthly spending in the CEX of $5,102 which is expected because the CEX also includes additional categories which we did not elicit in the survey as well as larger durables such as car purchases and larger appliances. Excluding these categories moves the two averages closer to each other. As for debt payments which include student loans we see larger expenditures in the January wave than in the CEX which does not have a separate category for student loans. Housing related expenses including rent and maintenance among other expenses compare closely with monthly expenses of $616 in our survey and $535 in the CEX. Similarly, for utilities which also includes phone and internet, and food which includes groceries, dine out, and beverages, both surveys report spending of $429 and $532 (KNPC) and $455 and $709 (CEX), respectively. As for clothing and footwear, we find averages of $126 in the KNCP and $220 in the CEX. For expenditures on gasoline, the category which matches closest across surveys, we indeed find almost identical averages, $174 versus $176. Overall, we conclude that the survey-elicited expenses line up reasonably closely to averages we can find in the CEX and suggest our subsequent analysis provides meaningful insights. Another advantage of our survey design relative to repeated cross-sections is the fact that we can do comparisons across survey waves in the same sample population which allows us to difference out systematic misreporting (i.e., some survey respondents systematically over- or underreporting certain categories).

Table 2 reports the overall monthly dollar spending as well as the split down by categories. Note that households can report zero spending for a given category in a wave and average spending in columns (1) and (2) includes households with zero spending. To make descriptive statistics more comparable to the results we report below, we also compute the growth rate of $\log(1 + Spending)$, that is, $\overline{\log(1 + Spending)_{April}} - \overline{\log(1 + Spending)_{January}}$. We do this particular transformation of the data to handle the skewness of consumer spending and to take into account variation in the extensive margin,

that is, some households stop spending on some categories. We see that overall spending over the last three months drops by \$1,000 per month between January and April. The decline in the averages corresponds to a drop of 31 log percentage points in spending. Across categories, we see the largest average drops for travel, clothing, debt payments, and housing with decreases of 150, 110, 92, and 88 log percentage points, respectively.[6] To better understand the nature of these declines, we also report extensive and intensive margins of each spending category in columns (4)-(6) and (7)-(9) respectively. The extensive margin measures whether a survey participants has spent any money in a given category, whereas the intensive margin reports average dollar spending conditional on any spending. We observe large declines in the extensive margin not only for travel (the share of household reporting spending on this category declines by 31 percentage points) and clothing (22 percentage points) but also for debt payments and housing (which includes rent), by 12 and 15 percentage points, respectively. Hence, households mainly curb their discretionary spending and adjust their non-discretionary spending by less, which is consistent with D'Acunto et al. (2019). Furthermore, we observe that even for those that have positive debt payments, the size of the payment declines by approximately 15 log percentage points, while for housing (rent) the change in the intensive margin is zero (i.e., conditional on paying rent, households pay the full rent). These results suggest that constrained households stop servicing their debt and housing payments. Results for the intensive margins of other categories suggest that households downsize their purchases conditional of buying goods/services in a category. Given the importance of mortgage defaults for the severity of the Great Recession, these results suggest a sluggish recovery and substantial defaults in the coming months absent adequate policy interventions (Mian et al., 2013).

Table 2 also reports spending on durables over the previous six months, both at the extensive margin, any durable purchase, and the intensive margin, the realized dollar spending. The survey question specifies durables as a house (apartment), a car, or a large appliance. We see a slight increase in the frequency of spending on durables over the last six months in our April survey wave but no difference in the intensive margin. Because the reference period is the previous six months and the speed at which the COVID crisis has been unfolding, we are less likely to capture material variation between the pre-crisis and crisis periods.

The last row of Table 2 focuses on planned durable purchases (intensive and extensive margins) over the next twelve months. Here, we find large decreases in planned spending on durables during our crisis wave. On average, survey participants are 5 percentage points less likely to purchase durables during the crisis wave relative to the pre-crisis wave but conditional on a purchase the average amount is higher, which indicates possibly strong selection effects. When we measure the decline using log $(1 + Spending)$ which combines both margins, the planned purchases of durable goods decline by 30 log percentage points.

[6] These figures correspond to 77.8, 66.7, 60.1, and 58.5 percentage point declines.

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In short, we observe a massive decline in consumer spending and consumers anticipate reduced spending in the coming months, which is consistent with other data. For example, Baker et al. (2020) observe subsets of spending through a FinTech app and find decreases of restaurant spending of one third with overall average daily spending decreasing by two thirds between January and March but sharp increases in groceries early in the pandemic due to stockpiling with a decline during the end of March. Chen et al. (2020) use data from the largest bankcard acquiring and professional service supplier in China and find spending on goods and services decrease by 33%, whereas spending on entertainment and travel plummeted by about 60%. Anderson et al. (2020) uses transaction-level customer data from the largest bank in Denmark and documented that overall spending dropped by 25% with the largest decreases for food away from home and travel with more than 60% and almost 80%, respectively. Hence, our survey-based estimates are consistent with transaction-based analysis for several countries. Our analysis, though, has the potential advantage that we can observe overall spending and not only subsets of spending via credit cards or QR codes. From a historical perspective, these drops are large. De Nardi et al. (2012) use real personal consumption expenditure data and argue that overall consumption grew 15 percentage points less over the subsequent five years from 2007Q4 onwards compared to historical averages with even larger declines in services consumption.

B. Direct COVID19 Impacts

Table 3 reports several descriptive statistics for variables measuring welfare of survey participants in the context of the COVID crisis. First, we find that respondents have high levels of concerns about their household's financial situation. On a scale from 0 (not concerned) to 10 (extremely concerned), the mean response is 7.2 and the median response is 8. A third of respondents chose the maximum score of 10. Second, we find that even employed households report a considerable loss of labor earnings. Approximately 40 percent of the employed reported lost earnings because of COVID concerns. Conditional on losing earnings, the median loss is $1,500 but the mean loss is much higher at more than $5,000. Third, 54 percent of respondents with materially important financial wealth (worth more than one-month of household income) report losses in financial wealth because of COVID concerns. Because the distribution of wealth is highly skewed, the mean loss (approximately $33,500) is much greater than the median loss ($9,000). These statistics suggest that the COVID crisis has a significant impact on income and wealth of households. These numbers are similar to Hanspal et al (2020) who report average income losses of about $3,000 and wealth losses of about $50,000.

We also ask respondents to report the expected duration of lockdowns in their locations and the expected time before conditions return to normal in their locations. On average, lockdowns are expected to last 83 days and normalcy is expected to return in approximately six months. However, there is significant

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variation in these estimates: the standard deviation is 48 days for the lockdown duration and 140 days for the return time.

C. Lockdowns and COVID19 Infections

Figure 1 graphically illustrates the geographic spread of lockdowns at the county level according to our survey. The darker the color, the higher the fraction of the survey participants reporting being under lockdown. White represents counties without any data. We see substantial variation in the lockdown status with intensive lockdowns in the West, North East, and northern Midwest, which is consistent with the data reported in Baek et al. (2020).

To provide a sense for time variation in the distribution of lockdowns and COVID cases, Figure 2 shows the evolution of the fraction of counties with a lockdown as well as the fraction of counties with reported COVID cases above various thresholds. We take the timing of lockdowns at the county level from Baek et al. (2020) and the time series of confirmed COVID infections from Barrios and Hochberg (2020). We observe a significant spread of COVID cases before counties start to introduce lockdowns. Indeed, the fraction of counties with at least one confirmed COVID case leads the fraction of counties with a lockdown. For example, on March 22, 2020, more than 30 percent of counties had at least one confirmed COVID case, but only 10 percent of counties had a lockdown. Note that the fraction of counties with 10+ cases or with 100+ cases grows at a slower rate and as we increase the threshold for the number of confirmed cases, the fraction of counties with cases above a higher threshold generally lags the fraction of counties with lockdowns.

Given that lockdowns deterred social mobility substantially (Barrios and Hochberg, 2020), we now study how the COVID-induced lockdowns causally determine employment, consumer spending and expectations and whether lockdowns can account for aggregate economic conditions.

IV Econometric Framework for Measuring the Lockdown Effects

To estimate the effect of lockdown on economic activity, we need to address two related identification concerns. First, COVID infections may have a direct effect on the local economy. For example, workers may fail to show up at work because they fell sick with the virus or may have to take care of sick family members. Second, lockdowns are not applied randomly by policymakers and it could be that the same factors that lead policymakers to implement lockdowns also induce behavioral changes on the part of the population. For example, people concerned about the virus may self-quarantine thus depressing the economy before a shelter-at-home order is announced. Because of this behavioral response, a lockdown

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may appear to have a larger effect on the economy than its actual direct effect. In short, estimates of lockdown effects may be confounded by omitted variables.[7]

To tackle these concerns, we estimate the following econometric specification:

$$Y_{ijt} = \kappa_i + \psi \times Lockdown_{ijt} + \eta \times ShareCOVID_{jt} + error \qquad (1)$$

$$Lockdown_{ijt} = \alpha_i + \beta \times \mathbb{I}\{COVID_{j,t-s} > 0\} + \gamma \times ShareCOVID_{jt} + error \qquad (2)$$

where i, j index persons and counties and t and s index time. t are the January and April survey waves, $t - s$ shows the time of exposure to COVID s periods before wave t to determine variation in lockdowns in county j. Y is an outcome variable. κ_i is a person fixed effect. $Lockdown$ is a dummy variable equal to one if person i in county j reports being in lockdown at time t. $\mathbb{I}\{COVID_{js} > 0\}$ is a dummy variable equal to one if county j reported a positive number of COVID infections at time s. There is no lockdown or confirmed COVID case for any county in the January wave. $ShareCOVID_{jt}$ is the share of the population with confirmed COVID infection in county j at time t, the share is measured in percent (i.e., from 0 to 100). $ShareCOVID$ proxies for the first concern that COVID infections can have a direct effect on the economy by influencing health of workers and consumers, thus addressing the first identification concern. Data on local COVID infections are from Barrios and Hochberg (2020). Because variation in policy is at the county level, we cluster standard errors at the county level.

Equation (2) is the first-stage regression for $Lockdown$. Our identifying assumption is that local public health authorities are likely to impose a lockdown as soon as a single case of a COVID infection in a location is confirmed. The timing of this first case is largely random and can reflect idiosyncratic travel of local individuals, the ability or willingness of local authorities to do COVID tests, etc. Because the number of confirmed cases initially is very low (which we can achieve by choosing an appropriate date s), it is unlikely to generate a large public concern about contracting the virus or to have a direct health effect on the local population. Instead, the endogenous response of the local population to COVID concerns is more likely to reflect the prevalence of the disease locally, which would be captured by the $ShareCOVID$ variable. Note that with this identifying assumption, we effectively measure the effect of lockdowns by comparing late and early adopters of lockdown policies and therefore we may miss general equilibrium effects.

While we cannot statistically validate this identifying assumption, we can assess its quality indirectly by examining external data. First, we examine the distribution of COVID cases at the time when

[7] The effect of first confirmed COVID infections on the decision to introduce a lockdown can be heterogeneous across locations. For example, locations with a higher density of population could be more vulnerable to a fast dissemination of the virus and thus may implement lockdowns earlier than locations with lower densities. The public media also suggest that locations with a large share of Trump supporters appear to have a lower propensity to introduce lockdowns in response to COVID. We find some support for these hypotheses in the data (Appendix Table 3), but introducing heterogeneity in the propensity to adopt lockdowns has no material effect on our second-stage estimates and thus we consider a simple specification for the first stage.

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a lockdown is implemented. Figure 3 shows that approximately 75 percent of counties have less than 10 confirmed COVID cases at the time when a lockdown is implemented. Furthermore, going from zero cases to one case is associated with a 15 percent higher probability of a lockdown. Thus, it takes only a handful of cases—which is hardly enough to have a discernable direct health effect on the local economy—before a county is under a lockdown.

Second, we use event analysis to investigate how lockdowns and first reported COVID cases influence dynamics for proxies of economic activity. In particular, we use the insight of Baek et al. (2020) and estimate the following specification:

$$Mobility_{j\tau} = \alpha_j + \phi_\tau + \sum_{\varsigma=-8}^{14} \beta_\varsigma \times Lockdown_{j,\tau+\varsigma}$$
$$+ \sum_{\varsigma=-8}^{14} \psi_\varsigma \times \mathbb{I}\{First\ COVID\ at\ \tau\}_{j,\tau+\varsigma} + error. \qquad (3)$$

j indexes counties, τ, ς index time in days, $Mobility$ is the daily Google's Community Mobility Report (retail mobility),[8] $Lockdown_{j,\tau}$ is a dummy variable if county j has a lockdown at day τ (these data are from Baek et al. 2020), and $\mathbb{I}\{First\ COVID\ at\ \tau\}_{j\tau+\varsigma}$ is a dummy variable equal to one if county j reports its first confirmed COVID infection on day τ and zero otherwise. α_j and ϕ_τ are county and time fixed effects.

Estimated $\{\beta_\varsigma\}_{\varsigma=-8}^{14}$ and $\{\psi_\varsigma\}_{\varsigma=-8}^{14}$ provide event analysis of lockdowns and first confirmed infections. Our identification assumption predicts that the behavioral response to first infections should be small relative to the lockdown response. We report the estimates for $\{\beta_\varsigma\}_{\varsigma=-8}^{14}$ and $\{\psi_\varsigma\}_{\varsigma=-8}^{14}$ in Figure 4. We find weak (if any) pre-trends in the data for lockdowns (we replicate Figure 5 in Baek et al. 2020) or first COVID cases. Each event reduces mobility but mobility declines by an order of magnitude more to a lockdown than to a first COVID case. Given consumer spending and/or employment are highly correlated with mobility (Baker et al., 2020), economic activity is unlikely to be materially affected by reports of a first confirmed COVID case. We conclude that our identifying assumption is plausible.

Table 4 reports estimates for the first stage regression (equation (2)) for various choices of s, the date that we use to determine whether a county has confirmed COVID cases. We see that the dummy variable for confirmed COVID cases is a strong predictor of lockdowns at the local level across different time periods. The t-statistic on $\mathbb{I}\{COVID_{js} > 0\}$ is well above 10 thus suggesting a strong first stage, that is, the instrument is relevant. Note that the coefficient on $ShareCOVID_{jt}$ is statistically significant only when we use s equal to March 22, 2020 or later, while the survey is fielded in the first week of April (i.e., the lockdown dummy in the "crisis" wave refers to April 2-23, 2020). This suggests that the intensity of

[8] These data are described in https://www.google.com/covid19/mobility/. In short, Google uses anonymized sets of data from users who have turned on their location History setting. We use the retail mobility index which covers places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters.

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infections has predictive power roughly one week before a lockdown is implemented. To ensure that our results are not driven by direct health effects, we set s so that $t - s$ referes to March 15, i.e., two weeks before the survey.

V Perceptions, Expectations, and Choices during Lockdowns

We now causally study the effect of lockdowns on outcomes Y_{it} such as spending, employment, expectations, and perceptions via instrumental variable regressions.[9] These results can be an important input into policy discussions about adequate measures of fiscal and monetary policy to stabilize local economies but are also important to measure the economic costs of lockdowns that are key determinants for discussions about re-opening the economy.

A. Employment status

We first analyze the effect of lockdowns on labor-market statistics. Colum (1) of Table 5 shows individuals in counties under lockdown are 2.8 percentage points less likely to be employed relative to other survey participants. Compared to the overall drop in employment we document, we find that 60% of the overall decline is driven by survey participants in early lockdown counties. Column (2) studies the effect on labor-force participation and column (3) on unemployment. Lockdowns have a sizeable effect on both variables. Individuals under lockdown have a 1.9 percentage point lower labor-force participation and a 2.4 percentage point higher unemployment rate. The difference in the unemployment rate between individuals in counties under lockdowns and other counties corresponds to a third of the overall rise in unemployment during the Great Recession, whereas the difference in the labor-force participation corresponds to almost 80% of the decline between 2008 and 2016. Moreover, the rise in unemployment corresponds to even more than 100% of the overall average rise we document in Panel A of Table 1 suggesting redistributive effects across counties. In short, lockdowns appear to have immediate and large consequences of employment and can account for much of the deterioration in the labor market that has occurred in the U.S. in 2020.

B. Consumer spending

Does this dramatic change in labor market conditions due to COVID19 induced lockdowns translate into changes in spending patterns? Table 6 reports the second-stage results for $\log(1 + spending)$ for overall spending and for granular subcategories in the previous three months. We see that lockdowns are associated with a drop in overall spending equal to 31 log percent which is even slightly larger than the overall drop we document in Panel A of Table 2. Recreation, travel, and entertainment expenses, clothing and footwear,

[9] We report OLS estimates in Appendix Table 4 through Appendix Table 8. In general, we find that OLS estimates are smaller than IV estimates but the qualitative results are similar.

housing expenses including rent and maintenance, transportation, and debt payments including mortgages, auto, and student loans see the largest declines in spending with 184, 128, 110, 92, and 71 log percentage points, respectively. Gasoline also has a large decrease in dollar spending which could partially be driven by the large decrease in oil prices. Instead, for utilities, food, or education and childcare, we only observe modest drops consistent with findings in Andersen et al. (2020), and intermediate drops for small durables such as furniture and medical expenses. These heterogeneous responses in spending across categories to local lockdowns are consistent with supply restrictions, individuals no longer being able to travel and non-essential businesses being closed but also in part reflect differences between discretionary and non-discretionary spending (D'Acunto et al. 2020c). Moreover, these results suggest different sectors in the economy might be differentially exposed to drops in consumer spending. This has important implications for the design and implementation of government programs such as loans programs as well as for the overall speed and the differential speed of the recovery across sectors of the economy and geographic partitions. Our results can therefore inform the current debate on federal help for local economies and states.

We move on to study the effect of lockdowns on durable purchases that are the most cyclical component of consumption. Durable purchases are lumpy and occur infrequently and financial constraints might be an important impediment for these purchases. Hence, we first study whether survey respondents differ systematically in their financial constraints and past purchases of durables by lockdown status. We find no systematic difference exists in the degree to which individuals are able to cover an unexpected expense equal to one month of income (see Panel B of Table 7). Similarly, no difference exists in the degree to which survey respondents purchased durable goods in the last six months (Panel B of Table 6). Panel C of Table 6, instead, indicates large drops in plans to spend on durables both at the extensive margin and the intensive margin. Survey participants under lockdown are more than 3.5 percentage points less likely to purchase durable goods in the next 12 months and plan to spend almost 26 log percentage points less. This drop in planned spending is almost 100% of the aggregate drop in planned spending in Table 2 across the survey waves in January and April 2020.

C. Liquidity and portfolio allocations

During times of crisis and uncertainty, a flight to safety and quality often occurs, reflected in a surge in treasuries and the US dollar. To study whether similar phenomena also happen at the individual portfolio level, we now examine the sample of individuals that have savings larger than one month of income in Panel A of Table 7. Consistent with the macro trends, we find that survey participants in lockdown counties have a portfolio share in liquid savings that is 1.7 percentage points higher than other participants even though not statistically significant. The increase in portfolio shares in checking accounts is of the opposite sign to the average in Panel C of Table 1 suggesting that survey participants in late lockdown counties

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actually decreased their portfolio share by more. Moreover, we find a decrease in the share of foreign assets by 0.7 percentage points. Gold is often portrayed as a store of value and safety but only few households in our sample have any savings in gold and no difference exists in portfolio shares across survey participants by lockdown status. Panel B shows that no systematic variation exists in liquidity, that is, the ability to cover an unexpected payment equal to one-month of income. This result is important because it indicates that differentially binding financial constraints are an unlikely driving force for our spending results. We also find no difference in financial wealth, that is, savings larger than one month of income, by lockdown status. This null result is plausible because it is unlikely that the checking account balance, or the value of stock and bond portfolios should be differentially affected by local lockdown conditions.

D. Macroeconomic expectations

To what extent do local lockdowns spill over to subjective expectations? After all, most economic decisions are forward looking and therefore directly depend on individuals' expectations. Moreover, the effectiveness of fiscal and monetary policy measures crucially depend on the expectations of households (Bernanke, 2010) and Binder (2020) finds systematic revisions of GDP growth and inflation expectations due to news about COVID. Ex-ante, it is unclear whether the COVID crisis will result in higher or lower inflation. On the one hand, supply-chain disruptions could increase marginal costs and result in higher future inflation. On the other hand, depressed demand as currently reflected in low oil prices could instead put downward pressure on inflation. To shed more light on this matter, we first study the effect on inflation expectations and report results in Table 8. During the binding lower bound on nominal interest rates, inflation expectations translate one-to-one into changes in real interest rates (Euler equation) which can directly impact current and future consumption choices (Coibion et al. 2019, D'Acunto et al. 2016). We see in Panel A that survey participants under lockdown have on average 0.5 percentage point lower inflation expectations over the next twelve months. Lower inflation expectations imply higher perceived real interest rates which suggests additional downward pressure on household consumption. Household consumption, however, responds not just to the level of real interest rates but also to the dispersion in inflation expectations due to precautionary savings. We use the distribution question for inflation expectations and create a measure of uncertainty in expected inflation at the individual level as the standard deviation in one-year ahead expected inflation. Indeed, local lockdowns increase the uncertainty for future inflation by more than half a percentage point which might translate into increasing precautionary savings demand. These cross-sectional estimates for inflation expectations and uncertainty are large and correspond to about 100% of the difference across survey waves in Panel D of Table 1.

The remaining Panels of Table 8 study the perceptions of current unemployment and mortgage rates as well as the expectations for the next 12 months, or the end of 2020 and 2021 and the longer horizon

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(three to five years for unemployment and five to ten years for mortgage rates, respectively). Unemployment rates are a key indicator for the state of the economy and mortgage rates are the key transmission mechanism of monetary policy for many households and also directly shape the economic recovery given the importance of housing for business cycles (Mian et al., 2017). The perceived unemployment rate spikes up by more than 13 percentage points in lockdown counties and the expected unemployment rate stays at elevated levels for the next 12 months and only slowly decreases to an increase of 2 percentage points over the longer horizon (Panel B). These increases in cross-sectional estimates are even larger than the aggregate increases in expectations that we document in Panel E of Table 1. Results are similar in terms of persistence albeit slightly smaller in magnitude once we exclude extreme observations with perceptions and expectations larger than 40% (Panel C). These expectations suggest a rather sluggish and slow recovery, resembling a U shape in terms of recent policy discussions. As for mortgage rates, we see survey participants perceive a decrease of about two-thirds of a percentage point which persists until the longer horizon (Panel D). These expectations correspond to a level shift in the term structure of mortgage rates and are also consistent with a depressed economy for an extended period of time. Again, we find that the decrease in mortgage rates across counties is larger than the aggregate decreases across survey waves (Panel G of Table 1).

E. Political outcomes

Finally, we study whether local lockdowns affect the qualitative rating of several government institutions in Table 9 which we measure on a ten-point Likert scale with higher values reflecting higher approval ratings. We only elicited approval ratings in the April wave of the survey which is why our two-stage least squares estimation now exploits purely cross-sectional variation:

$$Y_i = \psi \times lockdown_i + \eta \times ShareCOVID_j + StateFE + error \qquad (4)$$

$$lockdown_i = \beta \times \mathbb{I}\{COVID_{js} > 0\} + \gamma \times ShareCOVID_j + StateFE + +error, \qquad (5)$$

where we use the same notation as in equations (1) and (2) and both equations include state fixed effects.

U.S. officials increasingly refer to the pandemic as a war situation[10] and typically, incumbents tend to observe a surge in support during war times with possibly important implications for the upcoming presidential elections. At the same time, the 'current war' also reflects a major economic hardship for many individuals and we might expect support to decrease for the president during poor economic times. We see in Table 9 that survey respondents in lockdown counties have a 6 point lower approval rating of the President than other survey respondents on a ten-point scale. No heterogeneity exists for other government institutions

[10] For example, Treasury Secretary Steven Mnuchin has noted, "This is a war, and we need to win this war and we need to spend what it takes to win the war."

(the Congress in row (2), the U.S. Treasury in row (3), the Federal Reserve in row (4)). The approval for the U.S. Center for Disease Control in row (5), though, is 3 points higher for survey participants in lockdown.

VI Conclusion

The arrival of the COVID19 pandemic resulted in major economic downturns around the world with large drops in employment, equity markets, and personal income. To slow the spread of the pandemic, many governments imposed restrictions in movements to slow the spread of the virus. We field large-scale customized surveys on a representative US panel of households to document the extent of economic damage and to study the impact of local lockdowns on realized and planned spending, income and wealth losses, macroeconomic expectations and approval ratings of political institutions. We observe a dramatic decline in employment and consumer spending as well as a bleak outlook for the next few years. Our estimates suggest that this economic catastrophe can be largely accounted by lockdowns. Furthermore, because we can only measure the immediate effect of lockdowns on labor markets and consumer spending, we likely underestimate the economic costs of these policies as more firms would gradually go out of business and more workers would be let go under continued lockdowns.

It is beyond the scope of this paper to establish whether this economic cost is sufficiently small to justify lockdown policies that likely save many thousands of lives. However, our analysis should inform policymakers about at least one part of the tradeoff they face because these costs are relevant in thinking about how long to maintain lockdown policies, especially since the costs are likely increasing with duration. The significant costs that we identify suggest that policymakers should be wary of focusing only on the benefits of lockdown policies and not carefully weighing them against their costs. Our analysis should also provide input for policies aimed to mitigate the consequences of the COVID recession. For example, we document that many households effectively default on their debt payments and rents which can start a wave of bankruptcies and evictions and thus delay the recovery. Low expectations for inflation and mortgage interest rates will likely limit the power of monetary policy. While households expect normalcy to return within six months, the ferocity and speed of this storm is such that the damage may be rather persistent. To avoid adverse hysteresis-like scenarios, policymakers may have to consider less conventional measures such as extended periods of fiscal stimulus, debt forgiveness, taking stakes in businesses (including financial institutions), and more aggressive quantitative easing.

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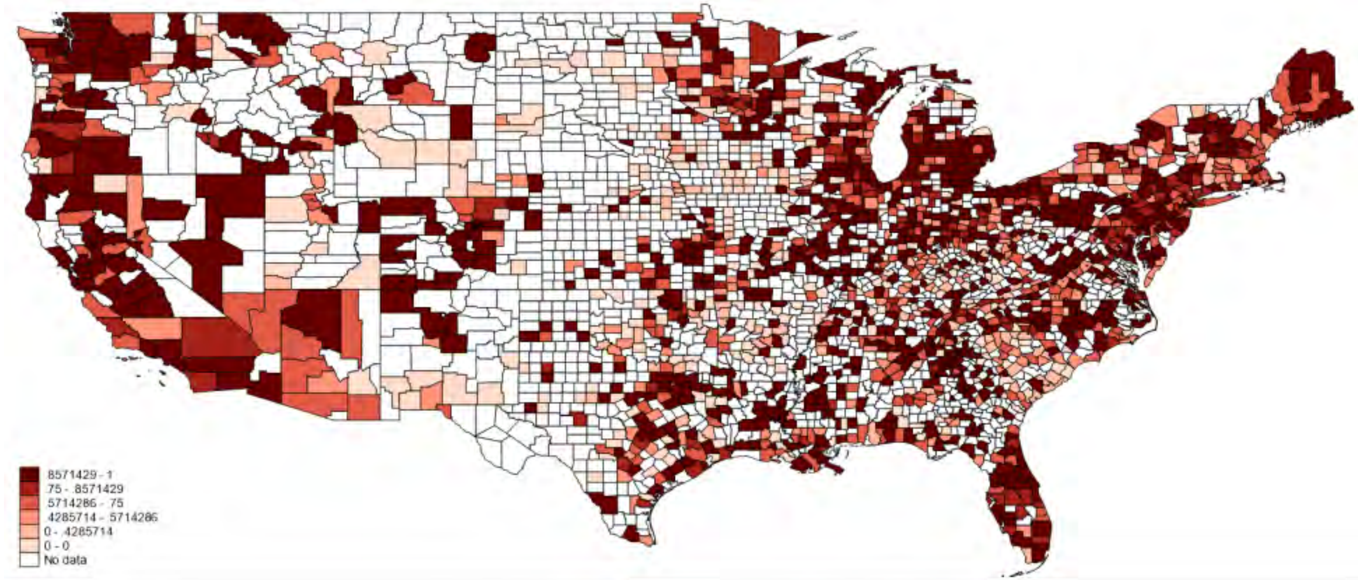
Figure 1. Share of population reporting a lockdown.



Notes: The figure shows the distribution of lockdowns as reported by respondents in the Kilts Nielsen Consumer Panel. Hawaii is a part of the sample but is not shown in the figure.

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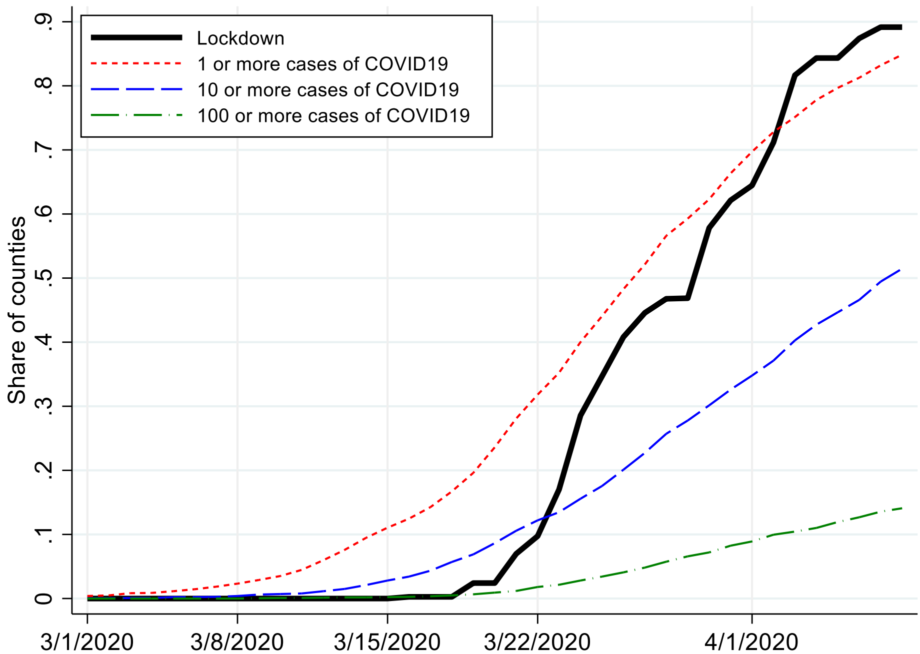
Figure 2. Evolution of COVID19 cases and lockdowns over time.



Notes: The figure shows time series for the fraction of counties adopting lockdown policies and the fraction of counties with confirmed COVID cases above a certain threshold.

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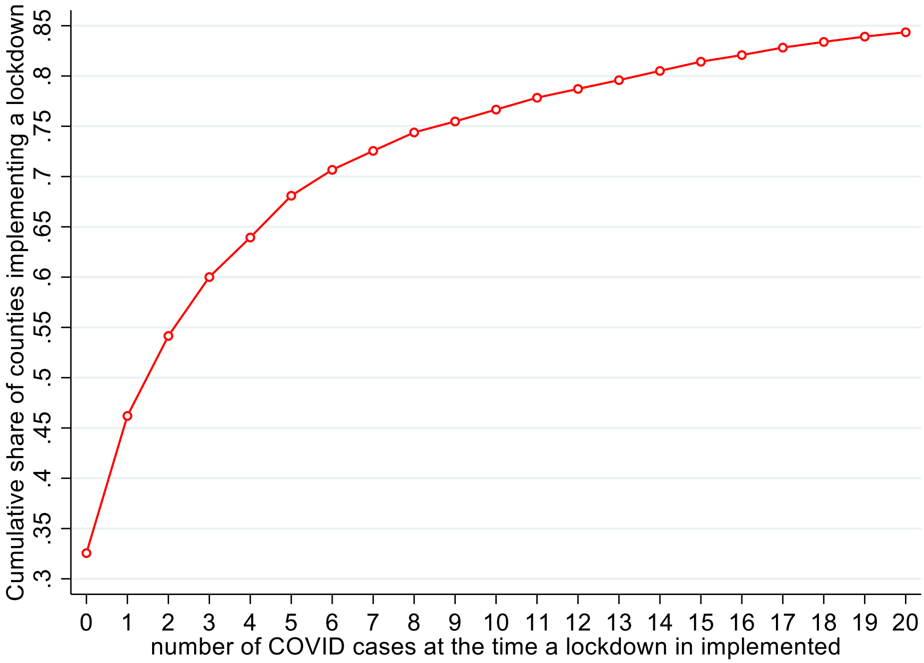
CEPR PRESS

Figure 3. CDF of the number of confirmed COVID cases at the time a lockdown is implemented.



Notes: The figure show the distribution of COVID cases at the time when a county implements a lockdown.

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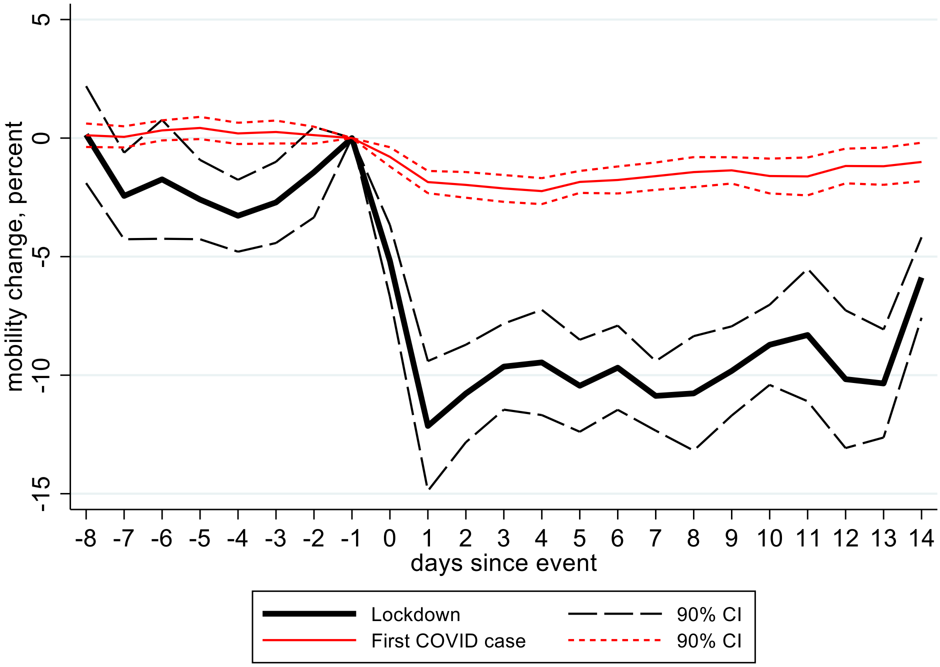
Figure 4. Retail mobility response to lockdown and the first COVID case.



Notes: the figure shows event analysis for lockdowns and first confirmed COVID infections. The estimates are based on specification (3). Standard errors are clustered by county and day. The outcome variable (vertical axis) is Google's retail mobility index which covers restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters. because of high coverage. The estimation sample is February 29, 2020 to April 3, 2020.

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Table 1. Descriptive statistics by wave.

	Pre-crisis	Crisis	Difference
	mean/(st.dev)	mean/(st.dev)	mean/[s.e.]
	(1)	(2)	(3)
Panel A. Employment statistics			
Employment	0.577	0.527	-0.050***
	(0.494)	(0.499)	[0.006]
Labor force participation	0.631	0.590	-0.041***
	(0.483)	(0.492)	[0.006]
Unemployment rate	0.086	0.106	0.020***
	(0.280)	(0.308)	[0.005]
Panel B. Liquidity and access to credit			
Ability to make an unexpected payment of one-month income	0.639	0.652	0.013**
	(0.480)	(0.476)	[0.006]
Share of households with significant financial wealth	0.504	0.517	0.013**
	(0.500)	(0.500)	[0.006]
Panel C. Share of financial wealth in:			
Checking account	44.152	43.619	-0.533
	(34.811)	(34.528)	[0.601]
Cash	14.342	13.591	-0.751**
	(21.532)	(20.514)	[0.367]
US Bonds	5.127	5.769	0.641***
	(11.578)	(12.466)	[0.205]
US Stocks	21.391	22.517	1.126***
	(27.193)	(27.524)	[0.472]
Foreign stocks and bonds	3.124	2.677	-0.446***
	(8.014)	(6.900)	[0.133]
Gold and precious metals	1.233	1.088	-0.145*
	(4.896)	(4.717)	[0.084]
Bitcoin and other cryptocurrencies	0.429	0.415	-0.014
	(3.615)	(3.426)	[0.062]
Other	10.203	10.323	0.120
	(23.082)	(23.366)	[0.401]
Panel D. 12-month-ahead inflation, distributional question			
Implied Mean	2.231	1.708	-0.524***
	(4.457)	(5.868)	[0.061]
Uncertainty (standard deviation)	4.107	4.385	0.278***
	(3.546)	(3.607)	[0.044]
Panel E. Unemployment rate, point prediction			
Current	10.466	21.783	11.317***
	(13.388)	(21.861)	[0.205]
One-year-ahead	10.704	20.747	10.043***
	(12.979)	(19.397)	[0.189]
In the next 3-5 years	11.827	13.049	1.222***
	(14.475)	(14.839)	[0.181]
Panel F. Unemployment rate, point prediction, response restricted to be less than 40%			
Current	7.856	12.055	4.199***
	(7.716)	(9.547)	[0.112]
One-year-ahead	8.152	12.863	4.712***
	(7.644)	(8.949)	[0.108]
In the next 3-5 years	8.436	9.371	0.936***
	(7.572)	(7.927)	[0.099]
Panel G. Mortgage rate, point prediction			
Current	6.553	6.164	-0.389***
	(7.372)	(7.735)	[0.093]
End of 2020	7.311	6.836	-0.475***
	(8.441)	(8.965)	[0.107]
End of 2021	7.759	7.362	-0.397***
	(8.690)	(9.012)	[0.109]
In the next 5-10 years	8.644	8.039	-0.606***
	(9.443)	(9.273)	[0.116]

Notes: Column (1) reports moments for the pre-crisis wave. Column (2) reports moments for the crisis wave. Column (3) reports the difference between crisis and pre-crisis averages. Standard errors for the difference are in square parentheses. Standard deviations are reported in parentheses in columns (1) and (2). ***, **, * indicate statistical significance at 1, 5 and 10 percent.

Table 2. Pre-crisis vs. Crisis Consumer Spending

	Spending			Extensive margin			Intensive margin		
	Pre-crisis	Crisis	Diff.	Pre-crisis	Crisis	Diff.	Pre-crisis	Crisis	Diff.
	Mean (st.dev)	Mean (st.dev)	Mean [s.e.]	Mean (st.dev)	Mean (st.dev)	Mean [s.e.]	Mean (st.dev)	Mean (st.dev)	Mean [s.e.]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Consumer non-durable spending									
Total spending	3999	3033	-0.310***						
	(3485)	(2805)	[0.013]						
Debt payments	1288	905	-0.917***	0.703	0.584	-0.119***	1832	1549	-0.148***
	(1836)	(1446)	[0.042]	(0.457)	(0.493)	[0.006]	(1948)	(1607)	[0.020]
Housing (rent, maintenance, home insurance)	616	524	-0.881***	0.810	0.661	-0.149***	791	826	0.000
	(906)	(853)	[0.034]	(0.392)	(0.473)	[0.005]	(1132)	(1137)	[0.020]
Utilities	429	361	-0.474***	0.956	0.891	-0.064***	467	417	-0.103***
	(403)	(362)	[0.020]	(0.206)	(0.311)	[0.003]	(550)	(463)	[0.011]
Food	532	454	-0.266***	0.984	0.963	-0.021***	561	486	-0.140***
	(511)	(452)	[0.016]	(0.127)	(0.189)	[0.002]	(664)	(579)	[0.011]
Clothing, footwear, persona care	126	81	-1.106***	0.850	0.627	-0.223***	166	138	-0.168***
	(168)	(132)	[0.025]	(0.357)	(0.484)	[0.005]	(373)	(248)	[0.016]
Gasoline	174	125	-0.538***	0.919	0.859	-0.060***	207	154	-0.286***
	(186)	(151)	[0.021]	(0.273)	(0.348)	[0.004]	(361)	(269)	[0.012]
Other transport (public transport, car maintenance)	58	36	-0.788***	0.465	0.293	-0.172***	154	151	-0.241***
	(128)	(107)	[0.027]	(0.499)	(0.455)	[0.006]	(413)	(414)	[0.028]
Medical	220	175	-0.544***	0.745	0.644	-0.101***	329	288	-0.082***
	(402)	(349)	[0.031]	(0.436)	(0.479)	[0.006]	(697)	(556)	[0.021]
Travel, recreation, and entertainment	162	94	-1.500***	0.641	0.328	-0.312***	300	342	-0.020
	(336)	(280)	[0.031]	(0.480)	(0.470)	[0.006]	(726)	(798)	[0.027]
Education and child care	79	53	-0.290***	0.174	0.121	-0.053***	609	566	-0.145**
	(280)	(235)	[0.025]	(0.379)	(0.326)	[0.004]	(1209)	(1071)	[0.068]
Furniture, jewelry, small appliances and other small durable goods	50	39	-0.471***	0.325	0.215	-0.110***	218	251	0.001
	(146)	(136)	[0.026]	(0.468)	(0.411)	[0.006]	(688)	(640)	[0.036]
Other spending	159	84	-1.004***	0.519	0.323	-0.196***	364	280	-0.140***
	(353)	(249)	[0.032]	(0.500)	(0.468)	[0.006]	(821)	(516)	[0.029]
Purchases of durables in the previous 6 months	4,426	4,830	-0.004	0.907	0.925	0.018***	10,416	10,917	0.236***
	(21,477)	(22,689)	[0.043]	(0.291)	(0.264)	[0.007]	(44,474)	(46,830)	[0.059]
Plans to buy durables goods in the next 12 months	9,949	9,002	-0.304***	0.236	0.189	-0.048***	46,939	52,024	0.226***
	(44,362)	(42,244)	[0.046]	(0.425)	(0.391)	[0.005]	(86,891)	(89,879)	[0.069]

Notes: Columns (1), (4), and (7) report moments for the pre-crisis wave. Columns (2), (5) and (8) report moments for the crisis wave. Columns (3), (6) and (9) report the difference between crisis and pre-crisis averages. Standard errors for the difference are in square parentheses. Standard deviations are reported in parentheses in columns. In column (3), the difference is computed for averages of $\log(1 + Spending)$. In column (6), the difference is computed as a simple difference in the shares between the crisis and pre-crisis waves. In column (9), the difference is computed for averages of $\log(Spending)$. ***, **, * indicate statistical significance at 1, 5 and 10 percent.

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Table 3. COVID19-related economic concerns and losses.

	Mean	St.dev.	Percentiles				
			10	25	50	75	90
Concerned about your household's financial situation (10=extremely concerned, 0 = no concerned at all)	7.18	2.96	2	5	8	10	10
Lost earnings							
Extensive (yes=1)	0.42						
Intensive	$5,293	$8,358	$200	$500	$1,500	$5,000	$20,000
Lost financial wealth							
Extensive (yes=1)	0.54						
Intensive	$33,482	$54,920	$300	$1,250	$9,000	$40,000	$100,000
Time before conditions return to normal in your location, days	186.3	140.5	61.0	91.5	152.5	227.5	366.0
The duration of lockdown in your location, days	83.0	47.7	30.5	45.5	66.0	101.5	181.5

Notes: the survey question for the first variable is "How concerned are you about the effects that the coronavirus might have on the financial situation of your household? Please choose from 0 (Not at all concerned) to 10 (Extremely concerned)". The survey question for lost earnings is "Have you lost earnings due to coronavirus concerns?" and conditional on responding "yes" the follow up question is "Could you provide an estimate of lost income? (Please round to the nearest dollar)". This question is only asked for people who are employed in the April wave of the survey. The survey question for lost financial wealth is "Have you lost any financial wealth due to coronavirus concerns?" and conditional on responding "yes" the follow-up question is "Could you provide an estimate of lost wealth? (Please round to the nearest dollar)". This question is asked only for people who reported having financial wealth (excluding housing wealth) greater than his/her household's one-month income. *The duration of lockdown in your location* is only asked for respondents who reported to be a lockdown. The survey question is "How long do you think the lockdown in your location will last?". Time before condition return to normal in your location is asked for all respondents. The survey question is "How long do you think it will be before conditions return to normal in your location?".

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Table 4. First stage by the time of COVID19 exposure.

Dependent variable: $Lockdown$ reported by person i in county j at time t	Date $t-s$ in $\mathbb{I}\{COVID_{j,t-s} > 0\}$ in the April 2020 wave				
	March 1	March 8	March 15	March 22	April 1
	(1)	(2)	(3)	(4)	(5)
$\mathbb{I}\{COVID_{j,t-s} > 0\}$	0.746***	0.766***	0.793***	0.777***	0.769***
	(0.057)	(0.043)	(0.018)	(0.014)	(0.013)
$ShareCOVID_{jt}$	0.957	0.545	0.156	0.083*	0.076**
	(0.863)	(0.510)	(0.121)	(0.043)	(0.035)
Constant	0.301***	0.234***	0.114***	0.040***	0.012**
	(0.023)	(0.010)	(0.005)	(0.006)	(0.006)
Number of households	6,064	6,064	6,064	6,064	6,064
R^2	0.307	0.427	0.636	0.753	0.795

Notes: The table reports estimated coefficients for equation (2). Standard errors clustered by county are reported in parentheses. ***, **, * indicate statistical significance at 1, 5 and 10 percent.

Table 5. Employment status.

	Dependent variable: Dummy variables for employment status		
	Employment	Labor force participation	Unemployment
	(1)	(2)	(3)
$Lockdown_{ijt}$	-0.028***	-0.019**	0.024**
	(0.008)	(0.009)	(0.009)
$ShareCOVID_{jt}$	-0.016	-0.018	0.002
	(0.015)	(0.015)	(0.018)
Number of households	6,064	6,064	2,927
R-squared	0.012	0.006	0.012
1st stage F-stat	1,968	1,968	1,281

Notes: The table reports estimated coefficients for equation (1) with employment status variables as the regressands. Standard errors clustered by county are reported in parentheses. ***, **, * indicate statistical significance at 1, 5 and 10 percent.

Table 6. Consumer spending.

Dependent variable:	$Lockdown_{ijt}$ Coef./(s.e.)	$ShareCOVID_{jt}$ Coef./(s.e.)	Number of households	R^2	1st stage F-stat
	(1)	(2)	(3)	(4)	(5)
Panel A. log(1+Spending)					
Total spending	-0.313***	0.002	6,064	0.050	1,968
	(0.036)	(0.072)			
Debt payments	-0.708***	0.399	6,064	0.037	1,968
	(0.103)	(0.243)			
Housing (rent, maintenance, home insurance)	-1.091***	0.168	6,064	0.069	1,968
	(0.130)	(0.267)			
Utilities	-0.447***	0.205	6,064	0.030	1,968
	(0.081)	(0.131)			
Food	-0.228***	-0.047	6,064	0.015	1,968
	(0.054)	(0.067)			
Clothing, footwear, persona care	-1.275***	-0.202	6,064	0.126	1,968
	(0.091)	(0.298)			
Gasoline	-0.541***	0.221***	6,064	0.049	1,968
	(0.058)	(0.071)			
Other transport (public transport, car maintenance)	-0.916***	0.225	6,064	0.072	1,968
	(0.097)	(0.182)			
Medical	-0.626***	-0.186	6,064	0.028	1,968
	(0.103)	(0.266)			
Travel, recreation, and entertainment	-1.846***	-0.143	6,064	0.165	1,968
	(0.108)	(0.176)			
Education and child care	-0.183***	0.085	6,064	0.011	1,968
	(0.061)	(0.142)			
Furniture, jewelry, small appliances and other small durable goods	-0.632***	-0.012	6,064	0.035	1,968
	(0.101)	(0.309)			
Other spending	-1.210***	-0.291	6,064	0.094	1,968
	(0.102)	(0.613)			
Panel B. Purchases of durable goods					
Extensive margin	-0.008	0.010	6,064	0.001	793
	(0.016)	(0.032)			
Intensive margin, $\log(1+Spending)$	-0.069	-0.203	6,064	-0.000	1,968
	(0.116)	(0.206)			
Panel C. Plans to buy durable goods					
Extensive margin	-0.035**	-0.029	6,064	0.008	1,968
	(0.015)	(0.035)			
Intensive margin, $\log(1+Spending)$	-0.259**	0.025	6,064	0.006	1,968
	(0.128)	(0.290)			

Notes: The table reports estimated coefficients for equation (1) with consumer spending (actual and planned) variables as the regressands. Standard errors clustered by county are reported in parentheses. ***, **, * indicate statistical significance at 1, 5 and 10 percent.

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Table 7. Liquidity and portfolio allocation.

Dependent variable:	$Lockdown_{ijt}$ Coef./(s.e.)	$ShareCOVID_{jt}$ Coef./(s.e.)	Number of households	R^2	1st stage F-stat
	(1)	(2)	(3)	(4)	(5)
Panel A. Share of financial wealth in					
Checking account	1.713	-0.044	2,995	0.003	1,439
	(1.723)	(1.961)			
Cash	-0.506	0.599	2,995	0.000	1,439
	(1.057)	(1.478)			
US Bonds	0.654	0.395	2,995	-0.002	1,439
	(0.661)	(1.477)			
US Stocks	-0.016	-0.898	2,995	0.000	1,439
	(1.285)	(2.770)			
Foreign stocks and bonds	-0.651**	-1.936***	2,995	0.010	1,439
	(0.318)	(0.395)			
Gold and precious metals	-0.033	-0.036	2,995	0.000	1,439
	(0.271)	(0.248)			
Bitcoin and other cryptocurrencies	-0.104	0.090	2,995	-0.004	1,439
	(0.074)	(0.095)			
Other	-1.056	1.831	2,995	-0.001	1,439
	(1.427)	(4.234)			
Panel B. Liquidity					
Ability to make an unexpected payment of one-month income	-0.013	0.014	5,398	0.002	1,895
	(0.013)	(0.042)			
Significant financial wealth	-0.018	0.016	6,064	-0.001	1,968
	(0.013)	(0.018)			

Notes: The table reports estimated coefficients for equation (1) with liquidity, access to credit, and portfolio allocations as the regressands. Standard errors clustered by county are reported in parentheses. Shares in Panel A are measured in percent from 0 to 100. Share are elicited only for household who report significant financial wealth. *Significant financial wealth* is equal to one if a respondent reports that his/her household has financial wealth (excluding housing) that is greater than combined monthly household income. ***, **, * indicate statistical significance at 1, 5 and 10 percent.

Table 8. Macroeconomic expectations.

Dependent variable: Macroeconomic expectations	$Lockdown_{ijt}$ Coef./(s.e.)	$ShareCOVID_{jt}$ Coef./(s.e.)	Number of households	R^2	1st stage F-stat
	(1)	(2)	(3)	(4)	(5)
Panel A. 12-month-ahead inflation, distributional question					
Implied Mean	-0.545**	-0.738	5,602	0.006	2,108
	(0.238)	(0.678)			
Uncertainty (standard deviation)	0.586***	0.261	5,602	0.017	2,108
	(0.123)	(0.299)			
Panel B. Unemployment rate, point prediction					
Current	13.751***	-0.162	5,973	0.205	1,887
	(0.848)	(1.194)			
One-year-ahead	12.952***	0.425	5,998	0.218	1,906
	(0.638)	(2.360)			
In the next 3-5 years	2.394***	-0.439	6,025	0.016	1,922
	(0.453)	(0.971)			
Panel C. Unemployment rate, point prediction, response restricted to be less than 40%					
Current	7.067***	0.243	4,885	0.208	1,682
	(0.453)	(0.954)			
One-year-ahead	8.194***	0.043	5,085	0.246	1,635
	(0.396)	(1.118)			
In the next 3-5 years	1.789***	0.211	5,516	0.028	1,767
	(0.259)	(0.655)			
Panel D. Mortgage rate, point prediction					
Current	-0.686***	0.190	6,045	0.005	1,966
	(0.240)	(0.458)			
End of 2020	-0.730***	0.148	6,046	0.007	1,956
	(0.270)	(0.399)			
End of 2021	-0.607**	0.164	6,048	0.006	1,980
	(0.297)	(0.564)			
In the next 5-10 years	-0.745**	0.666	6,045	0.007	1,970
	(0.322)	(0.551)			

Notes: The table reports estimated coefficients for equation (1) with macroeconomic expectations as the regressands. Standard errors clustered by county are reported in parentheses. ***, **, * indicate statistical significance at 1, 5 and 10 percent.

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Table 9. Approval of policies.

Dependent variable: Approval of policies (10 = extremely helpful, 0 = not helpful at all)	$Lockdown_{ijt}$ Coef./(s.e.)	$ShareCOVID_{jt}$ Coef./(s.e.)	Number of respondents	R^2	1st stage F-stat
	(1)	(2)	(3)	(4)	(5)
President	-6.247***	-0.113	9,247	-0.414	16
	(2.425)	(0.225)			
Congress	1.067	0.109	9,247	-0.016	16
	(1.503)	(0.125)			
US Treasury	0.710	0.003	9,247	-0.002	16
	(1.901)	(0.170)			
Federal Reserve	2.402	-0.078	9,247	-0.072	16
	(1.958)	(0.175)			
U.S. Center for Disease Control	3.134*	-0.226	9,247	-0.138	16
	(1.851)	(0.173)			

Notes: The table reports estimated coefficients for equation (4) with political approval variables as the regressands. The first stage is given by equation (5). State fixed effects are included but not reported. Standard errors clustered by county are reported in parentheses. Political approval data are collected only in the April 2020 wave. ***, **, * indicate statistical significance at 1, 5 and 10 percent.

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Appendix 1: Survey Questions

1. Which of the following goods and services have you spent money on over the last three months? (Select all that apply)
   - Debt payments (mortgages, auto loans, student loans, etc.)
   - Housing (including rent, maintenance and home owner/renter insurance, housekeeping and cleaning service, but not including mortgage payments)
   - Utilities (including water, sewer, electricity, gas, heating oil, phone, cable, internet)
   - Food (including groceries, dining out, take-out food, and beverages)
   - Clothing, footwear, and personal care
   - Gasoline
   - Other regular transportation costs (including public transportation fares and car maintenance)
   - Medical care (including health insurance, out-of-pocket medical bills and prescription drugs)
   - Travel, recreation, and entertainment
   - Education and child care
   - Furniture, jewelry, small appliances and other small durable goods
   - Other (including gifts, child support or alimony, charitable giving, and other miscellaneous)

2. Over the last three months on average, how much did your household spend (per month) on goods and services in total and for each of the individual components listed below? Please enter a number between 1 and 10,000 for each category. The sum of the expenditures for the individual categories should add up to the total amount.

   Total monthly spending
   Debt payments (mortgages, auto loans, student loans, etc.) $__________
   Housing (including rent, maintenance and home owner/renter insurance, housekeeping and cleaning service, but not including mortgage payments) $__________
   Utilities (including water, sewer, electricity, gas, heating oil, phone, cable, internet)
   $__________
   Food (including groceries, dining out, take-out food, and beverages) $__________
   Clothing, footwear, and personal care $__________
   Gasoline $__________
   Other regular transportation costs (including public transportation fares and car maintenance)
   $__________
   Medical care (including health insurance, out-of-pocket medical bills and prescription drugs)
   $__________
   Travel, recreation, and entertainment $__________
   Education and child care $__________
   Furniture, jewelry, small appliances and other small durable goods $__________
   Other (including gifts, child support or alimony, charitable giving, and other miscellaneous)
   $__________

$ Total ___________ [TOTAL ANSWERS FROM ABOVE]

3. Suppose that you had to make an unexpected payment equal to one month of your after-tax income, would you have sufficient financial resources (access to credit, savings, loans from relatives or friends, etc.) to pay for the entire amount?
    - Yes
    - No
    - Don't know/prefer not to answer

4. Does your household have total financial investments (excluding housing) worth more than one month of combined household income?
- Yes
- No

ASK IF: Q4=YES

5. What percent of your financial wealth (excluding housing) do you invest in the following categories? Put "0" if you do not invest in a given category.

	Wealth Investment Allotment
Checking and Savings Account, Certificate of deposits	___________percent
Cash	___________percent
US Bonds	___________percent
US Stocks	___________percent
Foreign Stocks and Bonds	___________percent
Gold and precious metals	___________percent
Bitcoin and other cryptocurrencies	___________percent
Other	___________percent
% Total [TOTAL ANSWERS FROM ABOVE – MUST SUM TO 100%]	___________

6. Over the last 6 months, did you buy a new home, car, or other major big-ticket item (fridge, TV, furniture, etc.)?
- Yes
- No

ASK IF: Q6=YES

7. Which of the following did you purchase in the last 6 months? Please select all that apply.
- A house/apartment
- A car or other vehicle
- A large home appliance or electronics
- None of the above

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ASK IF: Q7=YES

8. How much did you spend on the following?

- A house/apartment ___________
- A car or other vehicle ___________
- A large home appliance or electronics ___________

9. Do you currently plan to buy a new home, car, or other major big-ticket item (fridge, TV, furniture, etc.) in the next 12 months?

- Yes
- No

ASK IF: Q9=YES

10. Which of the following do you plan to purchase in the next 12 months? Please select all that apply.

- A house/apartment
- A car or other vehicle
- A large home appliance or electronics
- None of the above

ASK IF: Q10=YES

11. How much do you plan to spend on the following?

- A house/apartment ___________
- A car or other vehicle ___________
- A large home appliance or electronics ___________

We would like to ask you some questions about the overall economy and in particular about the rate of inflation/deflation (Note: inflation is the percentage rise in overall prices in the economy, most commonly measured by the Consumer Price Index and deflation corresponds to when prices are falling).

12. In THIS question, you will be asked about the probability (PERCENT CHANCE) of something happening. The percent chance must be a number between 0 and 100 and the sum of your answers must add up to 100.

    What do you think is the percent chance that, over the next 12 months…

Chance	Percentage
▪ the rate of inflation will be 12% or more	______
▪ the rate of inflation will be between 8% and 12%	______
▪ the rate of inflation will be between 4% and 8%	______
▪ the rate of inflation will be between 2% and 4%	______

- the rate of inflation will be between 0% and 2% ______
- the rate of deflation (opposite of inflation) will be between 0% and 2% ______
- the rate of deflation (opposite of inflation) will be between 2% and 4% ______
- the rate of deflation (opposite of inflation) will be between 4% and 8% ______
- the rate of deflation (opposite of inflation) will be between 8% and 12% ______
- the rate of deflation (opposite of inflation) will be 12% or more ______
- % Total ______

13. Do you have a paid job?
- Yes
- No

ASK IF: Q13=NO
14. Are you actively looking for a job? (Select one)
- Yes
- No

ASK IF: Q14=NO
15. Here are a number of possible reasons why people who are not working choose not to look for work. Please select all that apply to you.
- Homemaker
- Raising children
- Student
- Retiree
- Disabled, health issues
- Couldn't find a job
- On break
- No financial need
- Other

16. How much higher or lower do you think your household's total after-tax (i.e., 'take home') income will be over the next twelve months compared to the last twelve months? Please provide an answer in percentage terms.
- My after-tax income will rise by __________% [RANGE: 0-300, ONE DECIMAL]
- My after-tax income will stay the same
- My after-tax income will fall by __________% [RANGE: 0-300, ONE DECIMAL]

17. What is your best guess about what the current unemployment rate in the US is, what it will be in 12 months and over the next 3-5 years?
- Current unemployment rate: __________% [RANGE: 0-100, ONE DECIMAL]

- Unemployment rate in 12 months: ___________% [RANGE: 0-100, ONE DECIMAL]
- Over the next 3-5 years? ___________% [RANGE: 0-100, ONE DECIMAL]

18. What do you think is the current interest rate on a fixed-rate 30-year mortgage for someone with excellent credit and what do you think it will be in the future?

- Current rate? ___________% per year [RANGE: 0-100, ONE DECIMAL]
- At the end of 2020? ___________% per year [RANGE: 0-100, ONE DECIMAL]
- At the end of 2021? ___________% per year [RANGE: 0-100, ONE DECIMAL]
- In the next 5-10 years? ___________% per year [RANGE: 0-100, ONE DECIMAL]

19. Have you seen or heard anything in the news about COVID-19 or the Coronavirus?

- Yes
- No
- Don't know

20. How concerned are you about the effects that the coronavirus might have on the financial situation of your household? Slider from 0 (Not at all concerned) to 10 (Extremely concerned)

ASK IF: 9=YES

21. Have you lost earnings due to coronavirus concerns?

- Yes
- No

ASK IF: 21=YES

22. Could you provide an estimate of lost income? (Please round to the nearest dollar)

$_______________

ASK IF: Q4=YES

23. Have you lost any financial wealth due to coronavirus concerns?

- Yes
- No

ASK IF: Q23=YES

24. Could you provide an estimate of lost wealth? (Please round to the nearest dollar)

$_______________

25. Are you currently under lockdown in your location?
- Yes
- No

ASK IF Q26=YES

26. How long do you think the lockdown in your location will last?
    Months: _____________
    Days: _________________

27. How long do you think it will be before conditions return to normal in your location?
    Months: _____________
    Days: _________________

28. How would you rate the following government bodies in handling the current situation? Please assign a score ranging from 1 (Poor job) to 10 (Excellent job)
- President ___score [Don't know box]
- Congress ___score [Don't know box]
- US Treasury ___score [Don't know box]
- US Federal Reserve ___score [Don't know box]
- US Center for Disease Control (CDC) ___score [Don't know box]

29. Generally speaking, do you think that now is a good time or a bad time **to buy**…

A house or apartment A car or other vehicle Large appliances, furniture, electronics (incl. gadgets)	() Very good () Good () Neither good nor bad () Bad () Very bad

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Appendix Table 1. Descriptive statistics for households in the Nielsen Survey, January 2020 wave.

	Mean	Standard deviation
	(1)	(2)
Household income, annual, $	68,370	37,667
Household size	2.58	1.32
Age of the respondent	50.1	15.0
Share of white respondents	0.73	0.44

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Appendix Table 2. Consumer spending in the Nielsen Survey and the Survey of Consumer Expenditures.

Spending category	Nielsen Survey (KNCP)	Survey of Consumer Expenditures
	(1)	(2)
Total spending	3,999	5,102
Debt payments	1,288	250
Housing (rent, maintenance, home insurance)	616	535
Utilities	429	455
Food	532	709
Clothing, footwear, persona care	126	220
Gasoline	174	176
Other transport (public transport, car maintenance)	58	142
Medical	220	414
Travel, recreation, and entertainment	162	269
Education and child care	79	117
Furniture, jewelry, small appliances and other small durable goods	50	64
Other spending	159	1715

Notes: Columns (1) reports monthly spending in the January wave of the Nielsen survey. Column (2) reports monthly spending (annual divided by 12) from the 2018 Survey of Consumer Expenditures.

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Appendix Table 3. First stage by the time of COVID-19 exposure with heterogeneous responses to COVID infections.

Dependent variable: $Lockdown$ reported by person i in county j at time t	Date $t-s$ in $\mathbb{I}\{COVID_{j,t-s}>0\}$ in the April 2020 wave				
	March 1	March 8	March 15	March 22	April 1
	(1)	(2)	(3)	(4)	(5)
$\mathbb{I}\{COVID_{j,t-s}>0\}$	-0.674	0.600***	0.964***	1.072***	1.088***
	(1.082)	(0.220)	(0.096)	(0.079)	(0.073)
$\mathbb{I}\{COVID_{j,t-s}>0\} \times \log(PopDensity_j)$	-0.190	-0.036	0.012	0.025**	0.028***
	(0.146)	(0.033)	(0.014)	(0.011)	(0.010)
$\mathbb{I}\{COVID_{j,t-s}>0\} \times TrumpShare_j$	-0.043	-0.328	-0.165	-0.180*	-0.150*
	(1.222)	(0.310)	(0.121)	(0.094)	(0.088)
$ShareCOVID_{jt}$	1.139	0.575	0.116	0.002	-0.019
	(0.732)	(0.523)	(0.121)	(0.035)	(0.031)
Constant	0.301***	0.234***	0.114***	0.040***	0.012**
	(0.023)	(0.010)	(0.005)	(0.006)	(0.006)
Number of households	6,064	6,064	6,064	6,064	6,064
R^2	0.312	0.427	0.637	0.755	0.799

Notes: The table reports estimated coefficients for equation (2) with $\mathbb{I}\{COVID_{j,t-s}>0\}$ interacted with the share of Trump votes in the 2016 Presidential elections and log population density. Standard errors clustered by county are reported in parentheses. ***, **, * indicate statistical significance at 1, 5 and 10 percent.

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Appendix Table 4. Employment Status, OLS regression.

	Dependent variable: Dummy variables for employment status		
	Employment	Labor force participation	Unemployment
	(1)	(2)	(3)
$Lockdown_{ijt}$	-0.027***	-0.018***	0.023***
	(0.007)	(0.006)	(0.008)
$ShareCOVID_{jt}$	-0.018	-0.019	0.003
	(0.014)	(0.013)	(0.018)
Number of households	6,064	6,064	2,927
R-squared	0.012	0.006	0.012

Notes: This table reports OLS estimates of the specification estimated in Table 5.

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Appendix Table 5. Consumer spending, OLS regression.

Dependent variable:	$Lockdown_{ijt}$ Coef./(s.e.)	$ShareCOVID_{jt}$ Coef./(s.e.)	Number of households	R^2
	(1)	(2)	(3)	(4)
Panel A. log(1+Spending)				
Total spending	-0.243***	-0.085	6,064	0.054
	(0.027)	(0.119)		
Debt payments	-0.584***	0.246	6,064	0.038
	(0.070)	(0.309)		
Housing (rent, maintenance, home insurance)	-0.925***	-0.037	6,064	0.071
	(0.090)	(0.334)		
Utilities	-0.354***	0.091	6,064	0.032
	(0.056)	(0.192)		
Food	-0.175***	-0.114	6,064	0.016
	(0.038)	(0.087)		
Clothing, footwear, persona care	-1.004***	-0.535	6,064	0.134
	(0.070)	(0.519)		
Gasoline	-0.384***	0.027	6,064	0.058
	(0.040)	(0.143)		
Other transport (public transport, car maintenance)	-0.770***	0.044	6,064	0.074
	(0.066)	(0.249)		
Medical	-0.446***	-0.407	6,064	0.033
	(0.062)	(0.281)		
Travel, recreation, and entertainment	-1.390***	-0.702*	6,064	0.181
	(0.073)	(0.416)		
Education and child care	-0.177***	0.077	6,064	0.011
	(0.044)	(0.136)		
Furniture, jewelry, small appliances and other small durable goods	-0.509***	-0.164	6,064	0.037
	(0.065)	(0.396)		
Other spending	-0.981***	-0.572	6,064	0.099
	(0.076)	(0.776)		
Panel B. Purchases of durable goods				
Extensive margin	-0.007	0.005	6,064	0.001
	(0.011)	(0.031)		
Intensive margin, $\log(1 + Spending)$	0.019	-0.310	6,064	0.000
	(0.091)	(0.224)		
Panel C. Plans to buy durable goods				
Extensive margin	-0.039***	-0.024	6,064	0.009
	(0.011)	(0.035)		
Intensive margin, $\log(1 + Spending)$	-0.283***	0.053	6,064	0.006
	(0.088)	(0.284)		

Notes: This table reports OLS estimates of the specification estimated in Table 6.

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Appendix Table 6. Liquidity and portfolio allocation, OLS regression.

Dependent variable:	$Lockdown_{ijt}$ Coef./(s.e.)	$ShareCOVID_{jt}$ Coef./(s.e.)	Number of households	R^2
	(1)	(2)	(3)	(4)
Panel A. Share of financial wealth in				
Checking account	1.738	-0.071	2,995	0.003
	(1.236)	(1.787)		
Cash	-0.258	0.323	2,995	0.000
	(0.743)	(1.520)		
US Bonds	-0.081	1.215	2,995	0.000
	(0.455)	(1.569)		
US Stocks	-0.793	-0.032	2,995	0.001
	(0.879)	(2.248)		
Foreign stocks and bonds	-0.442*	-2.170***	2,995	0.011
	(0.251)	(0.525)		
Gold and precious metals	-0.049	-0.018	2,995	0.000
	(0.193)	(0.219)		
Bitcoin and other cryptocurrencies	0.035	-0.066	2,995	0.000
	(0.048)	(0.089)		
Other	-0.149	0.819	2,995	0.000
	(0.954)	(3.440)		
Panel B. Liquidity				
Ability to make an unexpected payment of one-month income	-0.014	0.016	5,398	0.002
	(0.010)	(0.041)		
Significant financial wealth	-0.005	-0.001	6,064	0.000
	(0.010)	(0.014)		

Notes: This table reports OLS estimates of the specification estimated in Table 7.

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Appendix Table 7. Macroeconomic expectations, OLS regression.

Dependent variable: Macroeconomic expectations	$Lockdown_{ijt}$ Coef./(s.e.)	$ShareCOVID_{jt}$ Coef./(s.e.)	Number of households	R^2
	(1)	(2)	(3)	(4)
Panel A. 12-month-ahead inflation, distributional question				
Implied Mean	-0.509***	-0.781	5,602	0.006
	(0.176)	(0.672)		
Uncertainty (standard deviation)	0.450***	0.420	5,602	0.018
	(0.090)	(0.259)		
Panel B. Unemployment rate, point prediction				
Current	11.810***	2.197	5,973	0.211
	(0.581)	(2.430)		
One-year-ahead	10.431***	3.507	5,998	0.229
	(0.486)	(4.175)		
In the next 3-5 years	1.937***	0.122	6,025	0.017
	(0.327)	(0.874)		
Panel C. Unemployment rate, point prediction, response restricted to be less than 40%				
Current	5.833***	1.689***	4,885	0.216
	(0.322)	(0.621)		
One-year-ahead	6.192***	2.422	5,085	0.271
	(0.290)	(2.644)		
In the next 3-5 years	1.338***	0.739	5,516	0.031
	(0.184)	(0.790)		
Panel D. Mortgage rate, point prediction				
Current	-0.539***	0.011	6,045	0.005
	(0.175)	(0.539)		
End of 2020	-0.714***	0.128	6,046	0.007
	(0.212)	(0.374)		
End of 2021	-0.684***	0.258	6,048	0.006
	(0.215)	(0.482)		
In the next 5-10 years	-0.757***	0.682	6,045	0.007
	(0.234)	(0.528)		

Notes: This table reports OLS estimates of the specification estimated in Table 8.

Appendix Table 8. Approval of policies, OLS regression.

Dependent variable: Approval of policies (10 = extremely helpful, 0 = not helpful at all)	$Lockdown_{ijt}$ Coef./(s.e.)	$ShareCOVID_{jt}$ Coef./(s.e.)	Number of respondents	R^2
	(1)	(2)	(3)	(4)
President	-0.365***	-0.525***	9,247	0.003
	(0.131)	(0.185)		
Congress	0.143	0.174**	9,247	0.001
	(0.097)	(0.079)		
US Treasury	0.236**	0.036	9,247	0.001
	(0.118)	(0.123)		
Federal Reserve	0.045	0.087	9,247	0.000
	(0.119)	(0.106)		
Center for Disease Control	0.207**	-0.021	9,247	0.001
	(0.104)	(0.125)		

Notes: This table reports OLS estimates of the specification estimated in Table 9.

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In crisis, we pray: Religiosity and the Covid-19 pandemic[1]

Jeanet Sinding Bentzen[2]

Date submitted: 16 May 2020; **Date accepted:** 17 May 2020

In times of crisis, humans have a tendency to turn to religion for comfort and explanation. The 2020 COVID-19 pandemic is no exception. Using daily data on Google searches for 95 countries, this research demonstrates that the COVID-19 crisis has increased Google searches for prayer (relative to all Google searches) to the highest level ever recorded. More than half of the world population had prayed to end the coronavirus. The rise amounts to 50% of the previous level of prayer searches or a quarter of the fall in Google searches for flights, which dropped dramatically due to the closure of most international air transport. Prayer searches rose at all levels of income, inequality, and insecurity, but not for the 10% least religious countries. The increase is not merely a substitute for services in the physical churches that closed down to limit the spread of the virus. Instead, the rise is due to an intensified demand for religion: We pray to cope with adversity.

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1 Introduction

The COVID-19 pandemic has brought sizeable costs for societies across the globe. A pandemic this size potentially changes our societies for years to come, especially if it impacts our ingrained values and beliefs. This research asks whether the COVID-19 crisis impacts one of the deepest rooted of human behaviors: Religion. Philosophers once predicted that religion would die out as societies modernize.[1] This has not happened.[2] Today, 83% of the world population believe in God and the role of religion is strengthening in some societies. Religion must be serving a purpose that modernization does not fulfill. Identifying who uses religion in crisis is paramount for understanding this role of religion and thus its' persistence and socio-economic consequences.

This research identifies empirically the extent to which the COVID-19 pandemic has induced people across the globe to pray, whether the phenomenon is global, and who prays in times of crisis. Google searches for prayer, as a share of all Google searches, provides a signal of peoples' interest in prayer in real time. Research documents that our behavior on the internet reflects our personal interests and the actions we take in the real world.[3] Likewise, whether or not we search for religious terms on the internet reflects our religious preferences (Yeung, 2019; Stephens-Davidowitz, 2015). Events that instigate intensified actual prayer are clearly visible in the data. Before the COVID-19 pandemic, the Ramadan contributed to the largest yearly increase in the global search intensity for prayer (Panel (a) of Fig. 1). Also, prayer search shares spike up on Sundays everywhere (Stephens-Davidowitz, 2015). Searches for prayer surged in Iran on January 7 2020, coinciding with the funeral of Qassem Soleimani, the Iranian major general killed by US troops, in Australia on January 5 2020, when the movement "Prayer for Australia" swept across Australia in the midst of the unprecedented bushfires, and in Albania on November 26 2019 when a 6.4 magnitude earthquake stroke the country. The countries that search more for prayer on the internet are also ranked in surveys as being more religious (Fig. A.1).

In March 2020, the share of Google searches for prayer surged to the highest level ever recorded, surpassing all other major events that otherwise call for prayer, such as Christmas, Easter, and Ramadan (Fig. 1, Fig. A.11, and Appendix C). The World Health Organization declared the COVID-19 a pandemic on March 11, 2020. The level of prayer search shares in March 2020 was more than 50% higher than the average during February 2020. For comparison, the surge in Google searches for prayer was 1.3 times larger than the rise in searches for

[1] Marx (1844); Weber (1905); Durkheim (1912); Freud (1927).

[2] Norris and Inglehart (2011); Stark and Finke (2000); Iannaccone (1998).

[3] Moat et al. (2016); Olivola et al. (2019); Goldstone and Lupyan (2016); Cavazos-Rehg et al. (2015); Ginsberg et al. (2009).

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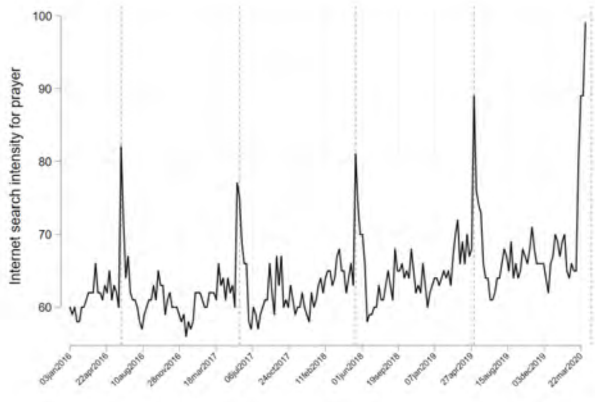
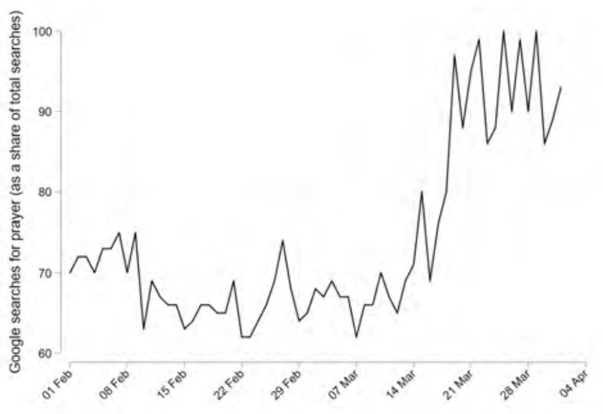
takeaway and amounted to 12% of the rise in Netflix searches or 26% the fall in searches for flights, which all saw massive changes globally, since most countries were in lock down and air traffic was shut down (cf. Appendix B.4).[4]

Figure 1: Worldwide Google searches for "prayer" during the past 4 years

(a) Jan 1 2016 - Apr 11 2020



(b) Feb 1 - Apr 1 2020



Google searches for prayer relative to the total number of Google searches. The maximum shares were set to 100 by Google Trends. The searches encompass all topics related to prayer, including alternative spellings and languages. The red vertical stippled lines in panel (a) represent the first week of the Ramadan. The period in panel (a) is the longest period for which comparable data was available at the time of writing. The period in panel (b) is the period used in the main analysis (before COVID-19 became a pandemic and before the onset of Easter and the Ramadan). Data source: Google Trends. For the development since 2004, see Fig. A.11. Find more details in Appendix A.1 and C.

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[4]In an attempt to limit the spread of COVID-19, most countries implemented lock downs and most air traffic was shut down. As a result, many people were at home ordering takeaway and watching Netflix much more than usual.

When googling prayer what you find is specific prayer texts to use when praying. Prayers may be recited from memory, read from a book of prayers, or composed spontaneously as they are prayed. In modern times, these books of prayer or verses of prayer can be found on the internet. The most common form of prayer in Christianity is to directly appeal to a deity to grant one's requests (Kurian and Smith, 2010). One of the most searched for prayers in March 2020 was "Coronavirus prayer", which are prayers that ask God for protection against the coronavirus, prayers to stay strong, and prayers to thank nurses for their efforts (Appendix Figures B.2 and B.3). According to a Pew Research Center survey from March 2020, more than half of Americans had prayed to end the coronavirus (Pew, 2020b).

Using daily data on Google searches for prayer for 95 countries across the globe, this research documents that the rise visible in Fig. 1 is not driven by a few countries, but instead is a global phenomenon. Google searches for prayer surge after March 11 for most countries, and even more so after their own populations had been infected. Prayer searches rose more for the more religious countries, and more for Christians and Muslims. Searches for topics related to God, Allah, Muhammad, Quran, Bible, and Jesus, and to a lesser extent Buddha, Vishnu, and Shiva, also rose (Fig. A.12). Last, prayer search shares rose more in poorer, more insecure, and more unequal countries, but this impact is exclusively due to these countries being more religious. Using the results and the Pew (2020b) survey, a back of the envelope calculation shows that more than half of the global population have prayed to end the coronavirus.

The main reason for the rising interest in prayer on the internet is religious coping: People use their religion to cope with adversity.[5] They pray for relief, understanding, and comfort. Research has documented that people struggling with cancer, death in close family, or severe illness are more religious, and also that adversity in the form of natural disasters *cause* people to use their religion more intensely.[6]

People may google prayer for a reason unrelated to religious coping. They may be searching for online forums to replace their physical churches that closed down in an attempt to enforce social distancing. Theoretically, we would not expect this to be the main explanation for the rising search shares for prayer. People tend to use mainly their intrinsic religiosity (such as private prayer) rather than their extrinsic religiosity (such as churchgoing) to cope with adversity.[7] In addition, a recent survey reveals that 95% of Americans who pray, pray alone, while only 2% pray collectively in a church (Barna, 2017). Another survey shows that 24% of Americans respond that their faith has strengthened since the coronavirus, which we would not have predicted if people are simply replacing their physical churchgoing with online church

[5]Pargament (2001); Norenzayan and Hansen (2006); Cohen and Wills (1985); Park et al. (1990); Williams et al. (1991).

[6]Bentzen (2019) and reviews by Ano and Vasconcelles (2005) and Pargament (2001).

[7]Johnson and Spilka (1991); Pargament (2001); Bentzen (2019).

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(Pew, 2020a). They must be doing something that strengthens their faith. The empirical results reveal that replacement of physical churches is not the main reason for the rise in Google searches for prayer (cf. Appendix C.3). For instance, searches for "internet church" also rise, but follow a distinctly different pattern than the prayer searches and is of a much smaller magnitude, the search shares on prayer continue to rise long after the church closures, and the rise in prayer searches is not limited to Sundays, where most masses are held, but occur on all days of the week, except Fridays.

There are reasons to believe that the rise in Google searches for prayer underestimates the true rise in prayer intensity, which is potentially much larger than what is visible from Fig. 1. First, most prayers are performed without the use of the internet, instead recited from memory or read from physical books. Second, among those who use the internet to find prayers, the data encompasses only those who google prayer, while those who enter their preferred prayer websites directly are not included. Third, the elderly, who were most severely affected by the pandemic, are not the most active internet users and thus, their prayer intensity will not show up in Google. Fourth, the month of March 2020 saw an even larger rise in internet searches on topics related to COVID-19 and other topics since people across the globe were at home due to lock downs (see also B.4). These searches enter the denominator of all other search shares, which mechanically reduces the search shares for these other searches, including prayer. Fifth, the data includes only countries with enough internet users and thus the poorest countries or countries with restricted internet access, such as China, are not included. Poorer countries are on average more religious (Inglehart and Norris, 2003) and thus more prone to engage in religious coping (Pargament, 2001).

This research contributes to the literature on religious coping. While previous research has documented a rise in religiosity in the aftermath of natural disasters (Bentzen, 2019; Bulbulia, 2004; Belloc et al., 2016), these disasters do not hit all countries. For instance, Northern European countries are rarely hit and studying disasters cannot reveal whether these societies use religion for coping. Instead, the COVID-19 pandemic hit the entire world and thus provides a unique experiment to study which types of societies use religion for coping.

More broadly, this research relates to a literature that regards cultural values as a fundamental determinant of economic outcomes (Nunn and Puga, 2012; Spolaore and Wacziarg, 2013). This literature has linked gender roles to past agricultural practices (Alesina et al., 2013), individualism to past trading strategies and migration patterns (Greif, 1994; Knudsen, 2019), trust to the slave trade in Africa and climatic risk (Nunn and Wantchekon, 2011; Buggle and Durante, 2017), time-preference to variation in land productivity (Galor and Özak, 2016), and anti-Semitism to the Black Death (Voigtländer and Voth, 2012). The current study links a cultural value with evident implications for economic outcomes (religiosity) to one of its

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potential roots: the need for coping in the face of disaster.

The results also relate to previous research documenting correlations between religiosity and socio-economic factors from peoples' ability to cope with stress and uncertainty and less criminal behavior (Guiso et al., 2003; Koenig et al., 1998; Miller et al., 2014) to lower GDP growth, lower innovation, and more traditional gender roles (McCleary and Barro, 2006; Campante and Yanagizawa-Drott, 2015; Inglehart and Norris, 2003). If the COVID-19 pandemic strengthens religion permanently, this may have socio-economic consequences later on.

More broadly, this research contributes to a literature on the mental health effects of the COVID-19 pandemic. Other research has documented symptoms of stress and anxiety among health personnel and the population in China (Wang et al., 2020; Xiao et al., 2020) and a rising economic distress in the US (Fetzer et al., 2020; Binder, 2020). The current results reveal that people from across the globe experience emotional distress in the face of the COVID-19 pandemic, and they use religion to cope. The economic consequences of these emotional effects may be large. A study found that the main part of the economic downturn in the face of COVID-19 are due to the perceived risk of the virus rather than government mandated lock downs of the economy (Andersen et al., 2020).

2 Religious coping

The tendency for people to use religion to deal with crisis can be understood within the religious coping terminology (Pargament, 2001; Bentzen, 2019; Norenzayan and Hansen, 2006; Cohen and Wills, 1985; Park et al., 1990; Williams et al., 1991). The theory states that people use religion as a means to cope with adversity and uncertainty. They pray, seek a closer relation to God, or explain the tragedy by reference to an Act of God. Research has documented that people who experienced adverse life events, such as cancer, heart problems, death in close family, divorce, or injury are more religious than others (Ano and Vasconcelles, 2005; Pargament, 2001). Novel research attests that the impact is global and causal: Adversity, caused by natural disasters, instigates people across the globe to use their religion more intensively (Bentzen, 2019).[8] They are more likely to rank themselves as a religious person, find comfort in God, and to state that God is important in their lives when hit by earthquakes, tsunamis, and volcanic eruptions. This surge in average religiosity occurs on all continents, for people belonging to all major religions, income groups, and from all educational backgrounds. However, religiosity of Catholics and Buddhists increased less than average, while religiosity of Muslims increased somewhat more than average. Recent research also found that people who

[8]Other research has documented an impact on religiosity of specific disasters, such as the 2012 Christchurch earthquake and the 1927 Great Mississippi river flood (Ager et al., 2016; Sibley and Bulbulia, 2012) and of ecological duress in more general (Botero et al., 2014).

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experienced conflict are more religious (Henrich et al., 2019) and that earthquakes increased the power of religious authorities in Medieval Italy (Belloc et al., 2016).

Using religion for coping is part of what is termed emotion-focused coping, in which people aim to reduce the emotional distress arising from a situation (Lazarus and Folkman, 1984). While people use religion for coping with various types of situations, religion is used mainly for coping with negative and unpredictable situations (Pargament, 2001; Bjorck and Cohen, 1993; Smith et al., 2000). Indeed, religiosity increases more in response to unpredictable natural disasters, such as earthquakes, tsunamis, and volcanic eruptions compared to more predictable ones, such as storms and in response to earthquakes in areas that are otherwise rarely hit compared to frequently hit areas (Bentzen, 2019). On the other hand, when we face perceived negative, but predictable events, such as an approaching job interview, we are more likely to engage in problem-focused coping, where we aim to directly tackle the problem that is causing the stress. Being a negative and highly unpredictable event, the COVID-19 crisis certainly fits the criteria for being an event that could instigate religious coping. As of April 20 2020, the COVID-19 had affected 210 countries and territories, infected more than 2.4 mio. individuals worldwide and taken more than 165,000 lives.

People are more likely to use their intrinsic religiosity to cope with adversity rather than their extrinsic religiosity (Johnson and Spilka, 1991; Pargament, 2001). Intrinsic religiosity involves private prayer and one's personal relation to God, while an example of extrinsic religiosity is going to church for social needs or other more ultimate ends than beliefs per se (Allport and Ross, 1967). When faced with adversity, people are thus more likely to use their private beliefs to cope rather than to go to church. Likewise, natural disasters increase private religious beliefs and affect churchgoing much less (Bentzen, 2019). We would therefore expect the COVID-19 pandemic to impact private prayer more than churchgoing, had the churches been open (in an effort to enforce social distancing, most churches closed down as the virus went global).

The intensified use of religion may translate into a permanently larger role of religion, even after the disaster has passed. While the main surge in religiosity occurred during the few years immediately following earthquakes, a residual of elevated religiosity remained and was passed on to future generations (Bentzen, 2019). This results in significant differences in religiosity depending on natural disaster risk in parents' country of origin, even for children of migrants who never lived in the disaster-prone countries. Thus, natural disasters have strengthened the role of religion across the globe permanently. Only time will show whether the same is true for the COVID-19 crisis.

Examples abound of people using prayer as a way of dealing emotionally with the uncertainty and fear surrounding the COVID-19 outbreak. While the title of a sermon at an

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Evangelical Christian megachurch in Dallas asks "Is the Coronavirus a Judgement from God?", political leaders from Mr. Akufo-Addo of Ghana to Mr. Morrison of Australia urge their populations to pray as the coronavirus finds its' way into their economies. Even in Denmark, one of the most secular countries, some people get together in online groups to pray. The rest of this paper examines the significance of this.

3 Data: The rise in prayer intensity

To identify which countries experienced an increased interest in prayer and whether some are more likely to use religion for coping, four types of databases were constructed (see also Appendix A). First, a database on Google searches for topics related to prayer as a share of total Google searches for the 95 countries in the world with enough internet users (downloaded from Google Trends). These searches include all topics related to prayer, including alternative spellings and searches for prayer in other languages. Two series of data were constructed: Daily data for all 95 countries for the period January 29 to April 1 2020 and global weekly data from 2016 to 2020. The series stop on April 1, well before the onset of Easter 2020 (Palm Sunday was April 5) and the Ramadan (first day of the Ramadan 2020 was April 24). The daily series start on January 29, after the January holidays and after the fires in Australia. January 29 is chosen to February 1 to get a sample consisting of full weeks, which does not matter for the analysis using daily data, but could matter for the analysis aggregating the daily data to weeks.

Google Trends provides two types of data: Time-series data and cross-section data. The time-series data is available for one a country at a time or as an average for the world. The cross-section data is available for countries or subnational regions as an average over a specified period of time.[9] For the time-series data, Google Trends normalized the search shares to equal 100 for the highest search share during the period for each country. For the cross-country data, the search share was set to 100 for the country with the highest search shares in the sample. This means that only the growth rates, and not the levels, of the time-series data have a meaningful interpretation and can be compared across countries. For the cross-country data, the levels *can* be compared across countries. The analysis includes country fixed effects throughout and thus does not compare countries, but in Section C.2 I identify the characteristics of the countries who pray more, which means that comparison across countries occurs. To construct a panel dataset, I combined the growth rates from the time-series data with the levels from the cross-section data. For each country, I downloaded the average prayer search shares for 2019 based on the cross-section data, set this to the search share on January

[9]The current analysis uses countries instead of subnational regions, as no time-series data exist for the regions.

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29 2020, and calculate the search shares for the rest of the period based on the growth rates from the time-series data.[10]

Most tables and figures are based on these comparable data, except Fig. 1 (and other figures in the Appendix that use world aggregates) which includes the raw data from Google Trends, Fig. 2 where the search shares in all countries are instead normalized to 1 on February 15 2020, Panel (a) of Fig. 3 and Tables A.9-A.10, which are based exclusively on the growth rates in the prayer search shares.

The google searches for prayer will fall as people access their prayer websites directly without googling them or memorize the prayers. Likewise, searches on prayer surge dramatically on the first week of the Ramadan only to drop the week after, even though Muslims pray every day during the Ramadan (cf. Fig. 1). An increasing prayer share reveals that new people are searching for prayer or people who already searched for prayer are searching for prayer again (one person googling prayer many times over a short period of time will not enter the search data many times, though). Thus, falling search shares for prayer are difficult to interpret. Therefore, observations are dropped after the prayer search shares reached their maximum level in Figures 2 and 3. Most remaining figures and maps include the full dataseries, unless stated otherwise. These are therefore conservative estimates.

A second database identifies what people are searching for when searching for the topic prayer (see also B.2). Apart from searches for prayer in different languages, the four search queries that contribute the most to the rise in search shares for prayer are "prayer for coronavirus", "pray for the world", "spiritual communion prayer", and "pray for italy" (cf. Fig. A.2). When googling "prayer for coronavirus", various websites offer prayers related to the coronavirus. These include prayers to prevent the virus from spreading and prayers to thank nurses and other care-takers for their work in relation to the pandemic (see Appendix B.2).

The third database consists of daily data on registered cases and deaths by COVID-19 for each country of the world (see also Appendix A.2). These numbers depend on the amount of testing in each country and general policies regarding registration of cases and deaths, and are therefore neither comparable across countries nor across time (where policies may change). Inclusion of country fixed effects throughout takes care of the difficulty of comparison across countries, but does not account for the difficulty of comparison over time. As an attempt to account of the latter, measures of the timing of the first case or death will be used, but the main results will depend on a measure independent of the registered cases and deaths: The point in time when COVID-19 was declared a pandemic; March 11 2020.

[10]For instance, the average prayer search share in 2019 was 3 for Denmark, while that in Morocco was 87. I therefore set the prayer search share on January 29 to 3 in Denmark and 87 in Morocco. From January 29 to 30, prayer search shares rose by 68% in Denmark and by 6% in Morocco. The prayer search share on January 30 2020 therefore amounts to 5.1 in Denmark and 92.4 in Morocco, and so forth.

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Fourth, to identify the characteristics of those who search more for prayer, the database with Google searches for prayer was combined with data on various characteristics of the countries, such as religiosity levels before COVID-19, the share of Christians, Muslims, Hindus, and Buddhists, and various socio-economic characteristics.

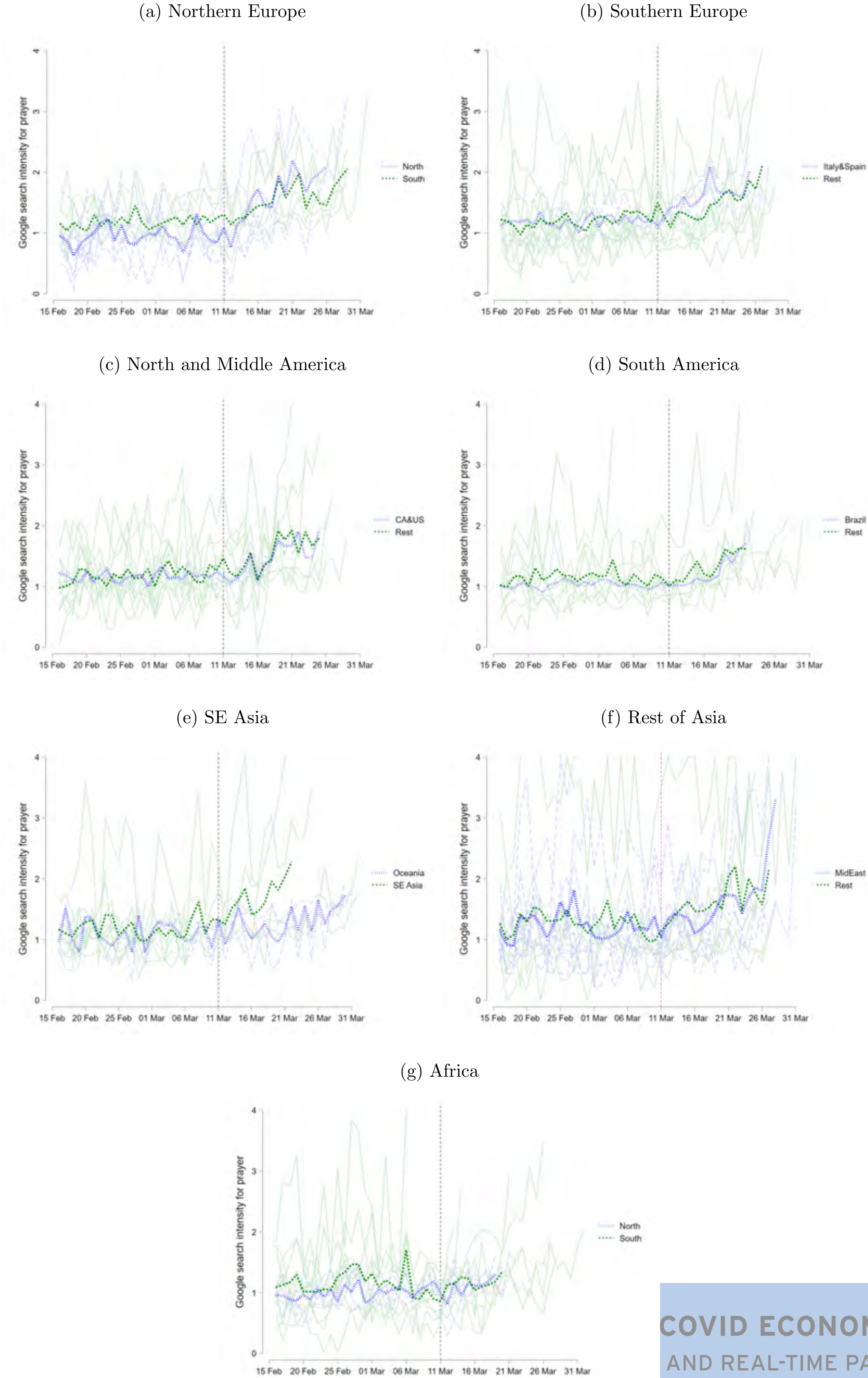
4 Results

To parsimoniously illustrate the findings, Fig. 2 shows daily search-shares for prayer during the period February 15 to April 1 2020 for all 95 countries, split into fourteen regions. Each panel shows two groups of countries within the particular region. The darker curves represent the average for the particular group, while the lighter curves represent the raw data for each country. The search-shares are set to 1 on February 15, which means that the figure shows the change in search-shares, relative the initial level of searches for prayer in the particular country. The vertical line represents March 11, where WHO declared the COVID-19 a pandemic. Search-shares for prayer rose around mid March for most regions, even for the most secular regions of Northern Europe.

The map in panel (a) of Fig. 3 also shows the relative changes in prayer search shares. The map illustrates the growth rate in prayer search shares from February to the highest level reached in March: $\frac{prayer_{march} - prayer_{feb}}{prayer_{feb}}$.[11] The growth rates are large for Northern Europe, where few people searched for prayer before COVID-19. Likewise, the somewhat smaller increases in Northern Africa are due to the high initial levels of prayer searches. Panel (b) of Fig. 3 documents the *absolute* increases in prayer search shares, which is the relevant metric to identify the global spread of intensified prayer. The largest absolute increases occur in South America and Africa, some of the most religious regions of the world. The econometric analysis will rely on the absolute changes, while robustness checks are performed in Tables A.9 and A.10 based on the growth rates.

[11]To prevent a general rise in prayer search shares from being associated with COVID-19, potential increases in February were subtracted from the numerator in both panels. The map is very similar without this correction. See more on the growth rates in Appendix C and Section C.4.

Figure 2: Daily Google searches for the topic "prayer" by region



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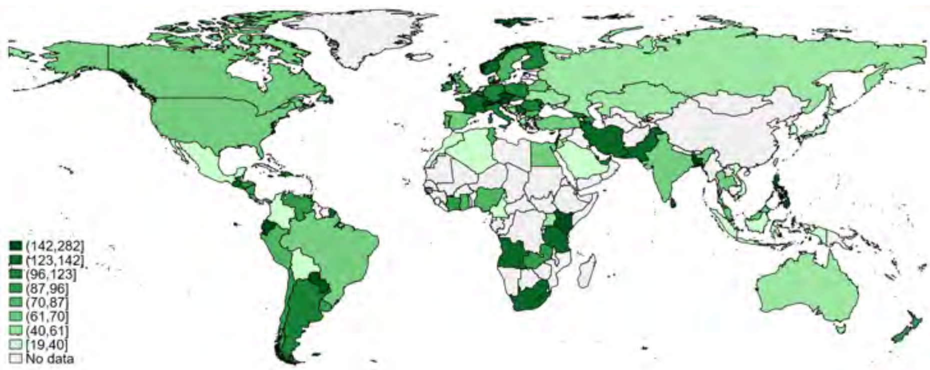
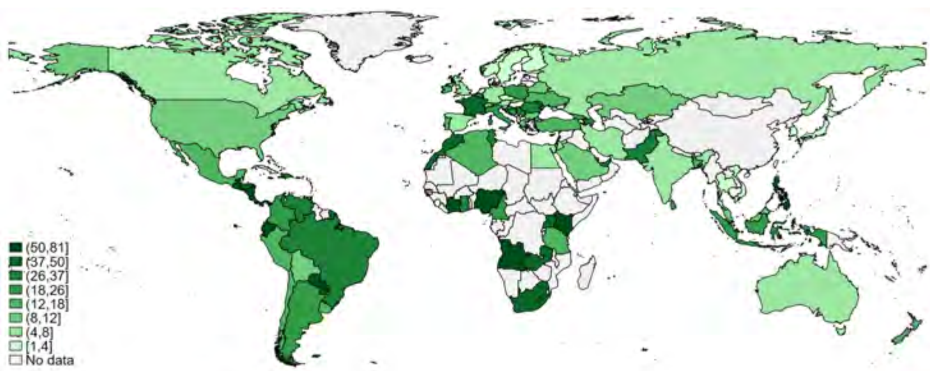
Google searches for prayer as a share of the total number of Google searches on the particular day, set to 1 on February 15 2020. A country drops out of the sample after it reaches its' peak during the period Feb 15 to Apr 1. The searches encompass topics related to prayer, including alternative spellings and languages. The light-coloured lines represent a country. The darker-coloured lines represent the average prayer intensity for the particular group. The countries behind the blue curves are italicized in the following. **Northern Europe**: *Belgium, Denmark, Finland, Netherlands, Norway, Sweden*, Austria, France, Germany, Ireland, Switzerland, United Kingdom. **Southern Europe**: *Italy, Spain*, Belarus, Bosnia and Herzegovina, Bulgaria, Croatia, Czech Republic, Greece, Moldova, Poland, Portugal, Romania, Slovak Republic, Ukraine, Yugoslavia. **North and Middle America**: *Canada, USA*, Costa Rica, Dominican Republic, El Salvador, Guatemala, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Panama, Trinidad and Tobago, **South America**, *Brazil*, Argentina, Bolivia, Chile, Colombia, Ecuador, Paraguay, Peru, Puerto Rico, Uruguay, Venezuela, **SE Asia**: *Australia, New Zealand*, **Rest of Asia**: *Cyprus, Iran, Israel, Jordan, Kuwait, Lebanon, Qatar, Saudi Arabia, Turkey, United Arab Emirates,* Azerbaijan, Bangladesh, Georgia, India, Kazakhstan, Pakistan, Russia, Sri Lanka, **Africa**: *Egypt, Morocco, Tunesia*, Algeria, Angola, Cameroon, Ghana, Ivory Coast, Kenya, Nigeria, South Africa, Tanzania, Uganda, Zambia. See more details in Appendix A.1 and C.

Figure 3: The rise in prayer search shares across the globe in March 2020

(a) Growth rate (%)



(b) Absolute increase



The map shows the rise in Google search shares from February 29 2020 to the highest level reached in March 2020 subtracted the rise in February 2020 in Panel (b). Panel (a) shows the rise as a percentage of the average level during February 2020 (the average rise was 91%, the minimum was 19%, and the maximum was 282%). Panel (b) shows the absolute rise (the average rise was 24, the minimum was 0.5, and the maximum rise was 81 units). Darker green indicates larger rises in prayer search shares. Missing data is indicated with grey. Find more details in Appendix A.1 and C.

Fig. 2 also showed that prayer search intensity rose around or just after March 11 for most of the fourteen regions, the date when WHO declared the COVID-19 a pandemic (see also Appendix B.5 and Fig. A.9 for a formal analysis of the timing of the rise).

4.1 Econometric analysis

To identify formally what Figures 1, 2, and 3 showed visually, the following equation was estimated:

$$prayer_{ct} = \beta + \gamma covid19_{ct-1} + \alpha covid19^2_{ct-1} + \delta t_c + \kappa_c + \varepsilon_{ct} \quad (1)$$

where $prayer_{ct}$ measures the number of google searches on prayer in country c on day t as a share of total google searches on the same day for the same country. $covid19_{ct-1}$ captures the exposure to COVID-19 using different measures: A dummy variable, *pandemic*, equal to one on March 11 where WHO declared COVID-19 a pandemic, measures of the total number of registered people infected by COVID-19 and the total number of deaths, a dummy equal to one after the country registered its' first case or death, days since the first case or death, and days since March 11 (cf. Table 1 and Tables A.1-A.3). These variables are lagged a day in the main analysis. Alternative specifications are investigated, such as adding squared terms, aggregating to weekly data (cf. Tables A.1-A.3), and examining growth rates (Section C.4).

t_c is a country-specific time-trend. This variable captures the general upward or downward trend in prayer search shares for each country.[12] κ_c is a list of country fixed effects, ensuring that results are only compared within one country at a time. When the $covid19_{ct-1}$ variable is the pandemic dummy or the first case or death dummy, γ can be interpreted as the average rise in prayer search shares after March 11 or after the first registered case or death, respectively (these are the measures used in Table 1).

While it is theoretically probable that the causality in equation (1) instead runs from religiosity to COVID-19 exposure, this seems a highly unlikely explanation for the results. The increases in prayer search shares documented here are the largest ever recorded. For reverse causality to explain the results, one would have to come up with another explanation for this sudden rise in prayer intensity. Also, the main results are based on the pandemic dummy, which does not suffer from reverse causality or other endogeneity issues, as the WHO announcement was done centrally and thus independent of country-specific conditions.

Table 1 documents the estimates of equation (1), including country-fixed effects and country-specific time trends throughout. The model in column (1) of Panel A documents that prayer search shares rose with 5.1 units since March 11. This amounts to 16.9% of the

[12]This is a generalization of the subtraction of $\Delta prayer_{feb}$ done for Fig. 3 (cf. Appendix C).

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average prayer search shares over the period (30.2, calculated at the bottom of each Panel in Table 1). The model in column (2) adds a measure of the number of days passed since COVID-19 was declared a pandemic. The model documents that prayer search shares continued to rise daily after March 11. After 10 days, prayer search shares had risen by 19.7% of the mean ((2.45+3.5)/30.2), after 20 days 31.3% of the mean. The increase will probably not continue linearly, especially since those who start to access their prayer websites directly without googling them are not captured by the google search shares (analyzed more formally in Tables A.1 and A.2). Only time will show how much further the search shares for prayer will continue to rise.

Columns (3) and (6) document that prayer search share rose after a country registered its' first case or death, but nearly half of this is due to the timing of the pandemic declaration by WHO (columns 3 and 7). Fig. A.1 shows that these results are not caused by a distinct cluster of observations. Instead, the likelihood of rising prayer shares varies very homogenously with the likelihood of having passed March 11 of having registered the first case or death.

Columns (5) and (8) show that prayer search shares rose more after March 11 in countries where the COVID-19 had already arrived. This result is even stronger when restricting the sample to the sample where observations after prayer search shares reached their maximum level are dropped (Table A.2).[13]

In an attempt to circumvent endogeneity issues and issues related to comparison of registered deaths and cases over time and space, the remainder of the analysis will use the pandemic dummy to measure the impact of COVID-19. Panel B of Table 1 splits the sample into the different regions of the world and documents that prayer search shares rose significantly in all regions after March 11. Again, the absolute rise is larger in the Americas and Africa, where the overall search shares for prayer are higher (cf. MeanDepVar at the bottom of the table, which measures the average prayer intensity in that region).

[13]The regression in column (5) may suffer from multicollinearity and results should be interpreted with care. In particular, the pandemic dummy and the interaction with the case dummy both have vifs of 12, which exceeds the critical value of 10, meaning that all coefficients in this regression may be biased.

Table 1: The impact of COVID-19 on prayer search shares

Dependent variable: Prayer search shares	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A								
Pandemic dummy	5.11***	2.45***		4.77***	2.07		4.49***	3.87***
	(0.752)	(0.762)		(0.752)	(1.835)		(0.795)	(0.839)
Days since Pandemic		0.35***						
		(0.059)						
First case dummy			2.92***	1.62**	1.05			
			(0.848)	(0.764)	(0.750)			
Pandemic x first case dummy					3.16*			
					(1.849)			
First death dummy						3.89***	2.47**	0.34
						(0.960)	(0.968)	(1.532)
Pandemic x first death dummy								2.84*
								(1.677)
R-squared	0.84	0.84	0.84	0.84	0.84	0.84	0.84	0.84
Observations	6080	6080	6066	6066	6066	6080	6080	6080
Countries	95	95	95	95	95	95	95	95
MeanDepVar	30.2	30.2	30.2	30.2	30.2	30.2	30.2	30.2
Panel B	All	N Europe	S Europe	N America	S America	SE Asia	Rest Asia	Africa
Pandemic dummy	5.11***	2.50**	2.87**	7.11***	8.72**	5.14*	4.34***	5.98***
	(0.752)	(0.912)	(1.281)	(2.054)	(3.906)	(2.499)	(1.458)	(1.503)
R-squared	0.84	0.91	0.77	0.73	0.78	0.92	0.63	0.70
Observations	6080	768	960	832	704	768	1152	896
Countries	95	12	15	13	11	12	18	14
MeanDepVar	30.2	10.0	24.5	50.4	40.7	15.5	19.3	53.0

OLS estimates. Units: Days $\times$ countries. Period: January 29 to April 1 2020. All regressions include a constant, country-specific time trends, and country fixed effects. The sample includes the full sample in panel A and in column (1) of Panel B, but varies across the remaining columns of panel B: Northern Europe in column (2), Southern Europe (3), North America (4), South America (5), South East Asia and Oceania (6), the rest of Asia (7), and Africa (8). Robust standard errors clustered at the country level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level. Find more details in Appendix A.1.

Result: Prayer intensity increases day-by-day after the WHO announces COVID-19 a pandemic for all regions. The rise is marginally larger in countries where the COVID-19 had physically arrived.

Google searches for prayer may rise for a reason unrelated to religious coping. Since the churches closed down to prevent the disease from spreading, part of the intensified prayer searches may be replacing physical church attendance. Theoretically, we would not expect this to be the main explanation for the rising search shares for prayer, as physical churchgoing belongs to extrinsic religiosity which is not the main type of religiosity used for coping with adversity (Johnson and Spilka, 1991; Pargament, 2001; Bentzen, 2019). Instead, the main type of religiosity used for coping is intrinsic religiosity, which includes private prayer. Surely, the pandemic would most likely have resulted in more churchgoers had the churches been open, just as experienced in the USA after the 9-11 attacks. The theory on religious coping suggests, though, that the rise in private prayer would be larger. In addition, a recent survey reveals that 95% of Americans who pray, pray alone, while only 2% pray collectively in a church (Barna, 2017).

There are also empirical indicators that the rise in searches for prayer is due to religious coping and not merely a shift from physical church to online church (Appendix C.3). First, data on the specific contents of the internet searches reveal that searches for topics related to "internet church" also rise, but compared to the rise in prayer search shares, the increase is

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indistinguishable from zero (Fig. A.2). Second, the search shares on prayer continue to rise long after the church closures (Fig. 2). Third, the rise in prayer searches does not only occur on Sundays, where most masses are held. While the rise on Sundays is higher than other days, the search shares rise on all days of the week, except Fridays. Last, the heterogeneity of the rise in prayer searches documented in the next section is consistent with the religious coping theory (the poor and vulnerable pray more).

4.2 Characteristics of those who pray more

While prayer search intensity rose in nearly all countries, this section examines differences in the size of the increase depending on previous religiosity levels, dominating religious denominations, and socio-economic characteristics. This is an estimation of the following equation (see also Tables A.4 - A.7):

$$prayer_{ct} = \beta + \gamma pandemic_{t-1} + \lambda pandemic_{t-1} \times characteristic_c + \delta t_c + \kappa_c + \varepsilon_{ct} \qquad (2)$$

where $characteristic_c$ includes different measures of country characteristics: the religiosity level in country c before the onset of the COVID-19 pandemic, a dummy equal to one for the dominating religious denomination, or various socio-economic characteristics. The rise in prayer search shares after March 11 now equals $\gamma + \lambda characteristic_c$. If the rise in prayer search shares after March 11 is larger for the more religious, certain religious denominations, or certain socio-economic characteristics, this is captured by $\lambda > 0$. Apart from the interaction term, the regression is otherwise the same with country-specific time-trends, δt_c and country-fixed effects, κ_c.

Panel (a) of Fig. 4 shows the estimates of equation (2) for different religiosity levels in 2019, measured by the average search shares for prayer in 2019.[14] The results show that prayer search shares rose more in more religious countries. Prayer search shares rose significantly for all levels of previous prayer intensity, but rose more for the countries that prayed more in 2019. For instance, prayer search shares rose more than five times more in the most religious quarter of countries, compared to the least religious. Using alternative measures of religiosity based on questions asked in global surveys conducted well before the COVID-19 pandemic documents that the rise in prayer searches is larger in countries where a larger share of the population reply that they prayed more, went more to church, or answered that God is important in their lives (Tables A.4 - A.6). Also, prayer searches rose significantly even in the 15% least religious countries for most measures of previous religiosity (Table A.4). Among the 10% least religious

[14] Four dummy variables were constructed based on the quartiles of the prayer search share in 2019. Equation 2 was run for each of them. Each dot in Fig. 4 represents $\gamma + \lambda$ for each of the dummies.

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countries, prayer search shares rose significantly only for 4 out of 9 religiosity measures. The 10% least religious countries are the Czech Republic, Denmark, Finland, Germany, Japan, the Netherlands, Norway, Sweden, Taiwan, Thailand, and Vietnam. Thus, Northern European countries, formerly communist countries (that prohibited religion), and Buddhist majority countries that were hit early by COVID-19.

Previous religiosity levels may be endogenous and correlate with various other country-characteristics. To exploit instead exogenous variation in religiosity, panel (b) documents a very similar relation with earthquake risk.[15] Previous research has documented that earthquakes increase religiosity (Bentzen, 2019; Bulbulia, 2004; Belloc et al., 2016) for the same reason that COVID-19 increase religiosity: Religious coping. In line with the results in panel (a), panel (b) shows that prayer search shares rose more in countries with more earthquake risk.

Fig. 4 shows that prayer search intensity rose for Christians (particularly Catholics), Muslims, Hindus, and Buddhists, but insignificantly so for the latter two. The countries are categorized into the major denominations based on there being at least 25% adherents to the particular denomination. The insignificance for Hindus and Buddhists is due to the larger standard errors and to a lesser extent smaller parameter estimates. There are rather few countries in these two groups, which produces larger standard errors. The two only countries defined as Hindu in the sample are India and Trinidad and Tobago, while countries defined as Buddhist are Japan, Sri Lanka, Taiwan, Thailand, and Vietnam. Fig. A.12 documents that global Google searches for god, allah, jesus, mohammad, bible, quran, buddha, vishnu, and shiva also rose in March 2020. For the latter three search terms, though, the rise in March is not larger than other holy events during the year, such as Buddhas birthday or Hindu holidays for Lord Shiva or Lord Vishnu. Thus, while Hindu and Buddhist traditions also use religion for coping, these traditions seem more focused on celebration than coping. Another interpretation of the lower impact among the Buddhist countries is that these countries were hit before the virus was declared a pandemic and they have experienced more pandemics than the rest of the world. Thus, the rise in fear and emotional distress may be lower in these countries.

[15]The measure is the inverse of the distance to high earthquake risk zones, as used in Bentzen (2019).

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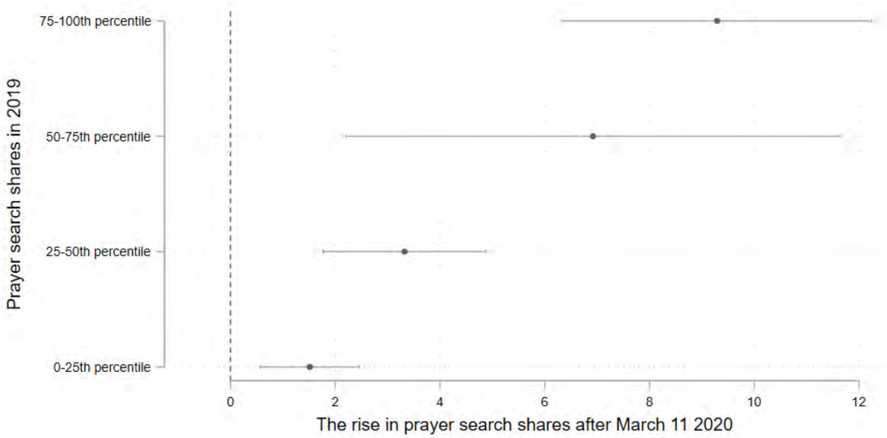
Figure 4: The rise in prayer search shares for different religiosity and denominations

(a) Prayer search shares in 2019



(b) Earthquake risk

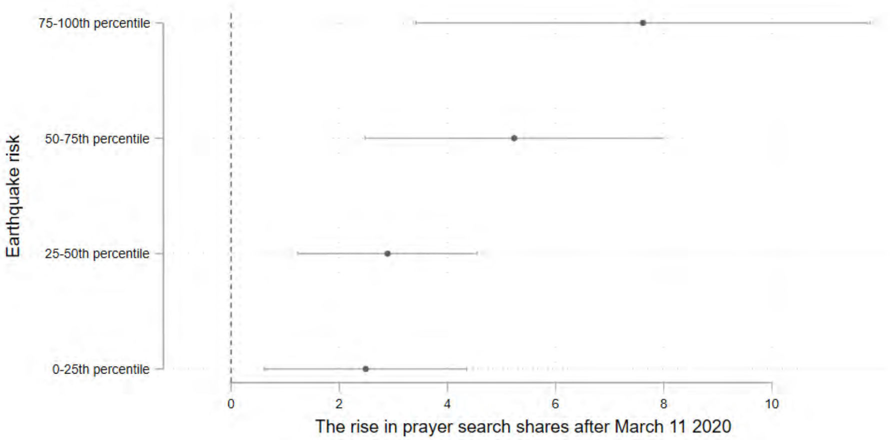


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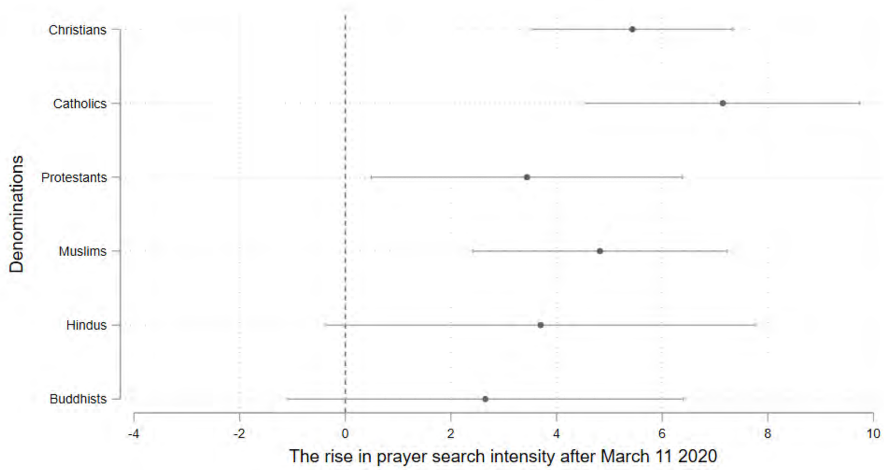
Figure 4: cont. The rise in prayer search shares for different religiosity and denominations

(c) Religious denominations



The rise in prayer intensity for different prayer search shares in 2019 in panel (a), different earthquake risk intensities in panel (b), divided into quartiles, and different major religious denominations in panel (c). Each dot represents the estimate of the rise in prayer search shares after March 11 in an OLS regression, where the rise in prayer search shares is allowed to vary with initial religiosity levels in panels (a) and (b) and with religious denominations in panel (c), controlling for country-specific time trends and country fixed effects. The denominations are defined based on there being at least 25% adherents of the particular denomination in a country. The horizontal lines represent the 95% confidence bounds. See more details in Appendix A.1 and C.2.

Result: Prayer intensity rose at all levels of previous religiosity and major religious denominations, but more in more religious countries and not significantly in Hindu and Buddhist societies.

Research argues that religion provides a sense of existential security, which is most needed among vulnerable populations, especially those living in poorer nations, facing personal survival-threatening risks (Norris and Inglehart, 2011). One could therefore expect that religion is used more extensively to cope with the COVID-19 pandemic in poorer, more unequal, and more insecure states (Norris and Inglehart, 2011). Table 2 investigates whether this is also the case for the COVID-19 pandemic, using different measures of economic development, inequality, and mortality measures.

The simple model in Panel A of Table 2 documents that prayer search shares rose more in poorer, more unequal, and more insecure countries. Prayer searches rose more in poorer countries, where development is defined by the share of people living below 1.9US$ a day (col 1), GDP per capita (col 2), the Human Development Index, which is an alternative measure of general well-being of a country (col 3), more unequal countries, where inequality is measured by the Gini coefficient of the degree of economic inequality (col 4) and a measure of the degree to which economic development is unevenly distributed (col 5), more fragile states (col 6), and in states with larger demographic pressures (col 7) or higher mortality rates (col 8).

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Panel B documents, though, that these effects are due to poorer and more insecure countries being more religious: When adding an interaction term with religiosity (measured by average prayer search shares in 2019), all of the mentioned effects turn insignificant.[16] The only significant variable is the interaction between the pandemic dummy and the prayer search shares in 2019: Religious countries are more likely to search for prayer on the internet in the face of COVID-19. The same results are found using other measures of religiosity based on surveys (Table A.7). However, these societies may be more religious because they are poor, unequal, and uncertain and thus some of the impact of the socio-economic confounders may work through religiosity. To account for this, Panel C exploits the exogenous variation in religiosity due to earthquake risk and instruments the interaction between the pandemic dummy and prayer search shares in 2019 with an interaction between the pandemic dummy and earthquake risk. The First stage F statistic is above 10 in most specifications, which means that the instrument is valid.[17] The results confirm that the heterogeneity with respect to the socio-economic characteristics is due to the fact that poorer, more unequal and insecure countries are also more religious.

This means that prayer shares rose in all countries, independent of their economic status, whether or not they are unequal, fragile or more mortal. The only thing that matters for whether people use religion for coping or not is how religious they are to start. That religion is not used more for coping in poor and uncertain societies may be because these populations do not feel more emotional distress when faced with COVID-19 compared to richer countries. One observation speaks for this explanation: COVID-19 arrived earlier in Western societies and thus the initial fear may have been larger in these societies. Alternatively, the availability of religion as a coping tool may be more important than the need for such a tool. Either way, the finding is consistent with previous research documenting that people use religion to cope with natural disasters at all levels of income and education (Bentzen, 2019). On a more technical note, studies documenting differential effects of religious coping for poor and insecure societies should be aware that these differential effects could be simply a result of higher religiosity levels in these societies. This matters for the conclusion whether people use religion for coping more because they need it or simply because they can. Here, COVID-19 generates a need for emotional coping, and societies use religion to cope, independent on whether they are rich or poor, uncertain or secure.

[16]This is not due to multicollinearity: The Variance Inflation Factor for the three main variables in Panel B is well below the critical value of 10 in all columns.

[17]The exclusion restrictions are rather unlikely to be violated: It is unlikely that earthquake risk influences the rise in prayer search shares after March 11 2020 through other channels (apart from previous religiosity levels) that are not already included in the regression.

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Table 2: The rise in prayer search shares across country characteristics

Dependent variable: Prayer	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: OLS	Poverty	GDP	HDI	Gini	Uneven	Fragile	Demography	Mortality
Pandemic dummy	5.34***	18.4***	13.0***	-4.45	0.34	1.76	1.08	2.91**
	(0.948)	(5.096)	(2.981)	(3.525)	(1.516)	(1.159)	(1.187)	(1.139)
Pandemic x Variable	0.32***	-1.48***	-11.0***	0.25**	0.95***	0.057**	0.86***	0.018**
	(0.083)	(0.519)	(3.602)	(0.100)	(0.355)	(0.024)	(0.280)	(0.008)
R-squared	0.85	0.84	0.84	0.84	0.84	0.84	0.84	0.84
Observations	4544	6016	5888	5248	5824	5824	5824	5888
Countries	71	94	92	82	91	91	91	92
Panel B: OLS								
Pandemic dummy	1.68*	4.21	0.48	-2.16	1.08	1.73	0.40	1.67
	(0.951)	(5.310)	(3.630)	(3.588)	(1.460)	(1.085)	(1.125)	(1.046)
Pandemic x Variable	0.040	-0.29	0.94	0.11	0.080	-0.0081	0.28	-0.0046
	(0.158)	(0.518)	(4.113)	(0.115)	(0.460)	(0.027)	(0.318)	(0.012)
Pandemic x Prayer 2019	0.16***	0.14***	0.15***	0.12***	0.14***	0.15***	0.13***	0.16***
	(0.052)	(0.037)	(0.041)	(0.042)	(0.049)	(0.041)	(0.040)	(0.046)
R-squared	0.85	0.84	0.84	0.84	0.84	0.84	0.84	0.84
Observations	4544	6016	5888	5248	5824	5824	5824	5888
Countries	71	94	92	82	91	91	91	92
Panel C: IV								
Pandemic dummy	-1.75	-7.39	-4.84	-3.21	-0.0036	-0.050	-2.47	-2.04
	(1.760)	(8.748)	(7.607)	(3.659)	(1.693)	(1.443)	(1.659)	(1.623)
Pandemic x Variable	0.20	0.56	3.83	0.075	-0.66	-0.060	0.46	0.0052
	(0.281)	(0.796)	(7.728)	(0.114)	(0.868)	(0.049)	(0.373)	(0.013)
Pandemic x Prayer 2019	0.31***	0.32***	0.31***	0.24**	0.36**	0.38***	0.24**	0.28***
	(0.118)	(0.102)	(0.113)	(0.093)	(0.154)	(0.131)	(0.095)	(0.094)
R-squared	0.88	0.87	0.87	0.89	0.87	0.87	0.87	0.87
Observations	3456	4352	4352	3904	4352	4352	4352	4416
Countries	54	68	68	61	68	68	68	69
FirstStageF	14.9	12.2	11.1	12.0	7.17	8.62	14.2	21.3

OLS estimates. Units: Days × countries. Period: January 29 to April 1 2020. All regressions include a constant, country-specific time trends, and country fixed effects. Panel A includes an interaction between the Pandemic dummy and various socio-economic variables described in the text and in Appendix A.4. Panel B includes also an interaction between the Pandemic dummy and prayer search shares in 2019. Panel C instruments the interaction between prayer search shares in 2019 and the pandemic dummy with an interaction between earthquake risk and the pandemic dummy. In panel C, the sample is restricted to countries within 1500 km of high-risk earthquake zones. The scalar FirstStageF is the Kleibergen Paap first stage F statistic. Robust standard errors clustered at the country level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level. See more details in Appendix A.1 and C.2.

Result: Prayer search shares rose more in poor, unequal, and insecure countries. But this is exclusively because these societies are more religious.

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5 The relative size of the rise in prayer

To get a sense of the relative size of the rise in prayer, the following back of the envelope calculation was made. The factor that matters most for the difference in the size of the rise in prayer is existing religiosity in each country. Combining this finding with results from a Pew Research Center survey from March 2020 showing that 55% of Americans had prayed to end the coronavirus (Pew, 2020b), we can back out the global average rise in prayer related to COVID-19. The average religiosity across all religiosity measures used in the analysis (cf Table A.4), weighted with the population size in each country yields the number 0.654 (with a standard deviation of 0.19).[18] The religiosity level in the US is 0.671. A back of the envelope estimate of the share of the people in the sample that prayed for the coronavirus is therefore very close to 55%.[19] The sample of 95 countries represents 68% of the world population[20] and the average religiosity level in the sample is no different from the average in the countries outside the sample with information on the survey-based religiosity measures.[21] Thus, the back of the envelope exercise shows that more than half of the world population have prayed to end the coronavirus. This large number is reconcilable with the finding that the rise in Google searches for prayer is larger than searches for the topic takeaway and amounts to 12% the rise in searches for Netflix, and 26% the fall in searches for flights, which all changed tremendously in the month of March 2020, where most of the world's countries were in lock down (cf Appendix B.4).

6 Conclusion

Google searches on prayer provides a measure of the intensity of prayer in real time. In March 2020, Google searches for prayer rose to the highest level ever recorded. The rise amounted to a quarter of the fall in Google searches for flights, which dropped dramatically as air traffic was shut down in an effort to enforce social distancing. People show an increased interest in prayer on the internet on all continents and for all religious denominations, but less for Buddhists and Hindus. In total, more than half of the world population have prayed to end the coronavirus.

The rising prayer intensity is a result of religious coping: When faced with uncertainty and adversity, humans have a tendency to use religion for comfort and explanation. The results thus reveal that many people from across the globe experience emotional distress in the face

[18] All religiosity measures were scaled between 0 and 1.

[19] The share of Catholics in the US is 23%, close to the global average of 17%, but the share of Protestants is 48.9%, much higher than the global average of 12%. Since the rise in prayer shares for Protestants is lower than both Catholics and Muslims, the estimate is conservative.

[20] 5.15 bio. / 7.55 bio. people

[21] On average, 21 countries outside the sample have information on the survey based religiosity measures.

of the COVID-19 pandemic, and they use religion to cope. The use of religion for coping is logically stronger for more religious societies, although the less religious also engage in religious coping. The use of religion is more pervasive in poorer, more unequal, and uncertain societies, but this is exclusively because these societies are more religious.

The emotional distress caused by COVID-19 may influence the economy on the short term through reduced spending, but a potential strengthened role of religion may also impact economies on the longer term. At this point in time, we can only guess whether religiosity and the role of religion will rise more permanently. Previous research found that natural disasters leave a long-lasting impact on religiosity, which is passed on through generations (Bentzen, 2019). Whether the COVID-19 pandemic will have similar long-term effects is yet to be seen. Furthermore, if the COVID-19 pandemic can have such a dramatic impact on one of the deepest rooted of human behaviors, what else can it influence?

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Appendix

A Data

A.1 Google searches for prayer and other religious terms

Google Trends provides access to a sample of actual search requests made on Google. It is anonymized (no one is personally identified), categorized (determining the topic for a search query) and aggregated (grouped together). The Google Trends data thus displays interest in a particular topic from around the globe. The data is available back to 2004, but there was a trend break on Jan 1 2016, where the data was improved. The data is downloadable from google.trends.

Google Trends normalizes the search data in the following way: 1) Each data point is divided by the total searches of the geography and time range it represents to compare relative popularity, 2) The resulting numbers are then scaled on a range of 0 to 100 based on a topic's proportion of all Google searches.

Google Trends filters out some types of searches: 1) Searches made by very few people: Google Trends only shows data for popular terms, so search terms with low volume appear as "0". 2) Duplicate searches: Google Trends eliminates repeated searches from the same person over a short period of time. 3) Special characters: Google Trends filters out queries with apostrophes and other special characters.

Google Trends provides two methods of accessing what people search for. *Search terms* show matches for all terms in a query, in the language given. If you search the term "prayer," results include terms like "prayer" or "coronavirus prayer". If you specify "coronavirus prayer," results include searches for "coronavirus prayer," as well as "prayer for coronavirus". *Topics* are a group of terms that share the same concept in any language. If you search the topic "London," results include topics such as "Capital of the UK" or "Londres," which is "London" in Spanish.

Google Trends provides two types of data: Time-series data and cross-section data. The time-series data is available for one a country at a time or as an average for the world. The cross-section data is available for countries or subnational regions as an average over a specified period of time.[22] For the time-series data, Google Trends normalized the search shares to equal 100 for the highest search share during the period for each country. For the cross-country data, the search share was set to 100 for the country with the highest search shares in the sample. This means that only the growth rates, and not the levels, of the time-

[22]The current analysis uses countries instead of subnational regions, as no time-series data exist for the regions.

series data have a meaningful interpretation and can be compared across countries. For the cross-country data, the levels *can* be compared across countries. The analysis includes country fixed effects throughout and thus does not compare countries, but in Section C.2 I identify the characteristics of the countries who pray more, which means that comparison across countries occurs. To construct a panel dataset, I combined the growth rates from the time-series data with the levels from the cross-section data. For each country, I downloaded the average prayer search shares for 2019 based on the cross-section data, set this to the search share on January 29 2020, and calculate the search shares for the rest of the period based on the growth rates from the time-series data.[23]

The data used throughout this paper are based on time-series data with searches for the topic "prayer". This means that the data is independent of languages and includes all searches related to the topic "prayer". The main data includes search shares for prayer during the period January 29 to April 1 2020. The period starts well in advance of the onset of COVID-19 as a pandemic and before the onset of Easter and the Ramadan, where prayer search shares may rise for reasons other than the COVID-19.

Some fluctuations in the data are too extreme to represent real fluctuations in the interest on prayer. Fluctuations are defined as "too extreme" when prayer search shares spike up (or down) on one day with more than 25 percentage points, only to fall down (or rise) again with 25 percentage points or more on the following day. For the data behind all Figures and Tables, except Figure 1, these extreme fluctuations were cut in half. Figure 1 shows the raw data from Google Trends. Single-day spikes that last more than one day are not affected by this correction, but were kept unchanged throughout. The correction affects 7.6% of the data, which includes mainly a few countries that each have many such extreme fluctuations. The countries with most of these extreme fluctuations are Tanzania, Qatar, and Finland with 22, 19, and 16, days, respectively with these extreme fluctuations out of a total of 61 days in the sample. These corrections matter mainly for the visual presentation of the results in Fig. 2. The econometric analyses would treat these fluctuations in the data as noise, which would enter the error term and produce slightly larger standard errors on the parameters estimated. Since standard errors throughout are quite small, this does not change the econometric results in any important way.

There are 99 countries with both time-series data for Google searches on prayer, $prayer_{ct}$ and globally comparable prayer search shares for 2019, $averageprayer2019_c$. Four of these are small islands or countries with many large fluctuations in the search share data: Martinique,

[23]For instance, the average prayer search share in 2019 was 3 for Denmark, while that in Morocco was 87. I therefore set the prayer search share on January 29 to 3 in Denmark and 87 in Morocco. From January 29 to 30, prayer search shares rose by 68% in Denmark and by 6% in Morocco. The prayer search share on January 30 2020 therefore amounts to 5.1 in Denmark and 92.4 in Morocco, and so forth.

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Mauritius, Reunion, and Senegal. These four countries were excluded from the dataset, meaning that the final dataset on prayer search shares includes 95 countries, listed in the notes for Figure 2.

The main period of analysis is January 29 to April 1 2020. The data thus ends one week before the onset of Easter and three weeks before the onset of the Ramadan, where search shares for prayer rise for other reasons that the COVID-19. January 29 was chosen to get as large a pre-period as possible, but still be able to zoom in on the COVID-19 pandemic. Some of the figures show longer periods.

A.2 Measures of the impact of COVID-19

Data on affected cases and deaths by the COVID-19 for the globe are provided by the European Centre for Disease Prevention and Control (ECDC). The data is available on a daily basis since December 31 2019 for all countries that were affected by the COVID-19. The main measure of cases measures the total number of registered people infected by the COVID-19. The variable does not account for who had recovered again, which means that the variable can only increase with time. Likewise, deaths by COVID-19 measures the total number of registered deaths by COVID-19. These two measures are both dependent on the extent of testing being done in the particular countries. Testing strategies vary across countries in terms of how much they test, both before and after death.

Pandemic dummy is a dummy equal to one after March 11 when the WHO declared COVID-19 a pandemic, and zero otherwise.

Days since Pandemic measures the number of days passed since March 11. The variable is equal to zero on March 11 and before.

First case dummy is a dummy equal to one after the country had its' first registered case of COVID-19, zero otherwise.

First death dummy is a dummy equal to one after the country had its' first registered death by COVID-19, zero otherwise.

Days since first case measures the days passed since the country had its' first registered case of COVID-19. The variable is equal to zero before that.

Days since first death measures the days passed since the country had its' first registered death by COVID-19. The variable is equal to zero before that.

A.3 Previous levels of religiosity

The analysis includes the following measures of religiosity before COVID-19. These are used mainly in Fig. 4 and Tables A.4, A.5 and A.6:

Prayer 2019: Average Google searches for prayer as a share of total Google searches from

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January 1 2019 to December 31 2019.

The remaining measures of religiosity in Table A.4 are based on answers to questions asked by the World Values Survey and European Values Study. These are surveys distributed to a total of 505,000 individuals across the globe over the period 1981-2014. The two surveys ask the same questions and the responses are therefore comparable.

Moments of prayer: The share of respondents in a country who answered yes to the question "Do you take some moments of prayer, meditation or contemplation or something like that?".

Ever prayed: This variable is based on the question "Apart from weddings and funerals, about how often do you pray these days?" Respondents can answer "More than once a week", "Once a week", "Once a month", "Only on special holy days", "Once a year", "Less often", or "Never, practically never". The variable "Ever prayed" measures the share of respondents in a country who answered anything but "Never, practically never". This variable was only asked in Muslim countries.

Weekly pray: The share of respondents in a country who answered "More than once a week" or "Once a week" to the above question.

God: This variable is based on the question "How important is God in your life? Please use this scale to indicate. 10 means "very important" and 1 means "not at all important". The variable "God" measures the share of respondents in a country who answered anything but "not at all important".

Very God: The share of respondents in a country who answered "very important" to the above question.

Ever church: This variable is based on the question "Apart from weddings and funerals, about how often do you attend religious services these days?" Respondents can answer "More than once a week", "Once a week", "Once a month", "Only on special holy days", "Once a year", "Less often", or "Never, practically never". The variable "Ever church" measures the share of respondents in a country who answered anything but "Never, practically never".

Weekly church: The share of respondents in a country who answered "More than once a week" or "Once a week" to the above question.

Earthquake risk: This variable is the inverse of the distance to the highest earthquake risk zones. Data on earthquake risk zones are provided by the United Nations Environmental Programme as part of the Global Resource Information Database (UNEP/GRID), who divided earthquake risk into five categories based on various parameters such as ground acceleration, duration of earthquakes, subsoil effects and historical earthquake reports. High risk earthquake zones are defined by Bentzen (2019) as zones 3 or 4. The reasoning for using distances instead of the average of earthquake risk zones is that the measure is meant to provide exogenous

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variation in religiosity. The impact of earthquake risk on religiosity is psychological and the use of religion for coping can be strong in areas close to high-risk zones, even though these areas face low risk of earthquakes (Bentzen, 2019). Therefore, distances are more relevant than averages across the earthquake risk zones. When using this measure, the sample is restricted to countries within at least 1500 km of a high-risk earthquake zone.

A.4 Data on economic and political uncertainty

The variables in Table 2 are chosen from a comprehensive dataset provided by the Quality of Government Institute (Teorell et al., 2020), which gathers data from various studies on the quality of government and related matters. The search was limited to variables available for at least 70 of the countries in the main sample.

Fragile States Index produced by Haken et al. (2019), 2016 at The Fund for Peace (http://ffp.statesindex.org/) measures the pressures on states, their vulnerability to internal conflict, and societal deterioration. The index is based on twelve primary social, economic and political indicators (each split into an average of 14 sub-indicators). For each indicator, the ratings are placed on a scale of 0 to 10, with 0 being the lowest intensity (most stable) and 10 being the highest intensity (least stable). Table 2 shows results using the index, but also some of the subcomponents of the index: 1) **Economic Decline Indicator** considers factors related to economic decline within a country. For example, the indicator includes patterns of progressive economic decline of the society as a whole as measured by per capita income, Gross National Product, unemployment rates, inflation, productivity, debt, poverty levels, or business failures. 2) **Security** includes measures related to internal conflict, small arms proliferation, riots and protests, fatalities from conflict, military coups, rebel activity, bombings, and political prisoners. The measure increases as security deteriorates. 3) **Service** includes measures related to policing, criminality, education provision, literacy, water and sanitation, infrastructure, quality healthcare, telephony, internet access, energy reliability, roads. The measure increases as public service deteriorates. 4) **Uneven Economic Development** measures the extent to which economic development is unevenly distributed. Includes measures related to the GINI coeffcient, income share of highest 10%, income share of lowest 10%, urban-rural service distribution, access to improved services, and slum population. 5) **Demography** includes measures related to natural disasters, disease, environment, pollution, food scarcity, malnutrition, water scarcity, population growth, youth bulge, mortality.

Poor measures the poverty gap at Purchasing Parity Adjusted 1.9US$ a day, 2011, measured by the World Development Indicators.

GDP per capita measures the logarithm of real PPP adjusted GDP per capita in 2000, provided by the Penn World Tables.

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Human Development Index measures the Human Development Index in 2010 from the U.N Human Development Report.

Gini is a dummy equal to one if the average Gini coefficient over the period 1991 to 2010 exceeded the median level. The Gini coefficient measures the degree of economic inequality.

Mortality measures the adult mortality rate per 1000 population, provided by the World Health Organization.

Table A.4 documents the summary statistics for the included variables.

Table A.1: Summary statistics

Variable	Mean	Std. Dev.	N
Google search share for prayer	30.17	26.383	6080
Growth rate in prayer search shares	0.172	1.691	6080
Pandemic dummy	0.328	0.47	6080
Case dummy	0.545	0.498	6080
Death dummy	0.219	0.413	6080
Average prayer search share 2019	26.158	20.03	6080
Earthquake risk	0.812	0.231	4864
Moments of prayer	0.732	0.188	4096
Ever prayed	0.828	0.174	2880
Pray weekly	0.589	0.261	2880
God important	0.917	0.096	5056
God very important	0.559	0.301	5056
Ever went to church	0.783	0.162	4992
Go to church weekly	0.339	0.23	4992
Fraction Christians	0.604	0.363	6080
Fraction protestants 2000	0.113	0.19	6080
Fraction catholics 2000	0.349	0.357	6080
Fraction Muslims	0.207	0.33	6080
Fraction Hindu	0.017	0.08	6080
Fraction Buddhist	0.038	0.137	6080
Poverty gap at 1.95USD a day	1.734	4.214	4544
GDP per capita 2000 (PPP)	8.987	1.161	6016
Human Development Index	0.712	0.145	5888
Avg gini 1991-2010	39.69	9.325	5248
Uneven Economic Development	5.188	2.08	5824
Fragile States Index	61.489	23.619	5824
Demographic Pressure	4.884	2.234	5824
Adult mortality rate	130.359	73.039	5888

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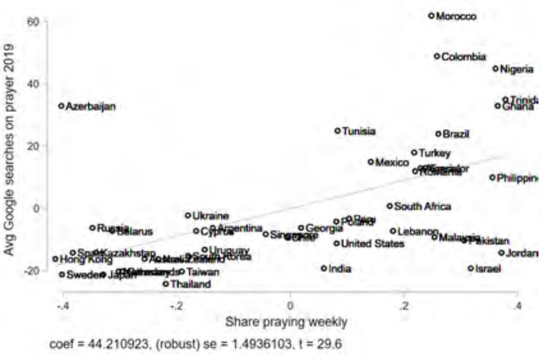
B Google searches

B.1 Correlation between Google searches and surveys

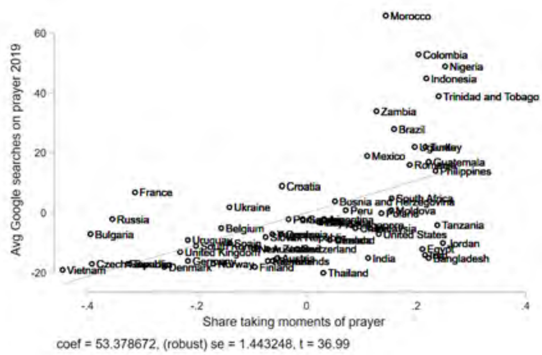
Fig. A.3 shows the correlation between average Google search shares for prayer in 2019 and the share of survey respondents who replied that they pray weekly in paneæs (a) and (c) and the share of respondents who replied that they take moments of prayer, meditation, and contemplation. Panels (a) and (b) show the raw correlation, while panels (c) and (d) removes variation across continents (i.e. a regression of Google searches for prayer on the particular survey measure and a list of continent dummies). The correlation is high and significant and substantiates that Google searches capture real prayer intensity stated in surveys.

Figure A.1: Relation between survey answers on prayer and Google search shares for prayer

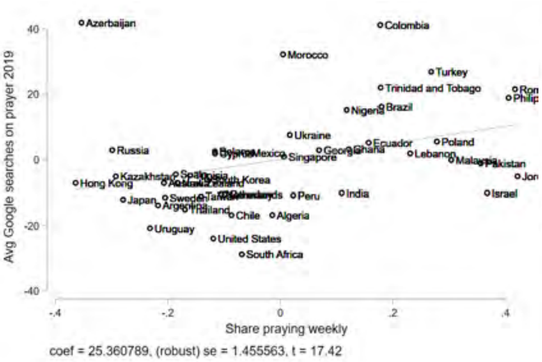
(a) Share praying weekly



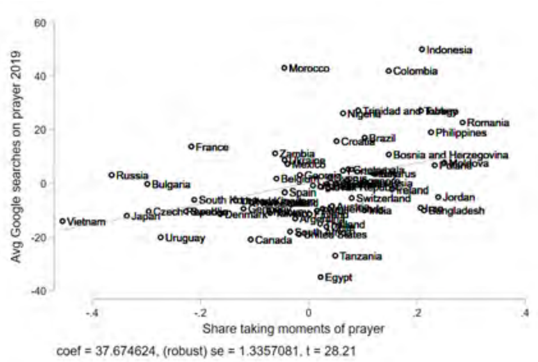
(b) Share taking moments of prayer



(c) Including continent fixed effects



(d) Including continent fixed effects



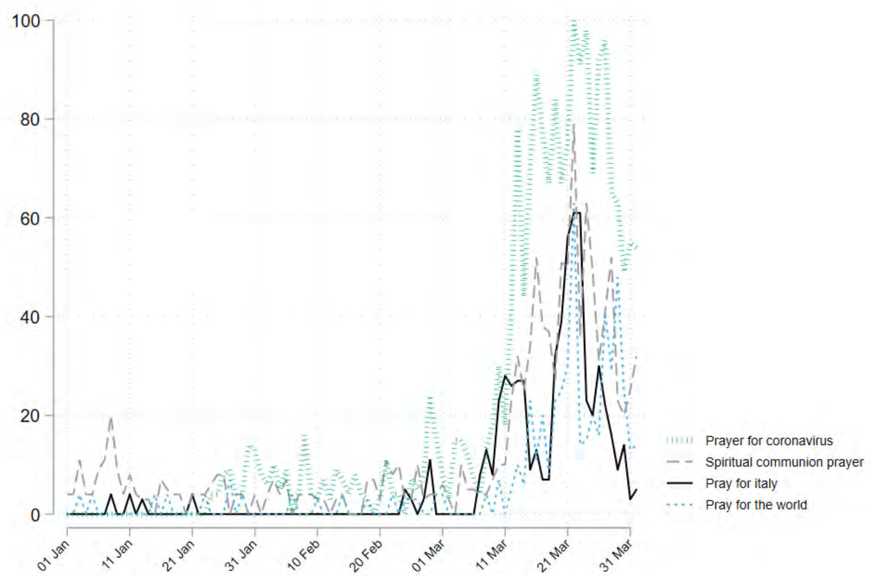
Correlation between the share of Google searches for prayer in 2019 and the share of survey respondents answering that they pray weekly in panels (a) and (c) and the share of survey respondents answering that they take moments of prayer, meditation, and contemplation in panels (b) and (d). Panels (a) and (b) depict the raw correlation, while panels (c) and (d) depict the correlation after controlling for continent fixed effects. The measures are described in Section A

B.2 Contents of Google searches for prayer

Fig. A.2 documents the development in the specific Google searches that contributed to the most to the rise in searches for the prayer topic. For each topic, Google Trends provides information on the top-25 search terms and the top-25 rising search terms. The combination of the two lists provides a list of search terms that are both large in levels and rising over the period. Four main search terms dominate the global pattern in searches for the topic "prayer". Fig. A.2 shows the development over time in these search terms. The "Pray for Italy" trend swept across the globe in March 2020 as Italy was the first country outside Asia affected by the COVID-19 virus. Spiritual Communion is a Christian practice of desiring union with Jesus Christ. Searches for spiritual communion spike every Sunday, particularly after March 11 and are examples that some Google searches for prayer are replacing physical church attendance.

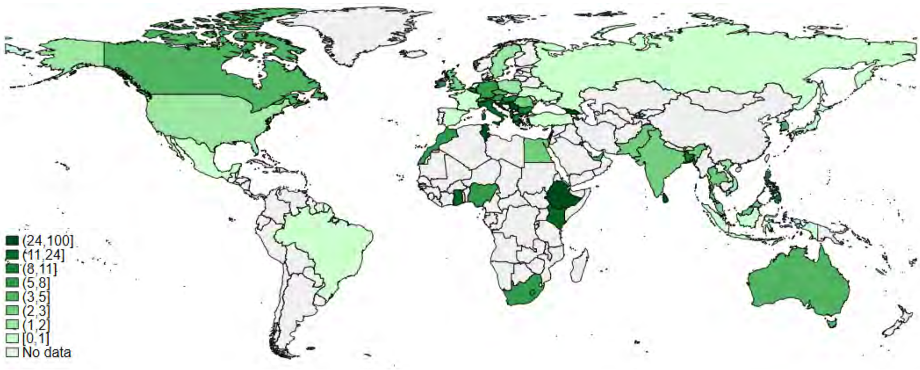
The map in Fig. A.3 shows the global spread in Google searches for "pray for italy". The map illustrates that searches that are specific to the situation in one country can surge in other countries, even far from the country in question.

Figure A.2: Top search terms within the topic "Prayer"



The three spikes in the search terms for "Spiritual communion prayer" are Sundays. Searches for "prayer for coronavirus" includes searches for "prayer for COVID-19".

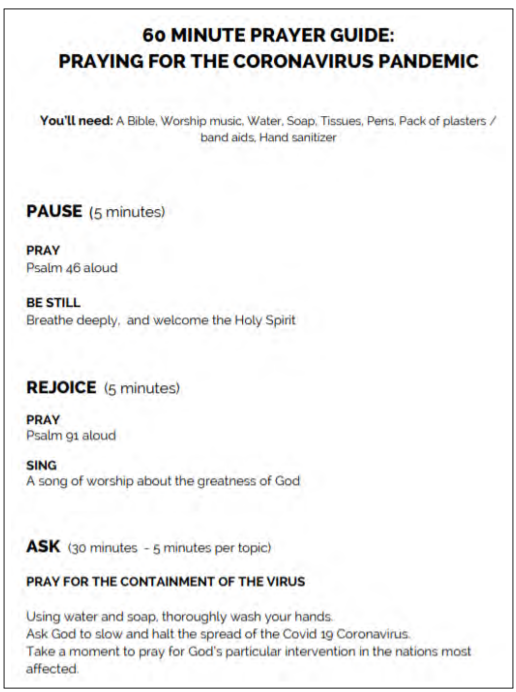
Figure A.3: Geographic spread of searches for "pray for italy" March 5-30 2020



B.3 Examples of prayer websites

Figures A.4 , A.5, A.6, and A.7 show screenshots of websites that one encounters when googling "coronavirus prayer". The websites contain instructions on how to pray as well as specific prayer texts.

Figure A.4: Example of a guide to a coronavirus prayer



60 MINUTE PRAYER GUIDE:
PRAYING FOR THE CORONAVIRUS PANDEMIC

You'll need: A Bible, Worship music, Water, Soap, Tissues, Pens, Pack of plasters / band aids, Hand sanitizer

PAUSE (5 minutes)

PRAY
Psalm 46 aloud

BE STILL
Breathe deeply, and welcome the Holy Spirit

REJOICE (5 minutes)

PRAY
Psalm 91 aloud

SING
A song of worship about the greatness of God

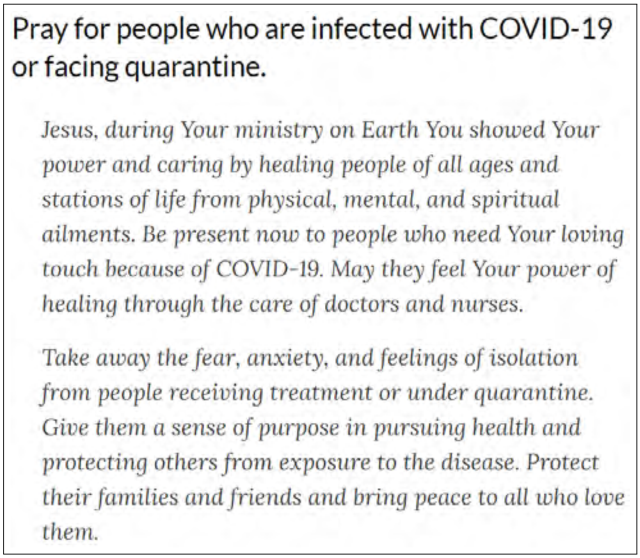
ASK (30 minutes - 5 minutes per topic)

PRAY FOR THE CONTAINMENT OF THE VIRUS

Using water and soap, thoroughly wash your hands.
Ask God to slow and halt the spread of the Covid 19 Coronavirus.
Take a moment to pray for God's particular intervention in the nations most affected.

The website of 24/7 Prayer: https://www.24-7prayer.com/60-minute-coronavirus-prayer

Figure A.5: Example of a coronavirus prayer



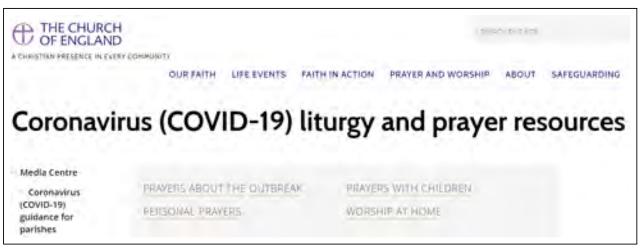
Pray for people who are infected with COVID-19 or facing quarantine.

Jesus, during Your ministry on Earth You showed Your power and caring by healing people of all ages and stations of life from physical, mental, and spiritual ailments. Be present now to people who need Your loving touch because of COVID-19. May they feel Your power of healing through the care of doctors and nurses.

Take away the fear, anxiety, and feelings of isolation from people receiving treatment or under quarantine. Give them a sense of purpose in pursuing health and protecting others from exposure to the disease. Protect their families and friends and bring peace to all who love them.

The website of World Vision: https://www.worldvision.org/disaster-relief-news-stories/prayers-people-affected-new-coronavirus

Figure A.6: Example of website with COVID-19 prayers



The website of the Church of England: https://www.churchofengland.org/more/media-centre/coronavirus-covid-19-liturgy-and-prayer-resources

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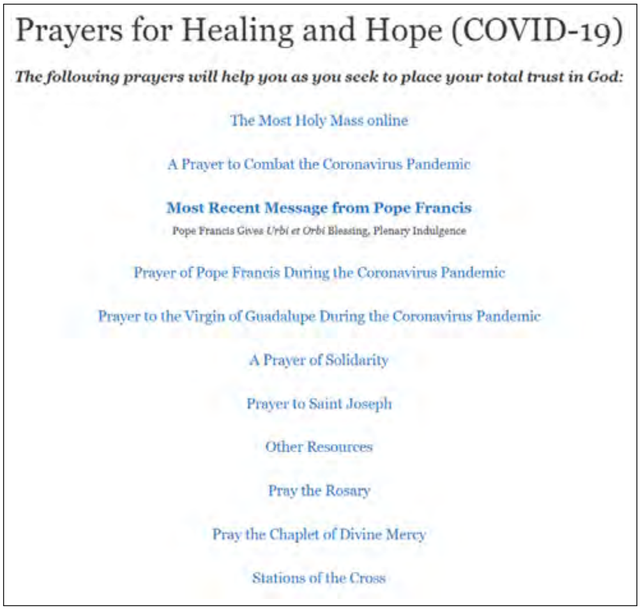
Figure A.7: Example of website with list of COVID-19 prayers



The website of website of My Catholic Life: https://mycatholic.life/catholic-prayers/a-prayer-for-healing-and-hope/

B.4 The relative size of the increase

Fig. A.8 shows the increase in Google searches for prayer relative to searches for other topics that rose during the COVID-19 pandemic. The purpose is to illustrate the relative size of the rise in prayer searches. The COVID-19 pandemic resulted in massive lock downs and quarantines across the globe, meaning that people were at home and not allowed to go out. In addition, most international air traffic was shut down.

Fig. A.8 shows that searches for topics related to take-out and Netflix rose during the month of March 2020, while searches for flights fell. The volume of searches for prayer was higher than searches for takeaway (by a factor 4.8), but lower than searches for Netflix (25%) and flights (28%). Like prayer, the Google searches for take-out, Netflix, and flights encompass all searches for topics related to these in all languages.

The relative sizes of the increases in the searches are calculated using the following formula for Netflix and take-out:

$$\frac{\Delta prayer}{\Delta other} = \frac{maxprayer_{mar} - avgprayer_{feb}}{maxother_{mar} - avgother_{feb}} \tag{3}$$

where $maxprayer_{mar}$ is the maximum level of search shares for prayer reached during the month of March 2020 and $maxother_{mar}$ is the maximum level of search shares for either Netflix or Take-Out reached during the month of March 2020. $avgprayer_{feb}$ is the average

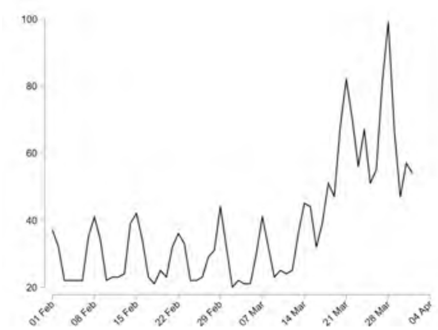
level of search shares for prayer during February 2020 and $avgother_{feb}$ is the average level of search shares for Netflix or take-out during February 2020.

Instead of $maxother_{mar}$, the calculation for flights included the $minother_{mar}$, which is the minimum level of search shares for flights reached during the month of March 2020. This way, the spike in searches for flight in early March does not influence the calculation. This surge may be due to people anticipating a change in rules for flight traffic.

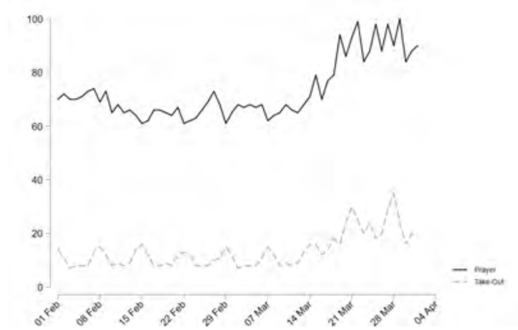
Searches for prayer rose by 134% the rise in Google searches for take-out, by 12% the rise in searches for Netflix, and by 26% the fall in searches for flights.

Figure A.8: Google searches for other terms affected by COVID-19

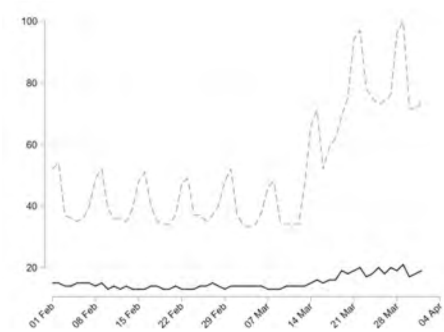
(a) Take-out



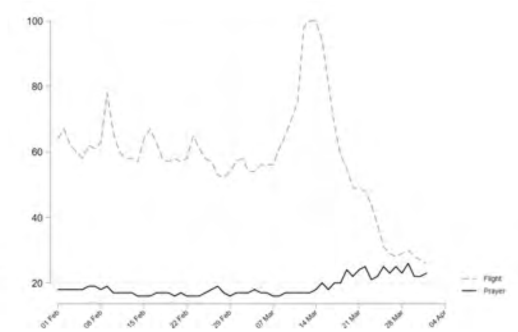
(b) Prayer and take-out



(c) Prayer and Netflix



(d) Prayer and flight



Global average of Google searches on different topics over the period Feb 1 to April 1 2020. The searches are set to 100 for the largest search within each panel. The size of the increases are therefore not comparable across panels, but they are comparable within one panel. **Result**: Google searches for prayer compares in size to movements in other tendencies that were impacted by COVID-19.

B.5 The timing of the rise in prayer searches

Fig. A.9 documents the distribution of the countries based on when the prayer search shares rose for the first time in each country. The figure illustrates the timing of the surge in Google searches for prayer. The following calculations define which increases in the prayer search

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shares are significant based on whether the increase exceeds one standard deviation.

$$prayer_{ct} > prayer_{ct0} + sd(prayer_c) \tag{4}$$

where $prayer_{ct}$ is the daily share of Google searches for the topic prayer for country c, as described in Section A.1. $prayer_{ct0}$ measures the average prayer search shares in the first week of February (period t0) and $sd(prayer_c)$ measures the standard deviation of the prayer search shares over the entire period from January 29 to April 1. Equation (4) defines an increase in prayer search shares as significant when the search share rose more than one standard deviation above the initial level in the beginning of February. For each country and for each day, one can calculate whether or not search shares rose above this level. Fig. A.9 depicts the first day that this level was reached for at least two consecutive days or with maximum one day in between. This occurred within the window of analysis (Feb 1 - Apr 1 2020) for 94 out of the 95 countries in the sample. The 94 countries are represented by the density mass in Fig. A.9. For 51 of these 94 countries, the significant rise occurred on March 11 or thereafter (the density mass at or to the right of March 11 in the figure).

Of the 43 countries, where the first day with significant increases in prayer search shares occurred before March 11 (the density mass to the left of March 11 in the figure), 19 were located in Asia, where the COVID-19 virus first hit, cf. Fig. A.10 which shows the development in registered reported cases worldwide.

Morocco is the only country in the sample not included in Fig. A.9. The search shares for prayer did rise above the mean of the first week of February for several days during the window of analysis, but with two or more days in between the spikes.

All in all, Fig. A.9 shows that most of the countries in the sample experienced their first large increases in search shares for prayer during the period March 14 to March 25.

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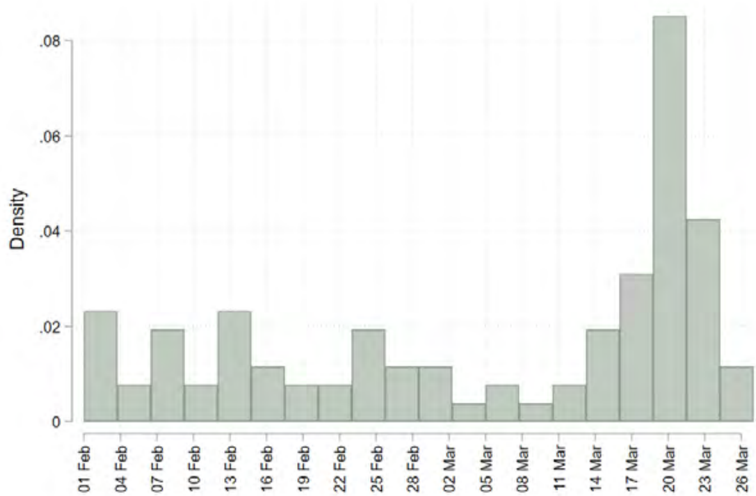
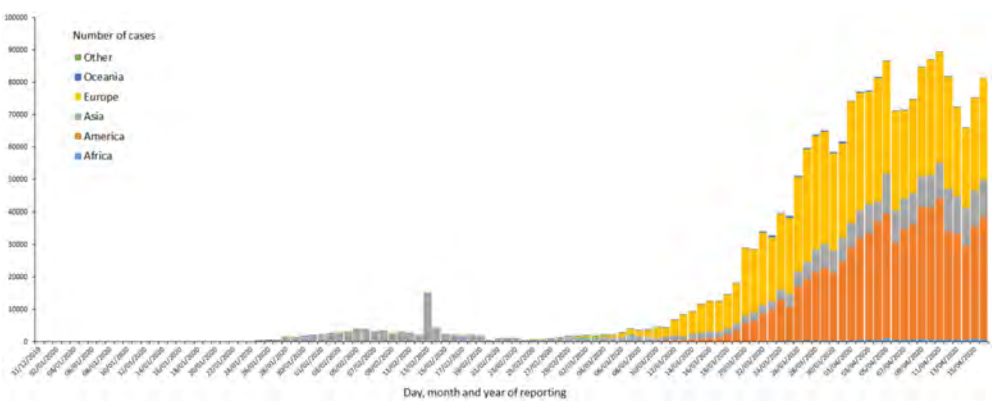
Figure A.9: Distribution of the countries based on first day with two-days rise in prayer search shares



The histogram shows the distribution of 94 countries in the sample, based on the day when their prayer search shares first rose more than one standard deviation above the level in the first week of February for two consecutive days or with maximum one day in between. All countries, except Morocco fulfil this criteria and are included in the figure.

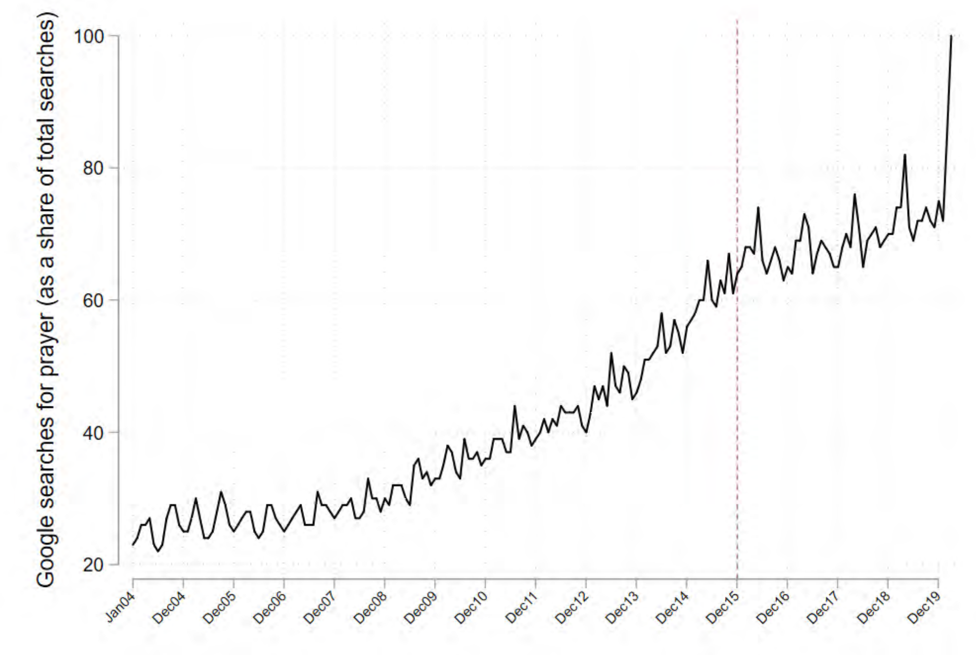
Figure A.10: Distribution of COVID-19 cases worldwide as of 16 April 2020



Distribution of cases of COVID-19 by continent (according to the applied testing strategies in the affected countries). Source: ECDC, https://www.ecdc.europa.eu/.

Fig. A.11 shows that the spike in Google searches for prayer is even visible in the data back to beginning of the Google Trends series, starting in Jan 1 2004. Note, however, that there is a trend break in the data on Jan 1 2016, where Google Trends' data collection method was improved.

Figure A.11: Global Google searches for prayer Jan 2004 to Apr 2020



The vertical line represents an improvement of Google Trends' data collection method.

B.6 Alternative Google searches for religious topics

Figure A.12 documents rising search shares for other religious search topics. The period includes the full year from Apr 14 2019 to Apr 14 2020, the latest date at the time of writing. The end date coincides partly with Easter 2020, which may influence the rise for the Christian search terms, but should not matter for the remaining religious terms.

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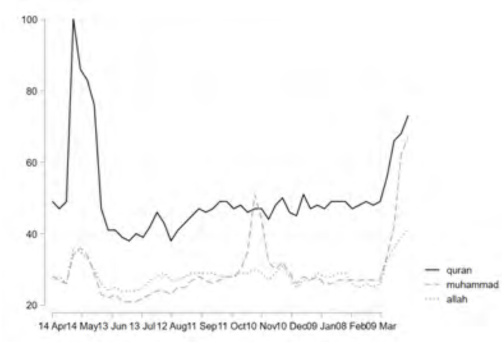
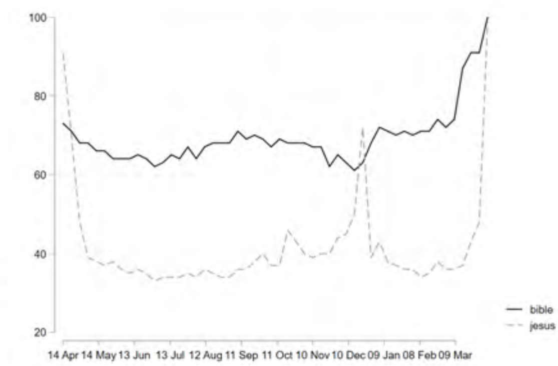
Figure A.12: Google searches for religious topics Apr 14 2019 - Apr 14 2020

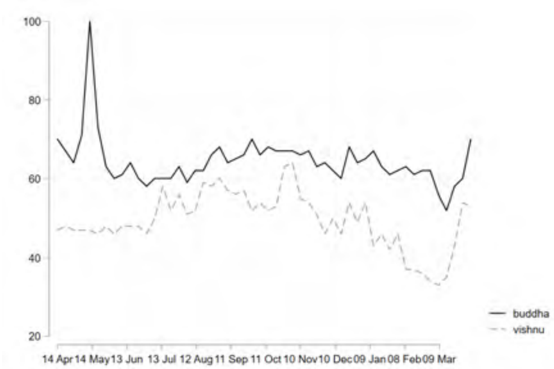
(a) Topics quran, muhammad, allah



(b) Topics jesus and bible



(c) Topics buddha and vishnu



(d) Topic shiva

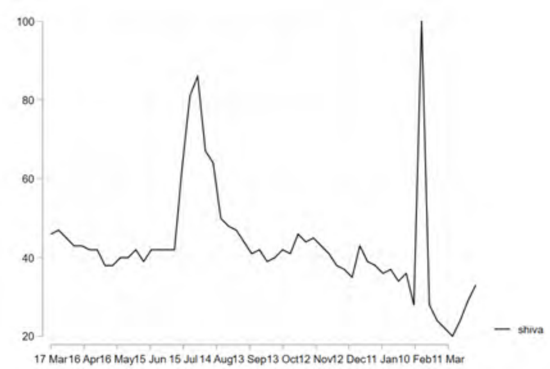
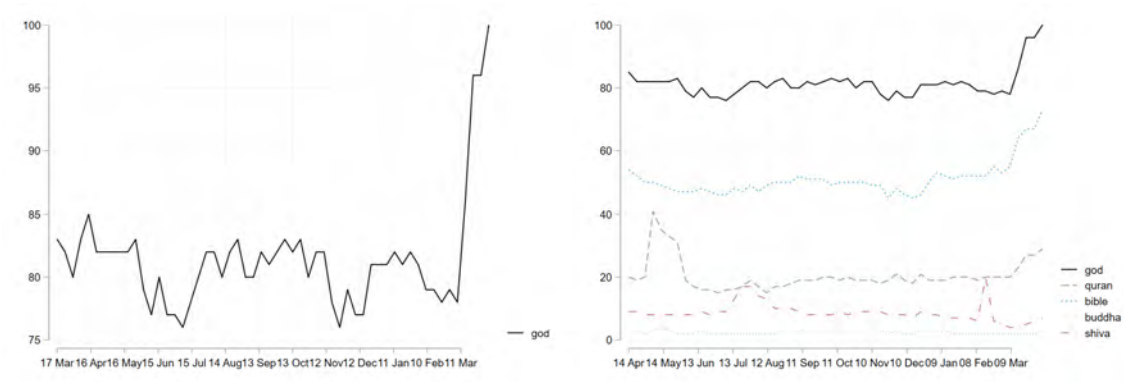


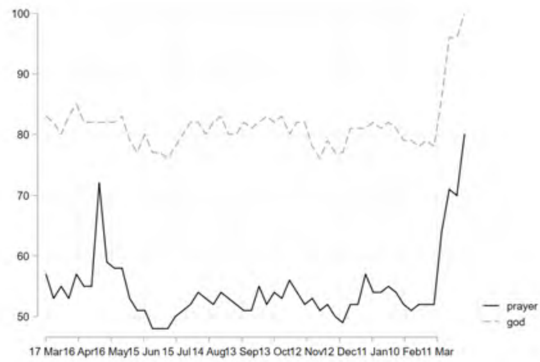
Figure A.12: Cont. Google searches for religious topics Apr 14 2019 - Apr 14 2020

(e) Topic god

(f) Topics god, quran, bible, buddha, shiva



(g) Topics god and prayer



Global average of Google searches on religious topics over the period April 14 2019 to April 14 2020. Google Trends sets the searches to 100 for the largest search within each time series. The search shares are therefore not comparable across panels, but they are comparable within one panel.
Result: Search shares rise in March 2020 for all religious terms. In March 2020, searches for muhammad, allah, bible, jesus, and god surpass the search shares across all other religious events during the year. Searches for buddha peak on May 12, Buddhas birthday, quran peaks on the first day of the Ramadan, vishnu peaks on Nov 10, Vaikuntha Chaturdashi, the Hindu holiday for Lord Vishnu and Lord Shiva, shiva peaks on Feb 21, Maha Shivratri, the worshipping of Lord Shiva.

C The motivating figures

This section contains supplementary information for Figures 1, 2, and 3. Fig. 1 documents the development in the global average of Google searches for the topic prayer. The data shown is the direct download from Google Trends, before the data corrections described in Section A.1. The time-line in Panel A is chosen as the longest possible window without data breaks. This means that the series starts on Jan 1 2016. Fig A.11 documents that the same picture emerges when extending the timeline back to 2004, which is the earliest available data from Google Trends. The series ends at the latest date available at the time of writing, April 11. Panel B of Fig. 1 restricts the period to the period used in the main analysis, starting on

January 29 2020 and ending on Apr 1 2020, before the onset of Easter 2020.

Fig. 2 is constructed based on the data on google searches for prayer, described in Section A.1. To construct the figure, data points were dropped after each country reached its' maximum search share for prayer during the period January 29 to April 1 2020. Interpretation of a fall in search shares is not straight forward, since the search shares mechanically fall when people start entering their preferred prayer websites directly instead of googling them first, even if the interest in prayer stays constant. The means within each group were calculated only when at least 2-5 countries had information on prayer search shares on the given day. Third, to increase comparability across the panels, the y-axis was cropped at prayer share values of 4, even in cases where some data points exceeded this value. These large fluctuations in the data occur mainly in Asia, particularly outside of South East Asia.

Fig. 3, panel (b) documents the absolute change in prayer search shares in March 2020, $\Delta prayer_{march}$, which is constructed using the following formula:

$$\Delta prayer_{mar} = maxprayer_{mar} - avgprayer_{feb} - \Delta prayer_{feb} \tag{5}$$

$maxprayer_{mar}$ measures the highest prayer search share reached after March 1. $avgprayer_{feb}$ measures the average prayer share during February 2020. $\Delta prayer_{feb}$ measures the change in prayer search shares from the first to the last week of February 2020. The rationale is to remove the general trend in prayer search shares, ensuring that we do not attribute a potential general rise in prayer search shares to the COVID-19 pandemic. If prayer search shares rose in February, this may be due to other things than the pandemic or the fact that COVID-19 started in Asia well before it was declared a pandemic. $\Delta prayer_{feb}$ is set to zero if prayer search shares fell during February 2020 to get a conservative measure of the rise in prayer search shares after March 1. The measure $\Delta prayer_{mar}$ now measures the absolute change in prayer search shares from March 1 to the day with the highest prayer search shares in March 2020, where the rise in prayer search shares in February are subtracted.

The relative increase in prayer search shares in panel (a) of Fig. 3 is calculated by dividing the absolute change in prayer search shares, $\Delta prayer_{march}$ subtracted the rise in February, with the average level in February, $avgprayer_{feb}$.

C.1 The impact of COVID-19 on prayer search shares

This section explores further the link between COVID-19 exposure and the rise in prayer search shares. First, Fig. A.1 shows that the results in Table 1 are not driven by specific observations. The figure shows the added variables plot of columns (1), (3), and (6) of Table 1, where observations are binned into 100 equally sized bins.

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Table A.1 tests for non-linearities in the measures of days since COVID-19 was declared a pandemic, registered cases, and deaths. Panel A includes the full sample, while Panels B and C restricts the sample to only include observations until the prayer search shares reaches its maximum over the period. This is to account for the fact that falling prayer search shares are difficult to interpret as some of the fall may be caused by people accessing their prayer websites directly instead of googling them. The rise in prayer search shares slows down as time passes or more cases and deaths are registered, except in the restricted sample where the rise in prayer search shares does not slow down as time passes. Panel C documents that the number of cases and deaths do not impact prayer search shares once days since COVID-19 was declared a pandemic is accounted for.

Table A.2 documents that the rise in prayer search shares after March 11 is larger when the country had also one or more registered cases or deaths in the restricted sample where observations are dropped after prayer search shares reached their maximum. This interaction, though, becomes insignificant once time fixed effects are accounted for.

So far, the analysis has included daily data. This means that the estimate on registered cases and deaths (γ in equation (1)) measures the daily change in prayer shares as cases or deaths go up on the day before. Fluctuations in the Google data may make these day-to-day comparisons rather imprecise. Table A.3 documents similar results when the data is aggregated up to weekly averages. Panel A documents that cases and deaths increase prayer shares, but not when accounting for the date when the WHO declared COVID-19 a pandemic (March 11). Further, columns (5) and (8) show that the rise in prayer shares after March 11 is *lower* as cases and deaths go up. This, however, may be due to the fact that the Google searches for prayer will mechanically go down as people find their preferred prayer websites, but cases and deaths rose exponentially in this early phase of the pandemic. The reason could also be that the fear of the disease rises more in the early stages, as people have a tendency to overestimate the mortality and contagiousness of the COVID-19 (Fetzer et al., 2020). Panel B includes instead days since the first case or death. Here, the rise in prayer shares is no larger or smaller depending on the days since the first case, but is slightly larger depending on days since first death.

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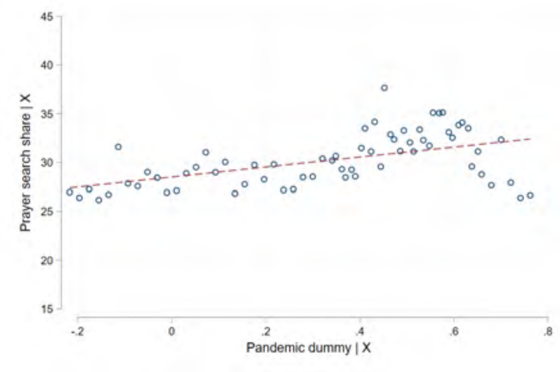
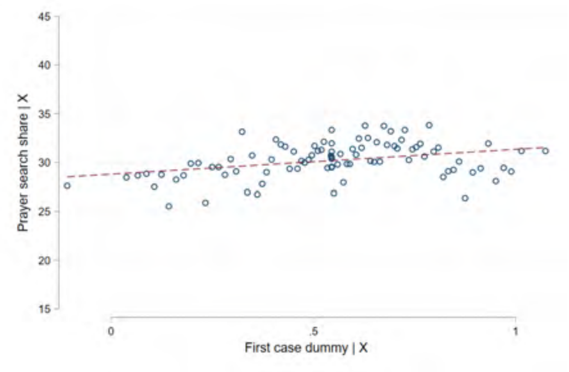
Figure A.1: Binned added variables plots of the rise in prayer search shares after different dates

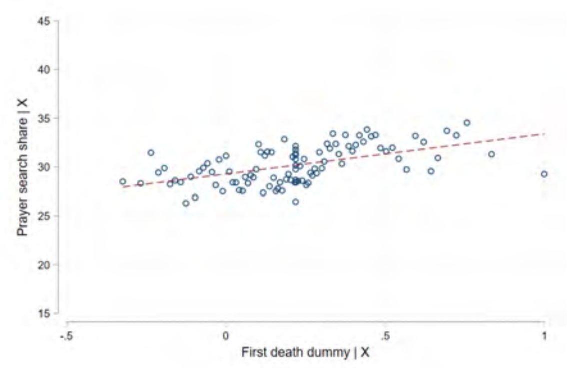
(a) The rise in prayer after March 11



(b) after the first registered case



(c) after the first registered death



The binned added variables plot of regressions of the prayer search share on the pandemic dummy in panel (a), the dummy equal to one after the first case is registered in panel (b), and after the first death is registered in panel (c). The regressions mirror those in columns (1), (3), and (6) of Table 1 and include country fixed effects and country-specific trends. The observations are binned into 100 equally sized bins.
Result: The results are not driven by specific observations.

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Table A.1: The impact of COVID-19 on prayer search shares I

Dependent variable: Prayer searches	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full sample						
Days since Pandemic	0.44***	1.25***				
	(0.057)	(0.180)				
Days since Pandemic squared		-0.043***				
		(0.008)				
COVID-19 infected cases			0.090**	0.30***		
			(0.044)	(0.101)		
Infected cases squared				-0.0019***		
				(0.001)		
COVID-19 deaths					1.35***	3.47**
					(0.427)	(1.364)
Deaths squared						-0.25**
						(0.117)
R-squared	0.84	0.84	0.83	0.83	0.83	0.83
Observations	6080	6080	6066	6066	6080	6080
Panel B: Restricted sample						
Days since Pandemic	1.02***	0.87***				
	(0.129)	(0.239)				
Days since Pandemic squared		0.011				
		(0.016)				
COVID-19 infected cases			0.36**	0.90***		
			(0.157)	(0.190)		
Infected cases squared				-0.0094***		
				(0.002)		
COVID-19 deaths					2.71**	9.62**
					(1.259)	(4.382)
Deaths squared						-1.07*
						(0.563)
R-squared	0.84	0.84	0.83	0.83	0.83	0.83
Observations	4345	4345	4331	4331	4345	4345
Panel C						
Days since Pandemic	1.02***	1.02***	1.05***	1.07***	1.02***	1.02***
	(0.129)	(0.129)	(0.138)	(0.143)	(0.133)	(0.135)
COVID-19 infected cases			-0.13	-0.37		
			(0.095)	(0.302)		
Infected cases squared				0.0039		
				(0.004)		
COVID-19 deaths					-0.57	0.36
					(0.560)	(2.153)
Deaths squared						-0.14
						(0.260)
R-squared	0.84	0.84	0.84	0.84	0.84	0.84
Observations	4345	4345	4331	4331	4345	4345
Countries	95	95	95	95	95	95

OLS estimates. Units: Days $\times$ countries. Period: January 29 to April 1 2020. All regressions include a constant, country-specific time trends, and country fixed effects. The sample is restricted to the sample where observations are dropped after the maximum prayer search share over the period is reached. Panel B replicates the regressions in Panel A, but includes the variable "Days since Pandemic". Robust standard errors clustered at the country level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level.

Result: The number of cases and deaths do not matter for prayer search shares when controlling for the number of days passed since WHO declared the COVID-19 a pandemic.

Table A.2: The impact of COVID-19 on prayer search shares II

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep var: Prayer search share								
Pandemic dummy	5.49***	0.069			5.22***	3.24***		
	(0.923)	(2.665)			(1.038)	(0.951)		
First case dummy	2.53**	1.82*	2.74***	2.62**		3.39***		
	(1.019)	(0.945)	(1.003)	(1.043)		(0.975)		
Pandemic x first case dummy		6.19**		0.93				
		(2.626)		(2.497)				
First death dummy					3.10*		-0.47	-1.33
					(1.572)		(1.363)	(2.056)
Pandemic x first death dummy						5.78***		1.33
						(1.553)		(2.289)
R-squared	0.83	0.83	0.84	0.84	0.83	0.83	0.84	0.84
Observations	4331	4331	4331	4331	4345	4331	4345	4345
Countries	95	95	95	95	95	95	95	95
TimeFE	No	No	Yes	Yes	No	No	Yes	Yes

OLS estimates. Units: Days $\times$ countries. Period: January 29 to April 1 2020. All regressions include a constant, country-specific time trends, and country fixed effects. In addition, time fixed effects are added in columns 3, 4, 7, and 8. The sample is restricted to the sample where observations after prayer searched shares reached their max are dropped. Robust standard errors clustered at the country level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level.

Result: Prayer search shares rose more after March 11 for countries that had already had their first case or death.

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Table A.3: The impact of COVID-19 on prayer search shares III

Dependent variable: Prayer searches	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A								
Pandemic dummy	6.49***	9.15***		9.06***	9.10***		9.08***	9.12***
	(0.854)	(1.176)		(1.218)	(1.221)		(1.192)	(1.195)
COVID-19 infected cases			0.34**	0.056	0.92***			
			(0.143)	(0.069)	(0.155)			
Pandemic x Cases					-0.79***			
					(0.123)			
COVID-19 deaths						2.50***	0.79+	13.7***
						(0.864)	(0.488)	(2.336)
Pandemic x Deaths								-12.2***
								(1.894)
R-squared	0.95	0.97	0.96	0.97	0.97	0.96	0.97	0.97
Panel B								
Pandemic dummy	6.49***	9.15***		7.82***	8.91***		8.89***	8.25***
	(0.854)	(1.176)		(1.316)	(2.170)		(1.242)	(1.203)
Days since first case			0.64***	0.18	0.17			
			(0.122)	(0.136)	(0.141)			
Pandemic x Days since 1st case					-0.039			
					(0.067)			
Days since first death						0.75***	0.082	-0.26
						(0.190)	(0.194)	(0.243)
Pandemic x Days since 1st death								0.35**
								(0.152)
R-squared	0.95	0.97	0.96	0.97	0.97	0.96	0.97	0.97
Observations	950	661	661	661	661	661	661	661
MeanDepVar	30.6	31.6	31.6	31.6	31.6	31.6	31.6	31.6
RestrictedSample	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

OLS estimates. Units: Weeks × countries. Period: January 29 to April 1 2020. All regressions include a constant, country-specific time trends, and country fixed effects. The sample consists of the full sample in column (1), but is restricted to the sample where observations are dropped after the maximum prayer search share over the period is reached. Panel A includes the number of registered cases and deaths. Panel B includes a measure of the days since a country had its' first case or death by COVID-19. Robust standard errors clustered at the country level in parentheses. +, *, **, and *** indicate significance at the 15%, 10%, 5%, and 1% level.
Result: The number of cases and deaths do not matter for prayer search shares when controlling for the dummy indicating when the WHO declared the COVID-19 a pandemic.

C.2 Who is praying more?

Table A.4 documents that the rise in prayer intensity is generally higher for populations that are already more religious, using different measures of religiosity: Average Google searches for prayer in 2019 in column (1) and measures based on various questions asked in global surveys (conducted before 2015) in columns (2)-(8): Whether or not respondents take moments of prayer, meditation or contemplation (col 2),[24] ever prayed (col 3), pray weekly (col 4), rank God as anything but unimportant in their lives (col 5), rank God as very important (col 6), ever went to church (col 7), or go to church on a weekly basis (col 8). Last, to obtain exogenous variation in religiosity, column (9) interacts instead with earthquake risk.

The rise in prayer searches is larger in countries where a larger share of the population

[24]While this measure captures more than religiosity, it correlates with more than .8 with the remaining measures of religiosity listed. This indicates that the majority of the affirmative answers cover some sort of religious prayer, meditation or contemplation.

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initially prayed more, went more to church, or answered that God is important in their lives, and faced higher earthquake risk. Prayer search intensity rose by more than 50% of the mean for the countries with the highest initial religiosity.[25]

Prayer search shares rose much less in the less religious countries, but even in the least religious countries, prayer searches rose for five out of the nine measures of religiosity (MinimumImpact in the bottom of the table).

The p-values, PvalueAtXPct, in the bottom of the table indicate the p-value of the following test, where the parameter values are indicated in equation (2): $\gamma + \lambda religiosity_c = 0$. Thus, the test indicates at what level of religiosity, the prayer search shares rose significantly. The value of $religiosity_c$ is the value at the 1st, 10th, 15th, and 20th percentiles, respectively. The calculations show that prayer search shares even rose significantly for the 1% least religious countries for 2 out of 9 measures of religiosity. These two are the measures available for most countries, indicating that the lack of a significant rise for the remaining measures is most likely due to lower precision in the smaller sample. For the 10% least religious, prayer searches rose significantly for 4 out of 9 religiosity measures, while they rose for 8 out of 9 measures within the 15% least religious countries. The measure that does not show a significant rise for this group is the religiosity measure available for the least countries. At religiosity levels as low as the 20th percentile, prayer search shares rose significantly for all measures of religiosity.

Tables A.5 and A.6 document the differential effects across different religiosity measures for more detailed levels of religiosity, based on the prayer and churchgoing measures in Table A.5 and based on the importance of God measure in Table A.6.

Table A.7 shows regressions similar to Panel C of Table 2, but for different measures of religiosity: Importance of God and churchgoing. Earthquake risk is a strong instrument for all measures and the conclusion remains: This larger rise in prayer search intensity for the poor and vulnerable is due to higher religiosity levels in these countries. There is one exception, though: The prayer search share rise more for the poor, even when allowing prayer search shares to vary with religiosity levels.

The variables included in Tables 2 and A.7 were checked for multicollinearity using the Variance Inflation Factor, VIF. None of the VIFs were above 10, which means that the degree of collinearity between the variables is acceptable.

[25]This calculation is based on the MaximumImpact scalar provided in the bottom of the table. This scalar measures the impact of the pandemic dummy in countries with the maximum level of the particular religiosity measure. In col (1), the maximum level of prayer search intensity in 2019 was 87, reached by Morocco. Thus, MaximumImpact was -0.086+0.08*87=6.85.

Table A.4: The rise in prayer search shares for different religiosity levels I

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep var: Prayer searches	Pray2019	MomentPray	EverPray	WeekPray	God	VeryGod	EverChurch	WeekChurch	EarthqRisk
Pandemic dummy	1.26*	-4.84**	-4.82	-0.84	-16.9***	-0.13	-6.37**	0.67	-7.76**
	(0.747)	(2.106)	(3.623)	(2.056)	(4.844)	(0.919)	(2.734)	(0.875)	(3.777)
Pandemic x Religiosity	0.15***	12.5***	12.0**	10.1**	23.9***	9.15***	14.4***	12.6***	14.4***
	(0.035)	(3.254)	(4.972)	(4.065)	(5.709)	(2.237)	(3.938)	(2.728)	(4.890)
R-squared	0.84	0.88	0.89	0.90	0.87	0.87	0.87	0.87	0.87
Observations	6080	4096	2880	2880	5056	5056	4992	4992	4416
Countries	95	64	45	45	79	79	78	78	69
MeanDepVar	30.2	23.8	27.6	27.6	25.9	25.9	26.0	26.0	25.1
MinimumImpact	1.41	-1.28	0.33	0.93	-3.08	0.72	-0.93	1.00	-1.14
MaximumImpact	14.0	7.45	7.19	8.94	6.98	8.77	7.95	11.8	6.61
PvalueAt1Pct	0.054	0.30	0.84	0.52	0.058	0.34	0.48	0.23	0.47
PvalueAt10Pct	0.0030	0.66	0.24	0.20	0.16	0.041	0.13	0.062	0.0020
PvalueAt15Pct	0.0010	0.016	0.039	0.13	0.0020	0.0080	0.0070	0.032	0
PvalueAt20Pct	0	0	0.0030	0.059	0	0.0020	0	0.012	0

OLS estimates. Units: Days × countries. Period: January 29 to April 1 2020. All regressions include a constant, country-specific time trends, and country fixed effects. The pandemic dummy is interacted with average google searches for prayer in 2019 (col 1), the share of the populations taking moments for prayer, meditation, or contemplation (col 2), ever prayed (col 3), pray weekly (col 4), answered that God is anything but important in their lives (col 5), answered that God is very important in their lives (col 6), ever went to church (col 7), or went to church weekly (col 8), and average earthquake risk (col 9). MinimumImpact (MaximumImpact) indicates the impact of the pandemic at the minimum (maximum) level of the particular religiosity measure. PvalueAtXPct indicates the p-value of the test that the impact of the pandemic dummy is insignificant, evaluated at the X percentile of the religiosity measure. Robust standard errors clustered at the country level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level.
Result: Prayer search shares rose at most levels of religiosity and rose more for more religious countries.

Table A.5: The rise in prayer search shares for different religiosity levels II

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Dep var: Prayer searches	Moments	Never	Ever	Yearly	Weekly	Daily	Never	Ever	Yearly	Weekly	Daily
Pandemic dummy	-4.84**	7.19***	-4.82	-3.80	-0.84	0.75	8.06***	-6.37**	-4.80**	0.67	3.59***
	(2.106)	(1.642)	(3.623)	(2.721)	(2.056)	(1.413)	(1.383)	(2.734)	(1.955)	(0.875)	(0.875)
Pandemic x Pray	12.5***	-12.0**	12.0**	11.8***	10.1**	9.26**					
	(3.254)	(4.972)	(4.972)	(4.288)	(4.065)	(3.731)					
Pandemic x Church							-14.4***	14.4***	14.3***	12.6***	9.08**
							(3.938)	(3.938)	(3.424)	(2.728)	(3.465)
R-squared	0.88	0.89	0.89	0.90	0.90	0.90	0.87	0.87	0.87	0.87	0.87
Observations	4096	2880	2880	2880	2880	2880	4992	4992	4992	4992	4992
Countries	64	45	45	45	45	45	78	78	78	78	78

OLS estimates. Units: Days × countries. Period: January 29 to April 1 2020. All regressions include a constant, country-specific time trends, and country fixed effects. Robust standard errors clustered at the country level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level.
Result: Prayer search shares rose more for more religious countries.

Table A.6: The rise in prayer search shares for different religiosity levels III

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dep Var: Prayer search share	Very:10	9	8	7	6	5	4	3	2	Not:1
Pandemic dummy	0.57	-0.13	-1.35	-2.51*	-4.06**	-6.85***	-8.46***	-11.7***	-16.9***	6.98***
	(0.832)	(0.919)	(1.122)	(1.325)	(1.663)	(2.248)	(2.599)	(3.406)	(4.844)	(1.050)
Pandemic x Importance of God	8.98***	9.15***	9.90***	10.7***	12.0***	14.3***	15.8***	18.8***	23.9***	-23.9***
	(2.307)	(2.237)	(2.327)	(2.434)	(2.723)	(3.221)	(3.538)	(4.307)	(5.709)	(5.709)
R-squared	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87
Observations	5056	5056	5056	5056	5056	5056	5056	5056	5056	5056
Countries	79	79	79	79	79	79	79	79	79	79
CountryFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MeanDepVar	25.9	25.9	25.9	25.9	25.9	25.9	25.9	25.9	25.9	25.9

OLS estimates. Units: Days × countries. Period: January 29 to April 1 2020. All regressions include a constant, country-specific time trends, and country fixed effects. Robust standard errors clustered at the country level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level.
Result: Prayer intensity rose more in countries where larger shares of the population rank God as important.

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Table A.7: The rise in prayer search shares across country characteristics

Dependent variable: Prayer								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A	Poverty	GDP	HDI	Gini	Uneven	Fragile	Demography	Mortality
Pandemic dummy	-25.3**	-30.1**	-28.7*	-24.5**	-29.5**	-34.0**	-26.4**	-26.9**
	(12.329)	(13.664)	(16.252)	(10.782)	(14.307)	(14.244)	(12.807)	(11.203)
Pandemic x Variable	0.46**	0.18	1.09	0.11	-0.21	-0.053	0.20	0.0094
	(0.191)	(0.593)	(5.492)	(0.109)	(0.618)	(0.043)	(0.515)	(0.011)
Pandemic x Importance of God	33.1**	36.2***	35.6**	27.6**	38.5**	45.7***	33.0**	33.3***
	(14.262)	(12.750)	(14.947)	(13.235)	(18.259)	(17.476)	(15.683)	(12.914)
R-squared	0.88	0.87	0.87	0.89	0.87	0.87	0.87	0.87
Observations	3456	4288	4288	3904	4288	4288	4288	4352
Countries	54	67	67	61	67	67	67	68
FirstStageF	27.4	24.3	21.0	26.8	14.8	14.3	16.6	34.4
Panel B								
Pandemic dummy	-10.8*	-11.0	-12.0	-13.5**	-11.5**	-12.6**	-11.6*	-12.2**
	(6.143)	(10.291)	(10.706)	(5.740)	(5.825)	(6.231)	(6.150)	(5.489)
Pandemic x Variable	0.26	-0.099	0.22	0.18*	0.34	-0.015	0.23	0.0085
	(0.256)	(0.683)	(6.015)	(0.101)	(0.459)	(0.036)	(0.535)	(0.012)
Pandemic x Ever Church	20.4**	21.3**	21.2**	14.9**	18.7**	23.2**	19.6*	20.2**
	(8.779)	(8.282)	(9.493)	(6.993)	(9.084)	(9.379)	(10.011)	(8.076)
R-squared	0.88	0.87	0.87	0.89	0.87	0.87	0.87	0.87
Observations	3456	4224	4224	3904	4224	4224	4224	4288
Countries	54	66	66	61	66	66	66	67
FirstStageF	25.4	18.5	17.1	19.9	15.2	16.9	13.7	24.3

Units: Days × countries. Period: January 29 to April 1 2020. All regressions include a constant, country-specific time trends, and country fixed effects. Two interaction terms are included: One between the pandemic dummy and the particular socio-economic characteristic and one between the pandemic dummy and the prayer share in 2019. Panel A shows the OLS estimates, while Panel B shows the IV estimates, where prayer search shares in 2019 are instrumented with earthquake risk. The sample in Panel B is restricted to countries within 1500 km of high-risk earthquake zones. Robust standard errors clustered at the country level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level.

Result: Prayer search shares rose more in poor, unequal, and insecure countries. This is due to higher religiosity levels.

C.3 Replacement of physical church or rise in prayer intensity

Around mid-March 2020, most churches across the globe closed in af effort to enforce social distancing. A concern for the analysis is whether the rise in prayer search shares is simply a replacement for the physical churches. According to the theory on religious coping we would not expect this to be the case, since people tend to use their intrinsic religiosity rather than their extrinsic religiosity to cope with adversity. Thus, even if the churches had been open, we would not expect churchgoing to rise as much as private prayer. This section tests this prediction empirically.

Fig. A.2 documents that Google searches for the topic ”internet church” also rises during the month of March 2020, but in a very different pattern. The three large spikes in panel (a) of Fig. A.2 are the three last Sundays in March. These rises coincide with the closure of the physical churches and they follow a very different pattern than the general rise in prayer shares documented throughout this research. Panel (b) shows that the rise in searches on internet church is insignificant compared to the total rise in prayer searches, indicating that the rise in demand for internet churches does not explain the rise in prayer shares.

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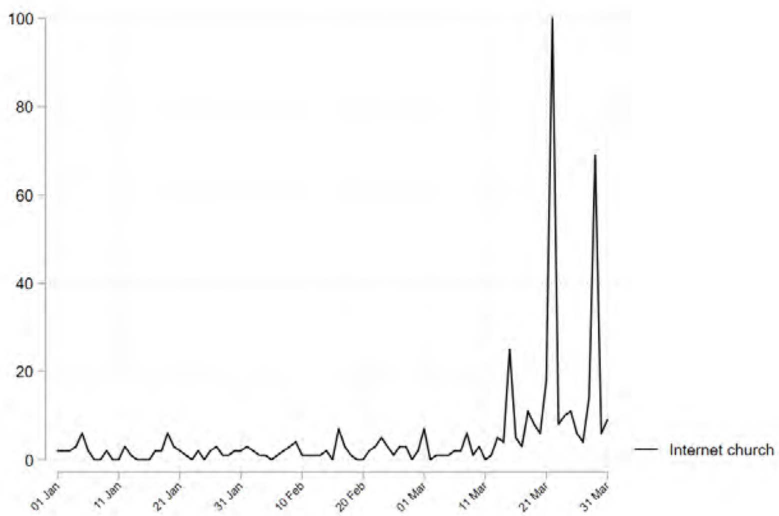
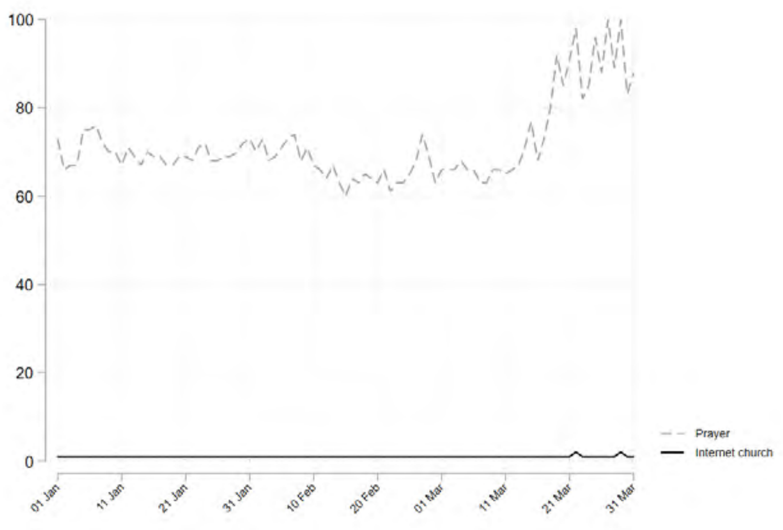
Table A.8 shows that prayer search shares rose every day of the week, except Fridays. The rise on Sundays is larger than the other days, which could be due to most masses being held on Sundays or simply that Sundays are the most holy day of the week for Christians, and thus the day of the week, where most choose to pray.

Figure A.2: Global Google searches for prayer and internet church

(a) Searches for the topic "internet church"



(b) Searches for the topics "internet church" and "prayer"



Global average of Google searches for prayer Jan 1 - Apr 1 2020. Searches for internet church also rise during the month of March 2020, but the share is minuscule compared to the size of the search shares for prayer. Furthermore, the searches for internet church rise mainly every Sunday and thus have a distinctly different pattern than the search shares for prayer.

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Table A.8: The rise in prayer search shares, by weekdays

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep Var: D.Prayer	Sun	Mon	Tues	Wed	Thur	Fri	Sat
Pandemic dummy	11.0***	3.22**	4.38***	4.58***	3.71**	1.13	6.77***
	(1.740)	(1.542)	(1.418)	(1.190)	(1.436)	(1.590)	(1.481)
R-squared	0.88	0.87	0.87	0.87	0.88	0.88	0.85
Observations	855	855	855	950	855	855	855
Countries	95	95	95	95	95	95	95
CountryFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MeanDepVar	30.7	29.6	29.6	30.1	30.0	31.3	29.9

OLS estimates. Units: Days $\times$ countries. Period: January 29 to April 1 2020. All regressions include a constant, country-specific time trends, and country fixed effects. The sample includes only Sundays in column (1), Mondays (2), Tuesdays (3), Wednesdays (4), Thursdays (5), and Fridays (6), and Saturdays (8). Robust standard errors clustered at the country level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level.

Result: Prayer search shares increased on all weekdays, except Fridays.

C.4 Growth rates

Instead of identifying the impact on the levels of prayer search shares, this section documents the impact on the growth rates, estimating the following equation:

$$gprayer_{ct} = \beta + \alpha prayer_{ct-1} + \gamma pandemic_{t-1} + \lambda pandemic_{t-1} \times characteristic_c + \delta t + \kappa_c + \varepsilon_{ct} \quad (6)$$

where $gprayer_{ct}$ is the growth rate in prayer search shares from time t-1 to time t in country c. $prayer_{ct-1}$ is the prayer search share at time $t-1$. To prevent day-to-day fluctuations in the search data to impact results, the data was aggregated to weekly averages, so that t represents a week. $characteristic_c$ is either religiosity or socio-economic characteristics. The main results from Table 1 are unaltered: The growth rate in prayer search shares rise after March 11 and after the first case was registered. The rise in growth rates, though is independent of there being any deaths registered and the rise after March 11 is not larger for countries where COVID-19 had infected the populations (Table A.9).

Panel A of Table A.10 documents that prayer search shares grew with similar rates, independent of the previous level of religiosity. This is not surprising and is consistent with panel (a) of Fig. 3. When accounting for the initial level of religiosity in Panel B, the growth rate in prayer search shares is higher in the more religious countries, consistent with the results on the absolute rise in prayer search shares.

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Table A.9: The rise in weekly prayer growth rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep Var: Prayer growth								
Pandemic dummy	0.051*	0.16***		0.16***	0.077		0.17***	0.17***
	(0.026)	(0.024)		(0.024)	(0.086)		(0.024)	(0.031)
Prayer t-1		-0.026***	-0.024***	-0.026***	-0.026***	-0.024***	-0.025***	-0.025***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Case dummy			0.089**	0.066*	0.058			
			(0.037)	(0.035)	(0.035)			
Pandemic x First case dummy					0.085			
					(0.089)			
Death dummy						0.040	-0.0096	0.0057
						(0.038)	(0.038)	(0.040)
Pandemic x First death dummy								-0.023
								(0.047)
R-squared	0.12	0.37	0.35	0.38	0.38	0.34	0.37	0.37
Observations	855	855	855	855	855	855	855	855
Countries	95	95	95	95	95	95	95	95
MeanDepVar	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045
RestrictedSample	No	No	Yes	Yes	Yes	Yes	Yes	Yes

OLS estimates. Units: Weeks $\times$ countries. Period: January 29 to April 1 2020. All regressions include a constant, country-specific time trends, and country fixed effects. The sample is the full sample in columns (1)-(2), but is restricted to the sample where observations are dropped after the maximum prayer search share over the period is reached in columns (3)-(8). Robust standard errors clustered at the country level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level.

Result: The growth rate in prayer search rises after March 11 and after the first case is registered.

Table A.10: The rise in weekly prayer growth rates for different levels of initial religiosity

Dependent variable: Prayer growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A	Pray2019	MomentPray	EverPray	WeekPray	God	VeryGod	EverChurch	WeekChurch	EarthqRisk
Pandemic dummy	0.080*	0.073	0.026	0.037	0.25	0.064	0.20*	0.061	0.20
	(0.041)	(0.122)	(0.142)	(0.070)	(0.256)	(0.062)	(0.115)	(0.051)	(0.172)
Pandemic x Religiosity	-0.0011	-0.0096	0.068	0.075	-0.22	-0.034	-0.19	-0.024	-0.15
	(0.001)	(0.149)	(0.164)	(0.109)	(0.273)	(0.094)	(0.138)	(0.113)	(0.192)
R-squared	0.12	0.12	0.16	0.16	0.13	0.13	0.13	0.13	0.13
MeanDepVar	0.045	0.044	0.045	0.045	0.043	0.043	0.044	0.044	0.047
MinimumImpact	0.079	0.070	0.055	0.050	0.12	0.061	0.13	0.061	0.13
MaximumImpact	-0.017	0.063	0.093	0.11	0.027	0.031	0.014	0.040	0.051
Panel B									
Pandemic dummy	0.10***	-0.043	-0.072	0.019	-0.12	0.068	0.039	0.080	0.021
	(0.039)	(0.119)	(0.137)	(0.066)	(0.262)	(0.062)	(0.125)	(0.053)	(0.178)
Pandemic x Religiosity	0.0023**	0.29*	0.31*	0.29**	0.30	0.17*	0.16	0.26**	0.18
	(0.001)	(0.147)	(0.166)	(0.112)	(0.280)	(0.095)	(0.154)	(0.120)	(0.201)
Prayer t-1	-0.026***	-0.029***	-0.026***	-0.026***	-0.027***	-0.027***	-0.027***	-0.027***	-0.027***
	(0.002)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
R-squared	0.37	0.33	0.36	0.37	0.34	0.35	0.35	0.35	0.34
Observations	855	576	405	405	711	711	702	702	621
Countries	95	64	45	45	79	79	78	78	69
MeanDepVar	0.045	0.044	0.045	0.045	0.043	0.043	0.044	0.044	0.047
MinimumImpact	0.11	0.041	0.062	0.069	0.058	0.083	0.10	0.087	0.11
MaximumImpact	0.31	0.25	0.24	0.29	0.19	0.23	0.20	0.31	0.20

OLS estimates. Units: Weeks $\times$ countries. Period: January 29 to April 1 2020. All regressions include a constant, country-specific time trends, and country fixed effects. Panel B also includes a control for the average prayer search share during the previous week. Robust standard errors clustered at the country level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level.

Result: The growth rate in prayer search shares is not larger for the more religious. Only when accounting for prayer search shares during the previous week.

Narrative economics, public policy and mental health

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This paper assesses the differential impacts on mental health of distinct public policy lockdown responses to the early part of the Covid-19 pandemic. It develops novel narrative economics of language approach born at the intersection of cultural economics, big data and narrative economic analysis. This approach is reliant on the study of language to extract cultural and behavioural insights with socioeconomic relevance. We sourced Google trend data for seed keywords, death and suicide, and employed difference-in-differences and regression discontinuity estimation techniques to conduct two investigations. First, we compared the amount of emotional distress experienced by British and Italian residents before and after the implementation of lockdown policies. Second, we extended our analysis to include a country that did not impose a lockdown, Sweden, as a control, which facilitated a natural quasi-experiment. Our main findings are that the lockdown policy affected public mental health, yet the dominant factor for public mental health was the cognitive bias of salient public death toll statistics. Countries had a pre-existing culturally relative disposition towards death-related anxiety, and the magnitude of their response to the pandemic varies in a cultural hysteresis manner. Searches for the keyword suicide decreased during the pandemic, while the interest in trivia remained unaffected, as indicated through searches for the keyword chair. Significant spillovers from one " specific national lockdown public policies to another country's mental health are identified.

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1. Introduction

Mental health exists on a spectrum of normality (Spiker et al., 2010; Gotts et al., 2012). The ability to maintain an individual's (or a societal's aggregate) mental health around that spectrum's central value is defined as psychological resilience (Fletcher and Sarkar, 2013). Psychological resilience is responsive to a socioeconomic context, to shocks in that context, and to uncertainty for survival (Cornum et al., 2011). Survival is the main evolutionary concern and fear for survival is one of the most important elements of the human psychological state (LeDoux, 1995; Akerlof and Shiller, 2010; Tversky and Kahneman, 1979). Consequently, the central question of survival is bound to be prominent in times of global shock, such as during the current COVID-19 pandemic

Socioeconomic context is not only a function of natural phenomena. A large part of the socioeconomic context is a function of organized life and the security network to which people rely on for their survival. This function is interwoven in the development of places and economies in which people live and function (Castells, 1996). Places and economies are governed by a series of socioeconomic policies. Although this embeddedness in multiple networks and socioeconomic policies have been previously recognized zwith regard to entrepreneurship (Kloosterman et al., 1999; Tubadji et al., 2020), it has not been recognized with regard to mental health. Socioeconomic policies and their implementation, especially during a crisis, are responsible for shaping the psychological context and general public sentiment, yet politicians tend to consider this only around elections (Norpoth et al., 1991). This paper examines how public policy affects the mental health of citizens during a negative exogenous shock, and specifically, we explored the effect of public policy on public psychological resilience during the early part of the COVID-19 pandemic.

Regional economic vulnerabilities have been a focus of attention in the economics literature (Reggiani et al., 2002; Bristow and Healy, 2020) but although recent literature has a focus on resilience in the context of economic policy, the link between economic policy, public policy and mental health has been explored very infrequently, even though it is known to be pertinent (Foucault, 1954, 1961). Public policy towards improving mental health has been narrowly defined as relating to the needs of and provision for citizens who are positioned at the extremes of the spectrum of normality (Frank and McGuire, 2000a,b) yet recent evidence shows a much deeper, causal and responsive link between public policy choices and a nation's average level of mental health. Moreover, public policy may be responsible for generating poor mental health across a country's population, which has also not been the subject of much investigation in the economics field. To the best of our knowledge, the present study is the first to examine how public policy decisions affect the mental health of the population.

To model our hypotheses on the causal relationships between national mental health and public policy management, we compared the mental health of the same nation under different public policy regimes and contrasted the varied reactions of different nations to the same Covid-19 pandemic. In the first case, a natural quasi-experiment assessed changes in public policy in Italy and then the UK, switching from "business as usual" to "complete lockdown". In the second case, a natural quasi-experiment studied the different policy applied in Sweden, where they endured the "business-as-usual" policy, while Italy and the UK switched policies to adopt a social distancing and lockdown stance. We took into consideration reported mortality rates as a confounding factor for the growing anxiety. Thus, our analysis provides an insight into the cognitive bias effect generated by the culturally dependent reporting of public mortality statistics (deathcount) and of the impact of this salient information on public mental health.

Our quantitative analytical approach to these two natural experiments applies the Culture Based Development (CBD) (Tubadji, 2012; 2013) paradigm and its emerging narrative economics of language method (Tubadji, 2020a; Tubadji, Pattitoni and Nijkamp, 2020). The novelty of this paper is that it applies this method to analyze the impact of public policy on mental health. The CBD paradigm seeks to explain economic choices that are subject to cultural bias. In this case, the choice under analysis is the public policy decision between "business as usual" and "complete lockdown". The narrative economics of language quantitative method (Tubadji, 2020a,b) is inspired by the father of behavioural economics Herbert Simon's treatment of Zipf's law of the distribution of words (Simon, 1955) and the recent epidemiology of language approach in narrative economics (Shiller, 2017, 2019). CBD combines these two approaches in order to study the cliometrics of language as a source of statistical record for the thinking, meaning making and history of ideas. In terms of the intensity in the social discourse, the CBD approach postulates that the thinking, meaning, making and history of ideas exists in a positive relationship to Zipf Law, which drives the statistical relationship of language with economic events and processes over time (Tubadji, 2020a). We contrast the search frequencies of two keywords, "death" (as a proxy for anxiety from death) and "suicide" (as a proxy for the propensity to seek death), on the Google search engine both before and during the COVID-19 pandemic. We analyzed the public policy of lockdown as a treatment that induces changes over time in the frequency of search for these words, which reflects the intensity of mental distress experienced in society under the fear of mortality from the COVID-19 virus. Our findings point towards public policymaking as a powerful endogenous source of information that affects public mental health.

The structure of this paper is as follows. Section 2 discusses the definition of psychological resilience and briefly reviews the literature on mental health, public policy, discourse and meaning. Section 3 summarises the regional economic literature on economic resilience of places. Section 4 offers the CBD approach to identifying the causal link between public mental health resilience and public policy. Section 5 describes our data and method, which relies on the use of linguistic statistics from Google trends and econometric methods for causal inference. This section offers our results and findings. Section 6 concludes and draws policy implications.

2. Psychological resilience, mental health and public policy

Psychological resilience has been defined in psychology at the individual level, primarily because of its proximal implications and impacts on daily life (Fletcher and Sarkar, 2013). Every individual is entitled to the right to maintain their psychological resilience, and this is a basic need and human right guarantee offered by the UN and most national constitutions (Malkina-Pykh, 2013). However, in policy evaluation, the individual is no longer the focus of attention. Mental health is considered differently and, typically, it is discussed with regard to the point of provision for institutionalized mental health care and is discussed in this manner even in some of the most social-behaviour minded studies (Dear et al., 1979; Wahl, 2003; Frank and McGuire, 2000b; Hatzenbuehler, 2010; Knapp et al., 2011).

The relationship between public policy and a population's mental health through the construction of socioeconomic context and discourse has been raised in the prominent work of Michel Foucault (Foucault, 1954, 1961). Foucault belongs to a constructionist philosophical school that assumes that all ideas and meaning are recorded in the language of the discourse (Derrida, 1967; Derrida and Dutoit, 1992; Tubadji, 2020). Foucault's example of this linguistic recording is based specifically on the language about madness and mental health. He explains how the mentally ill have been treated differently through public policy in

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different historical periods, and how this dramatically and negatively has affected their quality of life, especially institutionalized rather than allowed to remain in a social setting. Foucault's reasoning has been particularly influential on the anti-psychiatry movement (Crossley, 2006) and this was reflected in the public policy shift towards dehospitalization (Haveman, 1986), which is a policy change that has met with mixed sentiments across space (Stavis, 2000; Secru and Bracke, 2016). We argue here that Foucault's deconstructionist theory is not only relevant for his topic of interest, clinical mental health, and that public discourse also affects the mental health of the general public.

Foucault's considerations on the interplay between mental health and policymaking focused on the sufferings of an isolated vulnerable minority in the general population. The present study proposes a novel view that the Foucaultian constructionist mechanism has general applicability for the association between mental health and policymaking of the entire population. Our argument stems from the domain of positive psychology where every individual's mental health status is a finely balanced dynamic system that exists on a spectrum of normality (Selignam, 2002; Yates and Matzen, 2004; Brunzell et al., 2016) and the mental health of every member of society is potentially subject to change under conditions of stress (Babazono et al., 2005). This includes those conditions of stress that are induced by the national-level context and socioeconomic narrative, such as expression of social unrest, revolts and voting patterns, which reflect contemporary and evolving socioeconomic narratives (Benabou and Tirole, 2006, 2009, 2011, 2016). It has also been noted that episodes of social unrest are closely related to public policy (Hirschman and Rothschild, 1973). The COVID-19 pandemic, and its concomitant high level of uncertainty, has created the opportunity to explore the relationship between measures of aggregate mental health and socioeconomic public policy.

Economic resilience and socioeconomic context

Resilience is not consistently defined or consistently measured in economic terms. Outside of the fields of psychology and physics, the term resilience gained recognition first in ecological science where it was adopted to explain the fluctuation of animal populations (MacArthur, 1955). Subsequent ecological studies of resilience grew significantly (Neubert and Caswell, 1997; Reggiani et al., 2002) and one of the modern definitions of resilience states that it refers to "the ability of an entity or system to "recover form and position following a disturbance or disruption of some kind" (Martin, 2012: p. 4). Some of the most prominent approaches to economic resilience can be found in Nijkamp (1999), Reggiani et al. (2002), Bristow and Healy (2020) and Osth et al. (2018), which maintain concerns predominantly with the economic rather than the socioeconomic aspects of resilience. The use of resilience as a concept that connects the economy with aggregate mental health has not been attempted thus far even though the link is evidently clear. We summarise that in socioeconomic terms, Psychological Resilience of a Population (PRP) is a stability of the general public's mental health state that ensures the productive operation of the economic system.[1] We argue that public policy can significantly affect the aggregate mental health and its resilience in any locality.

Complexity theory argues that context is exceptionally important for the entire economic system. Context is a major factor underpinning entrepreneurial research, and the

[1] This statement clearly links to the literature on mass madness (Reich 1980; Ulman and Abse 1983; Tubadji and Nijkamp 2019), which is also developed as further point in relation to the radicalization of the European states and the narrative economics of language in Tubadji, Boy and Webber (2020). Another aspect of mass madness was the toilet paper mania during COVID-19, which resembles the behavioural dynamics of tulip mania (see Garber 1989).

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cultural historical institutional roots of a local context determines entrepreneurial success in a path-dependent manner (Acemoglu and Robinson, 2010, 2012). Diversity and entrepreneurship studies show that contemporary contexts affect the efficiency of a team and its ability to be innovative and achieve success (Brunow, Nijkamp and Poot, 2015; Brunow and Nijkamp, 2018). The more general cultural context is a source of multiple complex interactions in the socioeconomic system that vary across geographies and over time. These interactions made Nijkamp (2007) reason that no economic system can be studied successfully if the researcher assumes the *ceteris paribus* condition with regard to the cultural context.

Context and psychological characteristics (particularly personality traits) have been studied thoroughly in the literature as two closely interlinked entities. Economists have embraced the quantification of the Big Five personality traits for the study of the psychological milieu of places across Europe and the USA (Steel et al., 1997; Schmitt, 2004; Rentfrow, 2014). Modern entrepreneurship studies use the Big Five data as an indirect way to quantify the cultural contexts in which entrepreneurs are embedded (Obschonka et al., 2013; Fritsch et al., 2019; Fritsch et al., 2020). These studies align with earlier research employing the World Values Survey to explore daring attitudes as proxies for a psychological culture that is conducive to innovation (Shackle, 1949; Tubadji, Huggins and Nijkamp, 2020).

The influence of context on socioeconomic behaviour in relation to anxiety has a deep evolutionary behavioural explanation. Although the importance of socioeconomic context was suggested first in relation to financial behavioural economics (Shiller and Akerlof, 2010), we argue from an evolutionary perspective that people are another type of herd animal. It is possible to draw parallels with populations by studying herd animals who effectively decrease their anxiety from threats by using the herd as a signalling tool to identify the presence of a danger (Hall, 1966). Therefore, for humans it is both rational and instinctive (cognitively biased) to choose to adopt a herd behaviour during an external shock to the system, such as a pandemic (Kahneman, 2011). In line with Prospect Theory, an individual's alignment with a cultural homogenous herd ('love for birds of the same feather', McPherson et al., 2001) during normal times and positive shocks is likely to be observed in much greater intensity when experiencing greater uncertainty due to negative shocks, such as the COVID-19 pandemic. This instinctive evolutionary behaviour is the driving mechanism for psychological resilience ensuring survival when under threat. We argue here that humans not only learn about danger from the signalling behaviour of the herd, they can also use rational public policy to decrease anxiety-causing threats through their highly effective socialized communication skills. Therefore their anxiety levels respond to public policy.

The present study explores how such evolutionary psychological resilience mechanism generates a response to various culturally relative public policies across different countries during the Covid-19 pandemic. We advocate the use of a specific cultural economics paradigm that is consistent with a novel linguistic empirical approach for the analysis of the impact of public policy, as described in the next section.

3. Culture Based Development: psychological resilience and public policy

The Psychological Resilience of a Population (PRP) should be regarded as a spatially evolving endogenous element that affects our response to and was effected by the COVID-19 pandemic. This study examines the mental health effects of the Covid-19 pandemic directly, yet these mental health effects represent a secondary source of influence in the public's reaction to all further public policy interventions.

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The main operational definitions of the CBD paradigm (Tubadji, 2012, 2013, 2020) relevant to this study are culture, cultural capital, cultural milieu and cultural gravity. These operational definitions have been defined and analyzed elsewhere, but can be summarised as:

1) Culture is the set of beliefs and attitudes that exist in a place and inspire choice and action (Tubadji, 2013, 2013).

2) Cultural capital is the endowment of material and immaterial assets that quantify the stock of culture available in a place. Cultural capital has two main dimensions: cultural heritage (assets constructed in and inherited from historic periods that create path dependence) and living culture (assets that are being constructed in the present and represent cultural innovations and cultural change in the place) (Tubadji et al., 2020; Tubadji and Montalto, 2020).

3) Cultural milieu is the amalgam of predominant attitudes that form a context (or general discourse) which is created by the culture of a place and in which the rest of the socioeconomic processes are embedded (Tubadji et al., 2020).

4) Cultural gravity is the appeal of a place that attracts and concentrates human capital, and is based on the type of cultural milieu that the place has (Tubadji and Nijkamp, 2015).

From this CBD paradigm point of view, mental health is part of the cultural milieu; it creates the current context and records in the cultural heritage of a place. Therefore, preservation of a locality's healthy, favourable and attractive cultural milieu maintains care not only for the current members of the place but also for its regional development.

From a methodological perspective, the Narrative Economics of Language (Tubadji, 2020) is a novel CBD analytical method that is used to investigate the link between socioeconomic development and the context of thinking, meaning and ideas through the information recorded in the statistical characteristics of language. This CBD method is based on two priors: (i) statistical reasons to consider language as a reliable evolutionary record of thinking and meaning and (ii) empirical advantages for analyzing relationships between phenomena using time series of detailed big data. Thus, this approach is motivated by two considerations:

1) Zipf's distribution[2] (Zipf, 1935, 1949) was noted by Herbert Simon to underlie the distribution of many socioeconomic phenomena, such as the growth of cities, population and firms. The CBD narrative economics of language perspective builds on Simon's (1955) observation and suggests that the statistical dominance of a word among a distribution of words, which accords to the Zipf Law ranking, also corresponds to the dominance of the narrative in the contemporary public discourse. Similarly, psychology uses words as verifiable signifiers of emotional states (such as anxiety for mental health) (Loewe et al., 2008).[3] Thus, the CBD method considers words that are signifiers for a certain emotional state and that have a higher Zipf ranking to have stronger prevalence of the respective psychological trait in the local cultural discourse (or context).

[2] Word frequencies have a very heavy-tailed distribution, and can therefore be modeled reasonably well using a Zipf distribution.
[3] For more details on this motivation, see Tubadji (2020a,b).

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2) Publicly available big data from online sources, such as Google, Instagram, Facebook and Twitter, provide records of information in granular time-series form. For instance, Google search volume data can be mined for any keyword and timestamped for every 7.95-minute period over the past 15 years. We use this data here. Long time series of high frequency sample data provide an opportunity for causal econometric inference and predictions. It can be used for historical and continuous monitoring and for the forecasting of the public response to endogenous and exogenous treatments, such as a pandemic crisis. Above all, this is real behavioural data, which outsmarts any simulation model and allows for real-time analyses of public opinion and reactions to any public communication and economic policy.

The CBD paradigm and its novel narrative economics of language quantitative methodology is applied below in the case of the use and communication of public policy and its impact on mental health in the times of the COVID-19 pandemic. Our data, analyses and interpretations reveal implications for policymakers and underscore the value added that the CBD linguistic narrative economic methodology offers in terms of gaining fast and reliable insights at a low cost, which were previously not easily available to the researcher or the policymaker.

4. Data

Our linguistic dataset contains the frequency of keyword searches using Google trends. The keyword of primary interest is the word 'death', which we claim to be the best proxy for the mental state of anxiety from death during the Covid-19 pandemic. We also obtained the frequency of the word 'suicide' as a control for the opposite mental state of anxiety motivated by the desire for death. Finally, we obtained frequencies for a word that is neutral to anxiety, 'chair', in order to control for increases in keyword search behaviours due to the increased need to stay at home during the lockdown, and this enables us to distinguish between the increase in the use of the internet during the lockdown and the increase in the levels of anxiety as an experienced mental state.

Previous research shows that Google keyword searches vary depending on the day of the week (Boy and Tubadji, 2020) and therefore it is present also in our Google trend data. We employed day of week dummy variables in our regressions, which we use in the sense of fixed effects to capture the weekly seasonality in the data, but also use these dummy variables to reconfirm and analyze differences in experienced anxiety during the week.

We augmented the linguistic data with official statistics that record the number of deaths due to COVID-19 within each country of interest. Next, we added information about the dates for the imposition of the lockdown rule, which varies across countries. These dates were 12/03/2020 for Italy and 23/03/2020 for the UK. We created a dummy variable for each day, where the pre-lockdown periods were assigned a value of zero and a value of one for the lockdown period. We interacted these dummy variables with a time trend in order to obtain the policy impact interaction terms.

We considered the day of the WHO statement on the meeting of the International Health Regulations related to the COVID-19 pandemics, which was released on 23rd January 2020. This date has a particularly strong association with the Swedish data, which experienced a spike in keyword search behaviour for the word 'death' on this particular day. Finally, we constructed a model where the variation in the number of keyword searches in the linguistic data was explained by mortality data and the public policy decision to undertake a lockdown.

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5. Method

Culture is considered as a "programming of the mind" (Hofstede and Hofstede, 1991; Signorini et al., 2009) and is our motivation to claim that cultural differences in the lockdown policy will affect the general public's mental health. The rationale to believe that public policy has an effect on mental health is rooted in the evolutionary behavioural economics perspective that public behaviour is a response to the herd signalling uncertainty and anxiety (Hall, 1966; Akerlof and Shiller, 2010). In the contemporary era of a free flow of information, the public can observe, compare and contrast what their own and other nations do as a response to the pandemic. Our herd is ultimately beyond our cultural national herd and instinctively we perceive ourselves as part of the universal human herd. Thus, from a Culture Based Development viewpoint, we test three hypotheses relating to society's mental health behavioural response to the COVID-19 pandemic:

H01: Public policy on lockdown decreases public anxiety from death in the country of residence.

H02: Increases in the number of reported deaths escalates public anxiety from death in the country of residence.

H03: A country's decision to employ a lockdown policy increases public anxiety from death in other countries that have different lockdown policy regimes.

The above hypotheses rest on the assumption that public mental health is a function of quantifiable objective factors (such as death rates) and the public's emotional sensitivity to policy employed for handling the objective factors. This public policy reflects the culture of management of the Covid19 problem within a country, and in relative terms can be expressed as the difference in the time of imposition of a lockdown rule (or its complete avoidance) relative to other countries. The operational model through which we test our working hypotheses is:

$$ANXIETY\_FROM\_DEATH = \alpha + \beta_1 LOCK\_DOWN + \beta_2 DEATH\_NUM + \beta_3 X + e_1 \qquad (1)$$

where *ANXIETY_FROM_DEATH* is the frequency of search for the keyword 'death' on a particular day in a particular country, which our CBD methodology uses as a linguistic signifier for mental health anxiety at the national level. *LOCK_DOWN* captures the nation's psychological sensitivity to the imposition of a lockdown policy; it is a vector that includes a time trend on a daily basis and a dummy variable equal to one on and after the day of imposing the lockdown, as well as the interaction of these two variables. *DEATH_NUM* is the official number of reported deaths, and this is the salient number that affects the cognition of the public. *X* is a vector of other confounding factors, such as the date of lockdown in neighbouring countries. The inclusion of data capturing the lockdown date of neighbouring countries can be justified from the perspective that it signals the behavioural inconsistency in handling the same anxiety employed by another group of people and their different survival strategies under conditions of uncertainty. Such differences in policy choice and asymmetries in hesitation can raise anxiety further.

First, we employ a difference-in-differences approach using an OLS with time trend where the day of lockdown in the home country is considered a treatment and the effect of the difference-in-differences is the interaction between the daily time trend and the dummy

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equal to one from the day of treatment onwards (Conley and Taber, 2011). We correct for weekly seasonality and explore the impacts of the national and international lockdowns on anxiety levels as expressed in the keywords. Second, we employed an interrupted time series analysis (ITSA), where the interruption is the national or international lockdown, and used the above-mentioned seasonalities, the lockdown date in home country, and additional lockdowns as confounding factors.[4]

Sweden did not impose a lockdown, and it serves as a control group for the countries who did impose one, such as the UK and Italy. In order to use this natural quasi-experimental setting to explore the public mental health response to public policy, we calculated the daily differences in keyword searches between Sweden, the UK and Italy. This enabled us to explore how these differences in keyword searches changed as a function of the differences in the objective number of deaths between Sweden and the countries that did impose a lockdown and the differences in timing of the culturally-informed imposed lockdown.

To check the robustness of our cultural and linguistic methodology, we applied model (1) to explain the search for the words 'suicide' and 'chair'. The first one is related to our 'death' results, but instead of being concerned that death may come early, 'suicide' indicates an anxiety associated with the desire for death. Therefore, based on the CBD linguistic method we expect to detect a fall in the search of the word 'suicide' while searches for the word 'death' would increase, as these two notions signify linguistically the meaning of two opposing mental states. Next, the word 'chair' is expected to show, what we have coined as: the 'IKEA effect', approximating the "business as usual' attitude. The word 'chair' is a word that is neutral to the daily routine and indifferent to our mental states of interest, and a 'chair' is a piece of furniture with a particularly level of high importance for the liveability of a space (Kirkham, 2006).

6. Results

An initial look at the temporal evolution of the frequency of search for the word 'death' demonstrates that this word has grown in interest since the start of the Covid-19 pandemic, as shown in Figure 1a. This pattern is sinuous and varies in magnitude but the trajectory is upward for both Italy and the UK, which means that the pandemic has generally increased the experienced anxiety on average for both countries. We interpret the differences in the trends observed in Figure 1a as a reflection of the cultural differences across space in terms of cultural relativity. We also see different magnitudes in the responses to the same treatment across space, and this effect is termed by CBD as cultural hysteresis (Tubadji, Angelis and Nijkamp, 2016).

To crosscheck that we are observing a death anxiety effect and not simply a general increase in the volume of online searches due the requirement to stay at home during the lockdown, we compared the trend in searching for the word 'death' with the trend in searching for the word 'suicide', as shown Figure 1b. Instead of an upward trend, the search trend for the word 'suicide' was downward. This is a confirmation that our linguistic analysis approach captures the public mental state in a constructivist and deconstructionist manner, where notions and mental states build up attitudes towards the reality in a culturally contextualized manner and keywords signify and statistically record the evolutionary development of the context.

[4] We also undertook a third step where we checked for double-interrupted time series effects due to national and international lockdowns using the ITSA approach (Heckman et al., 1999; Hahn et al., 2001; Lee and Lemieux, 2010; Hausman and Rapson, 2018; McDowall et al., 2019). These results are consistent with the previous results, and are available upon request.

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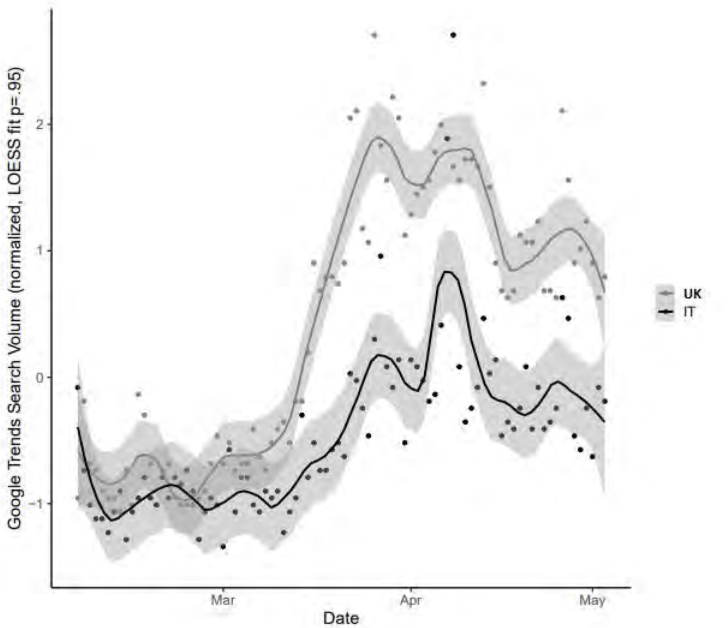

Figure 1a: Searches for 'death' before and during the pandemic

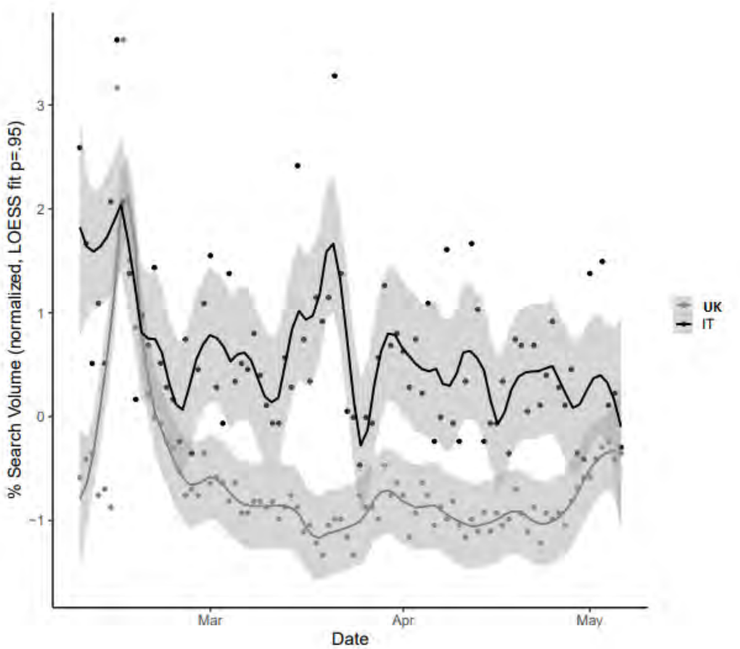

Figure 1b: Searches for 'suicide' before and during the pandemic
Note: Figures 1a & 1b are derived using Google trend data.

A closer look at the tendencies in the three countries under analysis can be gained by comparing descriptive statistics of the variables of interest before and during the pandemic, as shown in the Appendix. We compared keyword searches in the UK and Italy against the control country of Sweden and three main insights emerge. First, the population of Sweden (Italy) searched for the word 'death' least (most) often both before and during the pandemic. Second, the pandemic increased the frequency of search for the word 'death' across all countries. Third, the increase in the search for the word 'death' was greatest in the UK where it doubled, while in Italy there was only a 50 percent increase in the number of searches for the word " death'. These statistical observations are consistent with CBD-related expectations that there are different response magnitudes to identical negative shocks across space due to an underlying cultural bias (Tubadji, Angelis and Nijkamp, 2016). This cultural bias effect needs to be disentangled empirically from the timing of the lockdown effect and from the part that is related to the increase in deaths across the countries under analysis.

Difference-in-differences analysis

A difference-in-differences approach is selected to obtain deeper empirical insight into the preciding descriptive statistics. Table 1 presents the results for within country differences in anxiety from death before and after the implementation of the lockdown policy. Table 1 exhibits three specifications. Specification (1) tests H01 and explores the effects of lockdowns on national levels of public anxiety from death. Specification (2) tests H02 and explores the effects on national levels of public anxiety from death associated with the publically announced number of deaths, which signals uncertainty for life. Comparison of the results in Specifications (1) and (2) helps to distinguish whether the effects hypothesized in H01 or H02 dominates in model (1). Specification (3) augments the model by adding the treatment effect and its temporal and spillover interaction terms, thereby considering the effect of the Italian lockdown on anxiety in the UK and vice versa. This captures international spillover effects and tests H03.

Table 1 offers several insights. First, the early imposition of a lockdown in Italy had a detrimental effect on the mental health of both the Italian and UK populations. Once the lockdown was subsequently imposed in the UK, this decreased anxiety especially in the UK. This result is consistent with CBD assumptions about herd signalling and anxiety effects, as described in Hall (1966): the UK was experiencing increased anxiety because it was observing Italy taking much more intensive precautions under the same pandemic threat. The inconsistency of the UK policy was effecting negatively Italy as well. Across all countries, greater mortality had a positive statistically significant effect on anxiety by increasing both the explanatory power of the model and influencing the rest of the effects in the estimations, and this mortality effect on anxiety was more intense in Italy.

Between country differences in death reporting practices existed (e.g. whether deaths occurred in hospitals, care homes or domiciles), yet what plays a comparable role is the fact that the reported number of deaths is the salient effect of the pandemic that people observe. Thus, the response to the differences in the methods of counting and public announcement of numbers has an important behavioural effect rooted in cognitive biases (Tversky and Kahneman, 1979). The effect of the UK's decision to introduce a lockdown seems to have decreased anxiety in Italy; our interpretation of this is rooted in a behavioural explanation of signalling confirmation of the chosen strategy for survival.

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Table 1: Death anxiety: public policy, death numbers and spillovers

	Public Policy Effects						Salient Death Number Effects						Spill-Over Effects b/n countries					
	UK			IT			UK			IT			UK			IT		
dep. var.	*DEATH ANXIETY*																	
	coef.	t-value		coef.	t-value		coef.	t-value		coef.	t-value		coef.	t-value		coef.	t-value	
day_id	0.302	5.90	***	-0.115	-2.90	**	0.296	6.17	***	-0.135	-3.25	***	0.117	5.58	***	-0.125	-2.90	**
treatment_uk	104.324	2.15	*				229.767	1.89					268.977	2.46	*	-66.164	-0.71	
inter	-0.867	-1.62					-2.376	-1.62					-3.272	-2.50	**	107.506	0.97	
deaths_mean_uk							0.029	1.05					-0.016	-0.62				
treatment_it				-82.274	-3.29	***				-24.892	-0.95		-243.200	-7.20	***	-1.223	-0.91	
inter_it				1.248	4.07	***				0.351	0.97		3.473	7.60	***	0.938	0.75	
deaths_mean_it										0.030	2.96	**				0.017	1.12	
FE day_week	YES			YES			YES			YES			YES			YES		
_cons	25.016	9.65	***	56.196	17.25	***	25.123	9.76	***	57.037	17.16	***	29.828	19.38	***	56.793	17.19	***
N	94			94			94			94			94			94		
R	0.81			0.46			0.81			0.48			0.93			0.49		

Notes: The table presents regression for the frequency of search of the word 'death'. The table presents OLS with fixed effects for weekly seasonality, day detrending, and interaction effects between the day detrend and the lockdown date in the respective country as a direct treatment effect. Spillovers are considered through the additional inclusion of a treatment effect for the other country and the interaction between this additional treatment effect and the day trend

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Figure 2 provides a complementary examination of the data. Fitted linear trends for pre- and post-lockdown periods are presented for both the UK and Italy. Both countries seem to have experienced a visible disturbance in their linear trends when the lockdowns were introduced. Consistent with Table 1, the interruption of the trend is associated with an increase in anxiety in both countries after the imposition of the lockdown policy in Italy on day 72. Similarly, a decrease in anxiety from death occurred in both countries in response to the imposition of a lockdown in the UK on day 83; we argue this supports our CBD interpretation that the behaviour of related groups serves as a signal for confirming the appropriateness or enhancing the scepticism towards our own survival strategy during times of uncertainty.

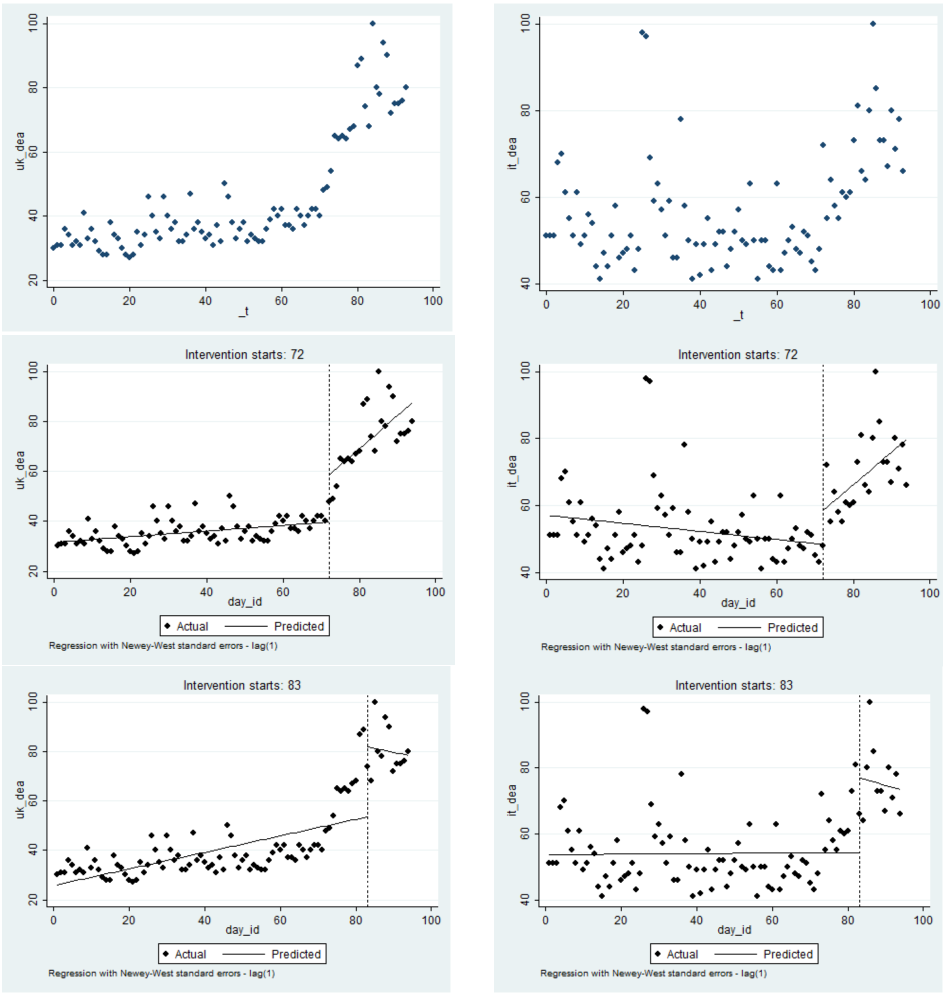

Figure 2: Death anxiety with different lockdown effects: UK vs. Italy

Notes: the left column are figures for the UK while those for Italy are on the right. The first row of figures shows the frequency of searches for the word 'death' in Google. The second row of figures considers the day of lockdown in Italy as a treatment for the interruption of the time searches in both UK and Italy (12 March 2020). The third row presents the interruption of the time series associated with the lockdown in the UK (23 March 2020).

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Figure 2 serves to justify the implementation of a policy impact assessment using an interrupted time series analysis (ITSA), which is a special case of the regression discontinuity technique where the treatment is identified at a point of time (Hausman and Rapson, 2018). Our ITSA is implemented with regard to the lockdown treatment in the home country and with regard to the lockdown decision in the other country. In both cases, we considered the alternative treatment date as a confounding factor. Table 2 presents these results[5] and again reveals the presence of the impact of the lockdown on mental health. The difference in the sign of the effects of the Italian and UK lockdowns is confirmed in this within-method triangulation, as was revealed in Table 1. Plots of the predicted values for both the UK and the Italian cases are supplied in Figure 3 and reveal trends typical for interrupted time series.

Table 2: Interrupted time series analysis for dealth anxiety

				Spec. 1							Spec. 2	
				UK							IT	
dep. var.							*DEATH ANXIETY*					
	coef.	z-value		coef.	z-value		coef.	z-value		coef.	z-value	
_t	0.117	4.86	***	0.119	5.08	***	-0.134	-2.63	**	-0.124	-2.44	**
_x83	-5.705	-0.91								5.624	0.67	
_x_t83	-2.954	-1.74								-1.582	-1.11	
_x72				7.342	3.12	***	5.556	1.18				
_x_t72				3.366	6.70	***	0.426	0.33				
deaths_mean_uk	-0.022	-0.74		-0.016	-0.65							
deaths_mean_it							0.016	1.12		0.016	1.21	
treatment_it	-257.606	-8.64	***							-83.450	-1.08	
inter_t_it	3.667	9.07	***							1.177	1.14	
treatment_uk				261.927	2.32	**	65.812	0.56				
inter_t_uk				-3.181	-2.34	**	-0.686	-0.49				
FE day_week												
2	3.954	1.88		3.728	1.76		1.917	0.60		2.186	0.70	
3	0.673	0.38		0.490	0.28		-2.280	-0.72		-2.090	-0.61	
4	4.608	2.08	*	4.458	2.03	*	-1.903	-0.63		-1.862	-0.61	
5	4.599	2.02	*	4.484	2.03	*	7.898	1.77		8.559	1.93	
6	-0.911	-0.41		-1.141	-0.53		-0.619	-0.13		-0.558	-0.12	
7	-2.001	-0.87		-2.230	-0.98		-3.464	-1.08		-3.440	-1.06	
_cons	30.002	17.91	***	30.112	17.99	***	56.996	15.88	***	56.591	15.87	***
N		94			94			94			94	
Treated	-2.837	-1.67		3.486	6.95	***	0.292	0.22		-1.706	-1.21	

Notes: The table presents an interrupted time series analysis, where the frequency of searches for the word 'death' is explained by the treatment, which is alternatively considered to be either day 72 (the 12 March 2020) or day 83 (the 23 March 2020) for Italy and the UK respectively. Spillovers included.

It is pertinent to consider these effects when compared to a country that did not introduce a lockdown policy, Sweden serves as this control. The Swedish population has been exposed to mortality information and thus represents an excellent control for isolating and analyzing the effect of the implementation of the public lockdown policy in the anxiety function presented in model (1).

5 We reestimated our ITSA with a double treatment effect, and the results are consistent with those presented Table 2. See footnote 4.

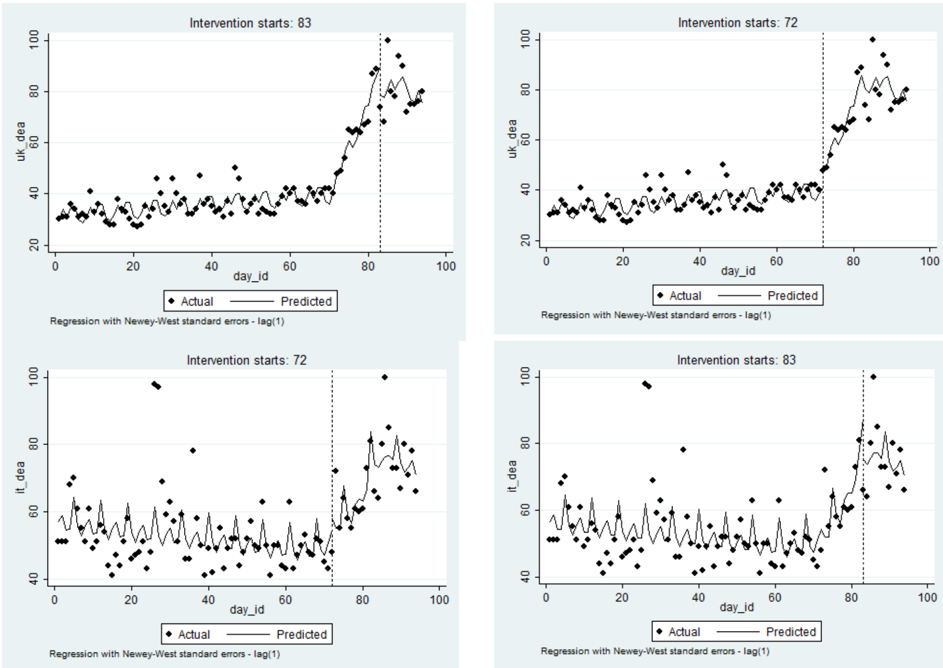

Figure 3: Predicted values of death anxiety as post-estimation from ITSA
Notes: The figure presents the predicted frequency of searching for the word 'death' in Google in the UK (first row) and Italy (second row), with respectively national and international (of the other corresponding country) lockdowns.

Sweden as a control for the lockdown public policy

The estimations using the differences between Sweden and the UK on the one hand, and Sweden and Italy on the other hand, follow the same logic as the estimations in the previous section. We implement three specifications: national effects, mortality effects, and finally cross-country spillover effects. However, in these estimations the dependent variable is the difference between the base country (Sweden) and the treated country (UK or Italy respectively). Results are shown in Table 3 and provide confirmation for the results in Tables 1 and 2 when using Sweden as a control. Moreover, the estimated effects are statistically stronger when attention is focused on the differences across space.

Results provide support for H01, H02 and H03. They indicate that mortality as an objective factor dominates the impact on the population's mental state, which is not void of public policy bias either, as the method of calculation and especially the reporting of numbers are subject to a policy decision making that responds to culture. Although this corroborates the idea that people are generally realistic and rational, it also emphasizes that we suffer cultural biases when acting under uncertainty. People may have been informed about the different ways that deaths were calculated in their country relative to another country, but the numbers reported generated have a similar type of effect. While these results reveal the sensitivity of the population's mental state to publicly reported deaths, we are not advocating the manipulation of reported figures but are instead underscoring that public policymakers should be aware of the repercussions of its announcements and actions as it plays a significant role in stabilizing a population's mental health.

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Table 3: Sweden as a control group for public policy in the UK and Italy

	Public Policy Effects						Salient Death Number Effects						Spill-Over Effects b/n countries					
dep. var.	*DIFF_UK_SE*			*DIFF_IT_SE*			*DIFF_UK_SE*			*DIFF_IT_SE*			*DIFF_UK_SE*			*DIFF_IT_SE*		
	coef.	t-value		coef.	t-value		coef.	t-value		coef.	t-value		coef.	t-value		coef.	t-value	
day_id	0.268	3.13	***	-0.144	-1.43		0.249	3.01	***	-0.166	-1.60		0.086	0.91		-0.163	-1.57	
treatment_uk	34.875	0.61					463.322	2.70	**				364.864	2.68	**	33.752	0.56	
inter	-0.033	-0.05					-5.180	-2.50	**				-4.137	-2.54	**	0.187	1.67	
DIFF_DEATHS_UK_SE							0.110	2.57	**				0.087	3.34	***			
treatment_it				-95.562	-2.57	**				-39.408	-0.76		0.252	2.60	**	0.030	1.41	
inter_it				1.435	3.12	***				0.543	0.73					-0.435	-0.51	
DIFF_DEATHS_IT_SE										0.033	1.36							
FE day_week	YES			YES			YES			YES			YES			YES		
_cons	12.099	2.05	*	43.177	6.69	***	12.679	2.17	*	44.167	6.61		16.150	2.91	**	43.949	6.55	***
N	94			94			94			94			94			94		
R	0.49			0.25			0.51			0.26			0.55			0.26		

Notes: The table presents OLS with fixed effects for weekly seasonality, day detrending, and interaction effects between the day trend and the lockdown date in the respective country as a direct treatment effect. Spillovers are considered through additional inclusion of a treatment effect for the other country and interaction between this additional treatment effect and the day trend.

Hourly Effects and Other Robustness Checks

To further cross check our findings, we engage in robustness checks of our narrative economics of language approach and its ability to explain the behavioural differences across countries in response to Covid-19 pandemic. A detailed exploration of the hourly profile of searches for the term death during an average day in the UK is presented in Figure 4. This figure splits the searches into forthnights pre-lockdown and post-lockdown periods and uses the beginning of the pandemic (1st-14th January) as a baseline. Figure 4 reveals three noteworthy facets. First, there is a peak in search intensity for the word death between the hours of 20:00 and 02:00.[6] Second, there is a temporal pattern of keyword search using Google for the word death that existed before and continues after the lockdown. Third, the lockdown policy has smoothed the frequency of searching for the word death in Google during the day, which illustrates more consistent levels of experienced anxiety among the UK population on a daily basis. Nevertheless, the hours leading up to bedtime remained the most difficult for handling anxiety from death.

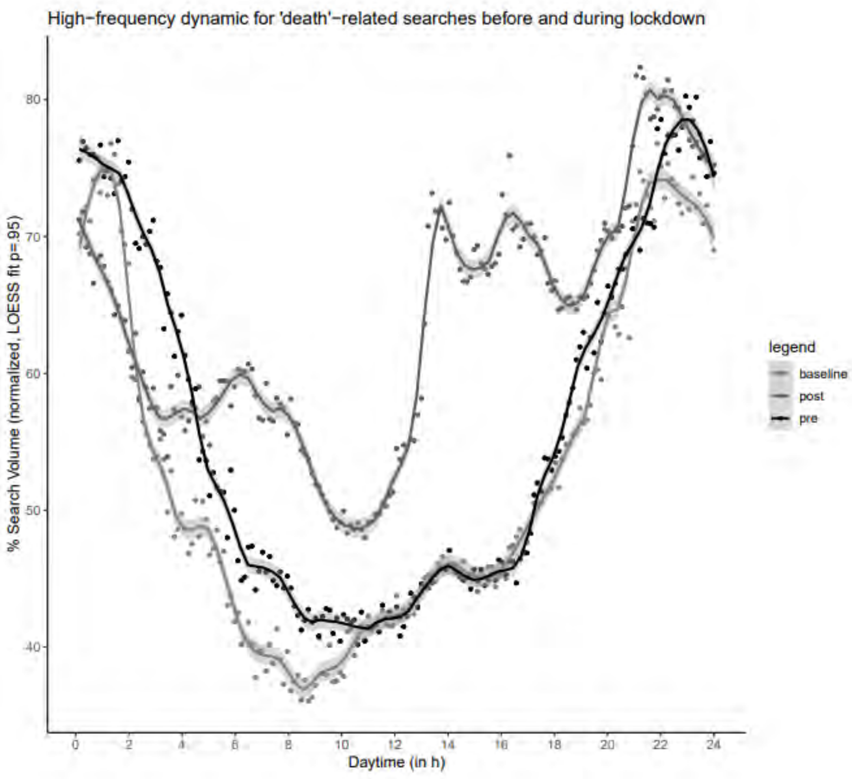

Figure 4: Granular data on daily death anxiety in the UK
Notes: The figure presents the frequency of searching for the word ‘death’ in Google, with baseline representing the pre-pandemic period in the UK, between 00:00 and 24:00 hours. Source: Google trend data.

6 This corroborate a tendency for increases in the search intensity for ultra-right preferences across Europe, as revealed by Tubadji, Boy and Webber (2020).

Figure 5 shows the temporal pattern of the search for the emotionally neutral word ‘chair’ in Sweden, the UK and Italy. For the UK and Italy, we also indicate the time of the lockdown period with a vertical line and fit a line in the observations before and after the lockdown was imposed in the respective country. There is no change in the frequency of search for chairs on Google in Sweden for this entire period. In contrast, the figures for Italy and the UK are less stable and a fitted line suggests a progressive decrease in interest in chairs in the early part of the pandemic before the lockdown and an increase in searches for chair after lockdown. This suggests that people engaged more intensively in online searches after the lockdown.[7] However, there is no discontinuity in the search trends, as was the case in the frequency of searches for the anxiety-related word ” death’. We interpret this as a demonstration of the impact that public policy can have on a population’s anxiety, which is not an identical and spuriously observed tendency across all words. Therefore, statistical explorations confirm this cultural narrative economics empirical approach as a reliable and meaningful tool for analysis. This is an important message in the time of big data, where linguistic evidence is abundantly available but yet to be harnessed for policy impact evaluation purposes.

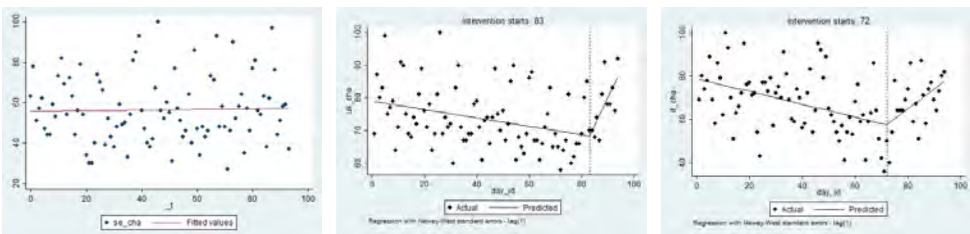

Figure 5: Lockdown policy on business as usual – the IKEA Effect
Notes: The figure presents the daily Google’s relative search frequency for the word ‘death’ in Sweden, the UK and Italy (from left to right) for the period 01/01/2020 to 03/04/2020. The figures for UK and Italy present the day of lockdown and fitted lines for pre- and post-lockdown periods.

7. Conclusion

Public policy creates a context in which the society operates and is a major factor that contributes to the complexities of socioeconomic decisions and behaviours that are embedded in a place. Context contributes to the explanation of differences in responses and effects of identical conditions across space and to the asymmetric responses to an identical shock. Following this reasoning, this paper suggests a Culture-Based Development approach for the analysis and understanding of the culturally embedded spatially diverse differences in public policy responses towards the Covid-19 pandemic, as revealed in imposition decisions on lockdown policy.

Comparison of the reactions to the lockdowns in the UK and Italy, and contrasting these reactions with the “business as usual” control case of Sweden, enables the analysis of three main groups of effects. First, we were able to study the effects of the public policy with regard to lockdown in the country where the policy was introduced, as well as its spatial spillovers across border to another country. Both Italy and the UK were intensely present in the international monitoring of the pandemic crisis through their media, and therefore they

[7] It might also signal the increase in use of a chair at home and therefore the need to purchase/renew one.

represent an excellent basis for studying cross-country spillovers. The analysis identified and distinguished the effects from the different public policy implementations and the effects from the objective factor of the number of deaths. The analysis distinguished between the inter-country cultural relativity from the inter-country cultural hysteresis during the pandemic. Hence, the differences were identified in the anxiety from death in Sweden, Italy and the UK before and after the pandemic, as were the differences in their population's psychological response to the public lockdown policies.

Using data from Google trend frequency of search data corresponding to the word " death', which signify the nation's anxiety experienced from death, we employ difference-in-differences and interrupted time series analysis approaches to establish the presence of any effects from the public lockdown policy in the UK and Italy. We took advantage of the presence of a natural quasi-experimental setting by including Sweden as a control, because Sweden did not have a public lockdown policy. Our results confirm that the early lockdown in Italy increased anxiety in both Italy and the UK, potentially because asymmetries in policy setting signalled high levels of uncertainty in tackling the Covid-19 pandemic. Consistent with this line of thought, we find that the introduction of the lockdown in the UK reduced anxiety in both the UK and in Italy, perhaps because it confirmed that the consensus is that lockdowns were the right survival strategy.

However, although the present results show a country's lockdown policies affected its population's mental health, the effect on mental health of cognitive understanding of daily death toll statistics was more powerful. As these death numbers were higher in Italy, they completely dominated other effects in this country, whereas the public policy in the UK continued to play a role throughout the pandemic. These results were crosschecked both through use of alternative words with connotations relating to anxiety for death (the word " suicide') and through the use of an emotionally neutral word (the 'IKEA-effect' driven word 'chair'). These robustness checks demonstrate that the narrative economics of language method, suggested by Cultural-Based Development approach, is strong enough to generate evidence for economically meaningful policy, and we showed how this approach can be used to evaluate the impacts of public policy and public statistics on the mental health of the general public. Finally, we presented a detailed analysis of anxiety for death during a representative 24-hour window, which showed that the most vulnerable times of the day, when feelings about morbidity are highest, are late in the evening and into the early hours of the morning.

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Appendix: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
se_dea	94	10.1	17.8	0	100
uk_dea	94	44.8	18.0	27	100
it_dea	94	56.7	13.0	41	100
deaths_mean_se	94	3.8	12.2	0	69
deaths_mean_uk	94	38.4	119.7	0	685
deaths_mean_it	94	156.2	280.9	0	969
treatment_uk = 0					
DIFF_UK_SE	81	28.5	19.9	-65	68
DIFF_IT_SE	81	43.2	20.6	-49	97
DIFF_IT_UK	81	14.7	12.2	-14	57
DIFF_DEATH_UK_SE	81	2.6	10.6	-1	65
DIFF_DEATH_IT_SE	81	59.3	147.1	0	789
DIFF_DEATH_IT_UK	81	56.7	139.0	0	737
treatment_uk = 1					
DIFF_UK_SE	13	73.4	12.1	48	94
DIFF_IT_SE	13	68.2	12.9	38	85
DIFF_IT_UK	13	-5.2	11.7	-21	20
DIFF_DEATH_UK_SE	13	233.8	202.7	17	635
DIFF_DEATH_IT_SE	13	732.2	99.7	598	941
DIFF_DEATH_IT_UK	13	498.5	217.0	81	788
treatment_it = 0					
DIFF_UK_SE	70	25.4	18.6	-65	47
DIFF_IT_SE	70	42.6	21.1	-49	97
DIFF_IT_UK	70	17.3	10.5	2	57
DIFF_DEATH_UK_SE	70	0.1	0.3	0	2
DIFF_DEATH_IT_SE	70	9.0	28.8	0	168
DIFF_DEATH_IT_UK	70	8.9	28.4	0	166
treatment_it = 1					
DIFF_UK_SE	24	62.1	18.7	18	94
DIFF_IT_SE	24	58.4	18.5	19	85
DIFF_IT_UK	24	-3.7	10.7	-21	23
DIFF_DEATH_UK_SE	24	135.3	183.4	-1	635
DIFF_DEATH_IT_SE	24	570.5	231.2	174	941
DIFF_DEATH_IT_UK	24	435.3	207.7	81	788

Notes: Derived differences between Sweden and Italy and the UK are presented for pre-treatment (pre-lockdown, treatment equal to 0) and during lockdown period (treatment equal to 1).

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The surprising effect of social distancing on our perception: Coping with uncertainty[1]

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Since the beginning of the COVID-19 crisis, our perception of the world significantly changed. In this paper we show the results of 3 studies that collectively illustrate a novel mechanism through which this has happened. We document the effect of social distancing on our perceptions, through the moderating effect of ambiguity aversion. In experiment 1 we show that ambiguity aversion predicts illusory pattern perception, defined as identifying faces in white noise pictures. In experiment 2 we show that ambiguity aversion also predicts higher cognitive level illusory pattern perception, defined as belief in conspiracy theories. Experiment 3 shows, through two uniquely timed questionnaires, that ambiguity aversion increases significantly from before to after the lockdown (due to the COVID-19 pandemic) for a sample of over 300 subjects. Remarkably, this difference in ambiguity aversion is no longer significant when we control for the drop in regular social contact over this period.

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1. Introduction

Since the start of the COVID-19 crisis, there has been a significant increase in spread of fake news and conspiracy theories (Caulfield, 2020; Šrol et al., 2020; Wadman et al., 2020). This paper proposes one fundamental explanatory mechanism for why this is happening now. In order to do this, we use the concept of illusory pattern perception, which describes the phenomenon of identification of non-existing patterns. For example, Prooijen et al., 2018 highlights a correlation between the tendency to see meaningful patterns in random stimuli and belief in conspiracy theories, while Whitson and Galinsky, 2008 shows that illusory pattern perception increases for people who are placed in a situation of lack of control. More recently, Hohwy, 2013 describes the situation of lacking control of Whitson and Galinsky, 2008 as akin to one with uncertainty. Along this line, we study the impact of uncertainty on illusory pattern perception, and we focus on the changes that the COVID-19 lockdown has had on our attitudes toward uncertainty.

A growing scientific literature pins down our complex social system as the foundation for our attitudes towards uncertainty (FeldmanHall and Shenhav, 2019; Berg and Wenseleers, 2018; Jonas and Mühlberger, 2017; Wesselmann et al., 2015). Notably, the effort to maintain control in the face of uncertainty influences our perception (Clark, 2016; Hohwy et al., 2008) as well as our decision-making processes (Cettolin and Riedl, 2019; Epstein, 2001; Gilboa and Schmeidler, 1989). In fact, mechanisms traditionally seen as behavioral biases to rationality become first best rules when modeled in a world including uncertainty (Dosi et al., 2020; Gigerenzer, 2015; Kahneman et al., 1982). Finally, when patterns become narratives, they may cause economic fluctuations of their own (Shiller, 2017). This paper complements these insights by showing that the current social distancing standard after the COVID-19 pandemic has important consequences for these basic human processes, translating into significant changes in the way we see and interpret the world.

We contribute to the literature by identifying a unified, measurable link between our ability or willingness to cope with uncertainty and the way we interpret the world: ambiguity aversion. Ambiguity aversion was first discussed as a relevant behavioral bias to rationality by Daniel Ellsberg (Ellsberg, 1961). He pointed out that people are normally willing to pay less money for a bet with unknown odds than for one with the same expected value, but with known odds. This bias, ambiguity aversion, is ruled out by the rationality of the Savage axioms (Savage, 1954) and it is known as the Ellsberg paradox. We show two novel results:

1. Ambiguity aversion predicts illusory pattern perception.
2. Ambiguity aversion increased after the lockdown, when the lockdown affected our regular social interactions.

These two results stand on a large body of literature, which provides a natural context for each of them.

Our research strategy uses data from three experiments. The first two experiments establish a connection between ambiguity aversion and illusory pattern perception. These two experiments are described in section 3. The third experiment studies the effect of the COVID-19 lockdown on ambiguity aversion. Section 4 describes the methods and results of this third experiment. Next section describes the concepts and gives simple definitions of risk and ambiguity aversion as we use them in this paper.

2. Risk aversion and ambiguity aversion

From a conceptual point of view, not all uncertainty is the same. Most notably, we define it in two forms[1]: risk and ambiguity. Risk is a quantifiable and well understood probability (like flipping a coin, or speeding on the highway back home from work), while ambiguity arises when a relevant probabilistic distribution is not available (Keynes, 1936). Some refer to ambiguity as Knightian uncertainty, after the work of Frank Knight (Knight, 1921). Neuroscientific research demonstrated that in situations with ambiguity we activate several brain areas more than in situations with risk, which is in line with using two distinct measures to model attitudes toward these two forms of uncertainty. Therefore we introduce risk and ambiguity aversion.

On the one hand, risk aversion is a familiar concept in economics and finance. We are risk averse when, given two assets, we are willing to accept the asset with lower return if it also has a lower perceived risk. For example, between a bet yielding 10 euros with 50% probability (and 0 otherwise), and a sure payoff of less than 5 euros we will consider and, depending on our risk attitudes, choose the sure payment to avoid the well-understood chance of being left with nothing. Under expected utility theory, well-known measures of risk aversion are absolute and relative risk aversion, depending on whether the decision is in terms of the absolute amount of Euros invested in the risky asset, or the proportion relative to wealth.
O'Donoghue and Somerville, 2018 gives a recent and insightful literature review on risk aversion in economics. Guiso et al., 2018 studies the reasons for time varying risk aversion. Chapman and Polkovnichenko, 2009 considers the impact of neglecting heterogeneity when computing risk aversion[2].

On the other hand, ambiguity attitudes are yet to be captured by one single, well-understood measure. The literature is wide and growing. Recent research from psychology shows that ambiguity attitudes, (in-) tolerance and aversion are different concepts both intuitively and at a neuro imaging level (Ghirardato et al., 2004; Tanaka et al., 2015). In particular, economics literature studied ambiguity aversion for a long time (Ghirardato and Marinacci, 2002; Cettolin and Riedl, 2019; Füllbrunn et al., 2014) and Rustichini, 2005 gives a compelling survey.
Intuitively, we are ambiguity averse when we would prefer a bet for which we know the probability distribution of the outcomes, to a bet for which we do not know the odds. Interestingly, ambiguity aversion varies with the source of ambiguity (Trautmann et al., 2008), and Fairley et al., 2012 and Li et al., 2019 study the connection between ambiguity aversion and social trust. Our work contributes to the literature on ambiguity aversion by defining its role in driving illusory pattern perception and by studying its increase following the lockdown.

Given the variety of measures in the literature for risk and ambiguity aversion, we limit our discussion here to the precise methods we used to compute them in this paper. For consistency, we computed ambiguity aversion and risk aversion with the same procedures across all our datasets. These measures are in line with the Ellsberg paradox and adjusted from Qiu and Weitzel, 2012. We describe them here.
The subjects answered the following two questions:

[1] According to Hansen & Sargent, 2019, uncertainty can be divided in three types, where risk and ambiguity are respectively uncertainty *within* a model and uncertainty *across* a set of available known models. The third type is uncertainty *about* each model, which is a model *misspecification.* We acknowledge this division and its potential for robust economic modelling, and we focus on the traditional division.

[2] For a study of the impact of heterogeneous risk aversion in an asset pricing model, see Gomez and Piccillo, 2019.

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1. There is an urn containing exactly 5 white balls and 5 black balls. Choose a color. How much would you be willing to pay at most for a bet yielding 10 Euros if you picked a ball of the chosen color? ______ Euros

2. There is an urn with 10 balls. You do not know the color (black vs white) proportion. Choose a color. How much would you be willing to pay at most for a bet yielding 10 Euros if you picked a ball of the chosen color? ______ Euros

Each subject's risk aversion was recorded by computing 5 Euros (the expected value of the bet) minus the answer to the first question. Each subject's ambiguity aversion was recorded by computing the chosen price for the first bet minus the chosen price for the second bet[3]. All our questionnaires for ambiguity and risk aversion were not incentivized. In experiment 1 and 2 the questionnaires were delivered on paper. For experiment 3 we used a digital platform. In all experiments we kept the same text and questions for computing risk and ambiguity aversion. For a picture of the page that subjects saw in the questionnaires, see the appendix.

3. Ambiguity aversion and illusory pattern perception

3.1 Experimental procedure experiments 1 and 2

Experiment 1: The goal of experiment 1 was to identify any link between ambiguity (and risk) aversion, illusory pattern perception, and personally salient uncertainty.
For experiment 1, all participants were bachelor students in the same course of a European university. Experiment 1 consisted of 2 questionnaires. The first questionnaire asked them to rate several statements on a 5 level Likert scale (strongly disagree to strongly agree). The second questionnaire measured their risk and ambiguity aversion and their illusory pattern perception.

The first questionnaire included 2 questions on their individual drive for performing well in the upcoming tasks. The two questions were:
- "I want to get high grades."

- "I want to be successful at what I do."

We used these answers to the first questionnaire and their performance on the course final exam (which counted for 100% of the grade) to deduce their state of salient uncertainty during the time of administration of the second questionnaire.

Intuitively, we conceptualize salient uncertainty as follows. A student has to undertake a task, which has an uncertain content. In this experiment, the task is the exam. The task is uncertain to varying degrees across the different students. The task is also salient (personally important) in varying degrees across the students. On average, we assume that a higher mark on the task means the student has a better understanding of the task, and therefore is facing less uncertainty. Therefore a student that will end up with a high mark on the exam in this procedure is assumed to be facing less uncertainty than a student who will end up having a lower mark, conditional on the same answer on questionnaire 1.
However students may have different preferences for their performances, which will likely drive their behavior and, importantly here, their feeling of salient uncertainty. Therefore if two students

[3] We are aware that there are a variety of different methods to compute risk and ambiguity aversion. Especially with focus on ambiguity aversion, the comparison between this, simple measure and others is a very interesting, open discussion. We are currently not in a position to address this discussion since we only recorded the answers to the questions above. However, we wish to make clear that it is this simple measure that is significantly correlated to illusory pattern perception, and this is the measure that also exhibited significant variation after the lockdown.

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perform equally on the exam (say a 6 out of 10), but one of them cares strongly about the grades, while the other one cares less than strongly, we assume that the salient uncertainty of the first student is higher. This is because the uncertainty she is facing in advance on the exam (reflecting the preparation which will lead to the mark 6), is more salient (personally relevant) for her than for the student who is less concerned with obtaining the high grade.
According to this concept we compute the salient uncertainty (SU) as:
SU= The answer to the question "I care about having high grades"- final grade.
For robustness, we computed SU using the answers to both questions above. Results are robust to both definitions of SU.

The students took the second questionnaire the week before the exam, 2 weeks after the first questionnaire. In the second questionnaire we tested their ambiguity attitudes (using the procedure described in section 2) and their illusory pattern perception as measured from the completion of a snowy picture task (Whitson and Galinsky, 2008).

The snowy picture task consisted of 24 pictures, and participants were truthfully instructed in that these pictures either contained a face, or nothing at all. Indeed, in 8 pictures there was a face, while in the other pictures there was nothing at all (see samples in the appendix). Subjects had no information over the exact number of faces present in the 24 pictures. This part of the questionnaire was lightly incentivized, as subjects were promised (and received) a small prize (a candy bar) for being the best in their group (made of 10 to 15 people).

Experiment 2: The goal of experiment 2 was to test the correlation between ambiguity aversion and higher order beliefs. We agree with the literature that uncertainty "is a pervasive fact of life" (Lawson, 1985). Therefore we ask whether people who systematically have a higher ambiguity aversion might over time develop more vivid illusory patterns.

Experiment 2 was done with one questionnaire, containing two tasks. The questionnaire was presented to the students from a different course than experiment 1. Also this questionnaire was given on paper and it was not incentivized. In the first task we asked whether (and how strongly) subjects agreed with 15 statements on world beliefs. The 15 statements were a validated questionnaire testing believes in conspiracy theories (Brotherton et al., 2013), and they measured 5 separate types of common conspiracy theories (government malfeasance, extraterrestrial cover-up, malevolent global, personal well-being, control of information). The full list of questions is listed in the appendix. Subjects could use a 5 level Likert scale (1: definitely not true; 2: probably not true; 3: not sure/cannot decide; 4: probably true; 5: definitely true). In this case we clearly do not have a "true" right or wrong answer on each question as we did for the faces on experiment 1. Therefore we computed the individual Conspiracy Theory Belief (CTB) by counting how many times the subjects answered "definitely true"[4]. The second task was the measurement of risk and ambiguity aversion with the same procedure and scheme as in experiment 1, described in section 2 above.

3.2 Data analysis

All data was analyzed using StataSE 15. Participants that indicated that they did not want to have their data used were removed from the sample. For experiment 1, this yielded 146 subjects for which we had all listed variables. For experiment 2 we had 154.
First, we excluded subjects who gave inconsistent or dominated answers, according to the following definitions: if the answer to either of the two urn questions on price they would be willing to pay 10 Euros or more, we cannot retain the subject, since this was a dominated choice by the clearly lower probability to get 10 Euros (these were 8 subjects in experiment 1, and 14 in experiment 2). Additionally, if both the prices listed were 0 Euros, we also had to exclude these points: when risk aversion was already so high, our own experiment set up would not allow to compute ambiguity

[4] For robustness we also looked at how many distinct conspiracy theories, out of the 5 tested, subjects definitely find true. Results do not change.

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aversion if the risky bet was already not being played (these were 3 subjects in experiment 1 and 3 subjects in experiment 2). This yielded 135 subjects in total for experiment 1, and 137 subjects in experiment 2. Between these two experiments, there was an overlap of 35 subjects, which participated in both. The two experiments took place about 7 months apart.

3.3. Results experiments 1 and 2

Over our whole sample, the amount of illusory faces identified by subjects (faces that our subjects said they saw in a noisy figure) was directly correlated to their individual ambiguity aversion (p-value = 0.018), see Column 1 of Table 1.

Further, we connected this correlation more precisely to the effect of temporary salient uncertainty by identifying those subjects that at the time of the experiment were likely facing more discomfort than the others on performance in relation to the upcoming exam. We identified them as scoring in the top one third of our sample on the variable of salient uncertainty.

Therefore we split the sample in two groups: the group with lower apparent discomfort in this dimension, and the group with high salient uncertainty. We show the outcome in columns 2 and 3 of table 1. The power of our model increased significantly when selecting the group facing salient uncertainty (column 3), with the correlation between ambiguity aversion and the number of illusory faces rising to 60%. Consistently, in the remaining part of the group, total illusory pattern perception as identified by our measure was significantly lower (ANOVA model with p-value = 0.02) and indeed the link between ambiguity aversion and illusory pattern perception disappeared (column 2 in table 1).

Table 1: Illusory Pattern Perception and Ambiguity vs Risk Aversion

	(1) Full sample	(2) Low SU	(3) High SU
Ambiguity Aversion	0.446	0.00852	1.011
	(0.018)	(0.969)	(0.003)
Risk Aversion	0.0702	0.179	-0.129
	(0.692)	(0.369)	(0.694)
Constant	6.336	6.576	6.183
	(0.000)	(0.000)	(0.000)
Observations	135	92	43
r2	0.0493	0.0109	0.369
F	3.422	0.492	11.70

p-values in parentheses

The results of experiment 2 are shown in Table 2. As in experiment 1, ambiguity aversion significantly affected illusory pattern perception, which this time was measured with conspiracy theory beliefs. This yields support to the idea that perceptions at the visual level and cognitive belief are modulated by the same mechanism (Prooijen et al., 2018).

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Table 2: Conspiracy Theory Belief and Ambiguity vs Risk Aversion

	(1) CTB	(2) CTB
Ambiguity Aversion	0.240	0.250
	(0.009)	(0.016)
Risk Aversion		0.0219
		(0.833)
Constant	0.900	0.860
	(0.000)	(0.002)
Observations	137	137
r2	0.0498	0.0501
F	7.078	3.537

p-values in parentheses

3.4 Discussion

We propose that when we struggle with salient uncertainty, we begin an active search for the key to our discomfort (Kelley, 1987). However, this search alone does not lead to the higher display of illusory pattern perception. It is specifically through our individual attitude towards ambiguity that we may become convinced of seeing patterns where there are none. In other words, it seems that ambiguity aversion makes us so uncomfortable with handling situations which we do not fully understand, that we naturally become eager to accept a solution, rather than facing the bleak possibility that we might not.

Further, a small number of subjects took both experiments 1 and 2. Therefore we can study whether this mechanism holds when subjects change their ambiguity aversion over time. For this purpose, we looked at the subset of subjects who were present in both of the previous experiments and that were facing salient uncertainty in experiment 1 (see: column 3 in table 1). We defined their change in illusory pattern perception between experiment 1 and experiment 2 as the difference between their relative position on illusory faces identified in experiment 1 and their relative position on conspiracy theory belief in experiment 2. Indeed, the change in illusory pattern perception was predicted by their change in ambiguity aversion over the several months period (p-value<0.01, n=13). This data suggests that even within subjects, changes in ambiguity aversion predict changes in illusory pattern perception.

4. Ambiguity Aversion after the lockdown

Our third experiment tested, using unique data from before and after beginning of the COVID-19 lockdown, if ambiguity aversion had increased from before to after the lockdown, with the ensuing drop in regular social contact.

Due to ongoing research on ambiguity aversion, we had the opportunity to study a uniquely timed dataset in this crisis. Experiment 3 was a natural experiment, which included the implementation of a lockdown policy in our subjects' country exactly in the time between when the two questionnaires

were administered[5]. The goal of this experiment became to learn whether individual ambiguity aversion increased after the lockdown (in line with our interpretation of the literature mentioned above)[6]. If it did increase, the experiment aimed at gaining more specific insights on the mechanism responsible for the change.

4.1 Experimental procedure experiment 3

1 week before the beginning of the lockdown, we administered a questionnaire which was used to assess student attitudes within a course. In this first questionnaire we measured ambiguity and risk aversion with the same procedure used in experiments 1 and 2 described above. Within 2 weeks after the beginning of the lockdown, we administered a second questionnaire. We included again the questions on risk and ambiguity aversion, as well as 7 other specific questions on habit changes in the two weeks since the beginning of the lockdown. The questionnaires were a part of a course which was not graded, and the answers were on a 5 level Likert scale (strongly disagree to strongly agree). They were not otherwise incentivized and were delivered on a digital platform.

The list of questions in the second questionnaire of Experiment 3 were:

Q1 Since the shutdown I decreased the amount of people (not only colleagues) I am in regular contact with every day.

Q2 The shutdown of the last few weeks has had a concrete impact on my usual study habits

Q3 Despite the shutdown I still regularly spend time with people.

Q4 Since the shutdown I study alone much more than earlier.

Q5 I find it feasible to keep up with the weekly routine of assignments online set up until the end of this week

Q6 My colleagues from the tutorial group and my tutor have helped me to establish a new routine for this course.

Q7 Overall, the last few weeks' events have increased the fundamental uncertainty I feel around me.

Subjects could answer on a 5 level Likert scale (Strongly Disagree to Strongly Agree).

4.2 Data analysis

Experiment 3 had several questions, not all of which were answered by everyone. Our total sample was at most 449 subjects. After we excluded the same groups as in experiments 1 and 2 we got 347 subjects. The relatively larger drop in subjects was due to subjects choosing inconsistent answers (prices of any bet of 10 Euros or higher) on the second questionnaire, after the lockdown, which accounted for 73 excluded subjects[7].

4.3 Results Experiment 3

[5] NB: Since the date of this lockdown was not known in advance, the precise timing of this questionnaire of a week in advance was purely coincidental, and not predictable by most. In fact, until the day before the lockdown, business and university activities were running as usual.

[6] The word “shutdown” was used as a synonym of lockdown.

[7] While we believe that choosing simply inconsistent strategies in the middle of a pandemic is in itself an interesting research behavioral reaction, we feel that we do not have enough data to study this new question properly, since this was not the goal of the experiment. Therefore, for consistency, we adopt the same cut off rule as for all other experiments on this paper.

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When we compared the ambiguity aversion after the beginning of the lockdown to the one before the lockdown, ambiguity aversion after the lockdown was significantly higher (p-value<0.09 for a two way t-test, p-value<0.07 for Wilcoxon signed-rank test, p-value<0.05 for a one way t-test). When we wanted to explain the reasons for the changes to the new ambiguity aversion variable after the lockdown, we got the results in Table 3.

Table 3: Social Distancing and Ambiguity Aversion

	(1) AA after	(2) AA after	(3) AA after	(4) AA after	(5) AA after	(6) AA after	(7) AA after	(8) AA after
AA before	0.643	0.642	0.642	0.635	0.629	0.629	0.627	0.627
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
#ppl in reg. contact		0.196	0.193	0.254	0.255	0.257	0.260	0.268
		(0.017)	(0.023)	(0.006)	(0.007)	(0.006)	(0.006)	(0.005)
change study habits			0.0107	-0.00353	-0.0164	-0.00978	-0.0154	0.00570
			(0.881)	(0.961)	(0.827)	(0.899)	(0.843)	(0.944)
amount time w people				0.0732	0.0735	0.0747	0.0717	0.0638
				(0.292)	(0.296)	(0.289)	(0.315)	(0.374)
study alone more					-0.0283	-0.0303	-0.0309	-0.0334
					(0.587)	(0.563)	(0.560)	(0.529)
satisfy requirements						0.0305	0.0322	0.0220
						(0.668)	(0.665)	(0.769)
team in new routine							-0.0301	-0.0257
							(0.701)	(0.743)
perc. uncertainty								-0.0759
								(0.331)
Constant	0.677	-0.190	-0.220	-0.571	-0.417	-0.551	-0.441	-0.227
	(0.000)	(0.610)	(0.604)	(0.260)	(0.452)	(0.387)	(0.512)	(0.748)
Observations	347	347	347	340	334	334	331	331
r2	0.457	0.466	0.466	0.463	0.456	0.456	0.453	0.455
F	290.1	149.9	99.66	72.25	54.99	45.74	38.22	33.56

p-values in parentheses

As the table shows, the best predictor of the new ambiguity aversion was (not surprisingly) the ambiguity aversion from 3 weeks earlier (column 1). However in this model, the constant was still significantly larger than 0. The lockdown 'treatment' had a positive impact on our variable of interest, ambiguity aversion.

In columns 2 through 8 we included the answers to the questions Q1 through Q7 above. When we introduced question Q1, the R^2 increased and the constant became not significant (column 2). No other variable was significant[8].

In line with the literature from sections 1 and 2 above, our stable social interactions could be an important element of our attitudes toward uncertainty. This was best expressed in our questionnaire by the changes to the amount of people the subjects were still in regular contact with daily (Q1).

5. Discussion and Conclusion:

In this paper, we analyzed three survey datasets. Drawing from a large and growing body of literature we know that people's attitudes towards uncertainty have an impact on their active perception, as well as on the higher order beliefs on the world. We also know that complexity of the human social system, as well as interpersonal relationships have often been studied in relation to our attitudes toward uncertainty. Yet a plausible, measurable link to make this proposition more specific has been missing until now. We suggest that this link might be the well-known measure of

[8]These results are not altered by the order in which we add other variables, and they hold using non parametric methods.

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ambiguity aversion: in a struggle to search for meaning in the face of uncertainty, subjects exhibit illusory pattern perception in a proportional measure with their own ambiguity aversion. We note that the level of ambiguity aversion necessary to significantly affect overall illusory pattern perception is not at the margins, therefore this mechanism can affect a substantial amount of people and it is not only of relevance in clinical conditions.

Of prime relevance in these times of COVID-19, we observe that ambiguity aversion has been significantly affected by the unintended and preventable consequences of the lockdown. We suggest that, especially in view of a continued social distancing standard, this mechanism should be studied further and taken into account when safety measures make it necessary to maintain this standard for a sustained period of time.

Some policy trade-offs that this insight can contribute to are:

- the opportunity to wear masks regularly and implement systemic wide-spread testing might be worth the cost, when these procedures will decrease the number of people who are homebound.

- making communication technology as widespread and affordable as possible, including contracts with telephone and internet providers to make sure that maintaining regular contact will be feasible for the largest amount of people.

- designing online workplaces with regular socializing moments made part of the workday.

- on a more targeted level, we do know that ambiguity aversion is akin (but not the same as) a personal trait, or preference (Borghans et al., 2009). Therefore it can still be affected by specific training (Trautmann et al., 2008). Indeed, research shows that ambiguity aversion may be lessened in some contexts through repeated games and specific interventions in the education system may be effective in increasing individual economic rationality (Kim et al., 2018; Liu and Colman, 2009). Investing in more targeted interventions already in the education system may be a long-run policy implication to consider moving forward.

Even with these precautions, it is likely that on a wider societal base an increase in fake news (aiding conspiracy theories and illusory pattern perception) might be temporarily relevant, and it will require special attention in the near future. This is of special relevance when we note that conspiracy theories and illusory pattern perception have been tied to populist voting preferences (Norris et al., 2019; van Prooijen et al., 2015).

Finally, our work suggests that the role of ambiguity aversion on individual perception and decision making is deeper than previously thought and that this trait, while persistent in normal times, is also subject to changes over time. We raise two questions. The first question is in regards to economic modeling of the results of ambiguity aversion and uncertainty. As highlighted in Rustichini, 2005, economic research has rationalized ambiguity aversion through a framework based on loss aversion in decision making choices. Our work suggests that the impact of ambiguity aversion in periods of high uncertainty will be underestimated by this framework alone. This is when a wider phenomenon of illusory pattern perception in the effort to decrease perceived uncertainty might become economically relevant as well. Second, this mechanism points to a precise root for animal spirits defined in a wider sense (for example, as narratives in Shiller, 2017), as people are actively looking for meaning in a changing world. To the extent that beliefs are affected by illusory pattern perception, economic choices and investment decisions will be too. For this reason, continued research is needed to identify any further systemic consequences of ambiguity aversion and the real world scope for policy.

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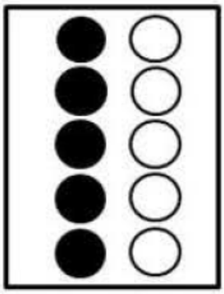
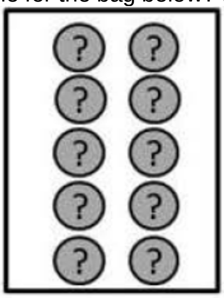
Appendix: Additional material

Ambiguity aversion:

Below the scheme with the two questions adjusted from (Qiu and Weitzel, 2012), which we show our subjects (without incentive) to compute ambiguity aversion.

“There is:

- a bag (below left) filled with exactly 5 black balls and 5 white balls,
- and a second bag on the table (below right) filled with 10 balls that are black or white, but you do not know their relative proportion.”

Suppose that you are offered a ticket to the game that is to be played as follows: First, you choose a color (black or white). Next, without looking, you are to draw a ball out of the box below. If the color that you draw is the same as the one you predicted, then you will win 10 Euro; otherwise you win nothing. What is the most that you would pay to play such a game for the bag below? (0-10 Euro)  The most that I would be willing to pay for a ticket to play the game with this bag **(5 black; 5 white)** is: __ , __ Euro	Suppose that you are offered a ticket to the game that is to be played as follows: First, you choose a color (black or white). Next, without looking, you are to draw a ball out of the box below. If the color that you draw is the same as the one you predicted, then you will win 10 Euro; otherwise you win nothing. What is the most that you would pay to play such a game for the bag below? (0-10 Euro)  The most that I would be willing to pay for a ticket to play the game with this bag **(? black;? white)** is: __ , __ Euro

Based on these two questions above, risk aversion for each subject is computed as: 5 (the expected value of the bet) minus the answer to the question on the left. Ambiguity aversion is computed as: the answer to the question on the left minus the answer to the question on the right.

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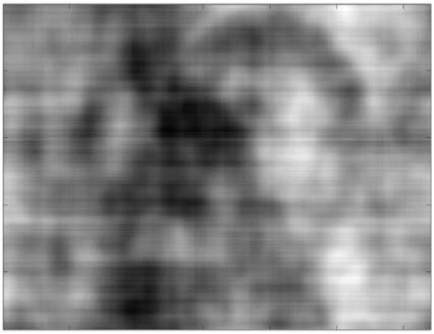
Experiment 1 - Figures with faces:

Below are 2 examples of the figures shown for experiment 1. Image 1 contains a face. Image 2 does not.



C6277

IMAGE 1

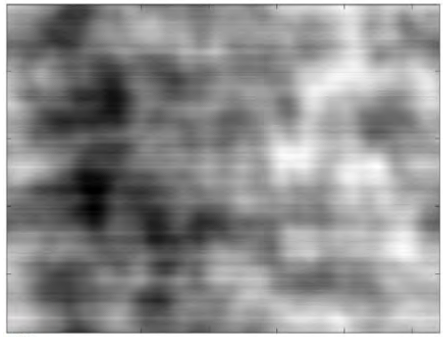


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IMAGE 2

Experiment 2 - Questions:

The government is involved in the murder of innocent citizens and/or well-known public figures, and keeps this a secret

The government permits or perpetrates acts of terrorism on its own soil, disguising its involvement

The government uses people as patsies to hide its involvement in criminal activity

The power held by heads of state is second to that of small unknown groups who really control world politics

A small, secret group of people is responsible for making all major world decisions, such as going to war

Certain significant events have been the result of the activity of a small group who secretly manipulate world events

Secret organizations communicate with extraterrestrials, but keep this fact from the public

Evidence of alien contact is being concealed from the public

Some UFO sightings and rumors are planned or staged in order to distract the public from real alien contact

The spread of certain viruses and/or diseases is the result of the deliberate, concealed efforts of some organization

Technology with mind-control capacities is used on people without their knowledge

Experiments involving new drugs or technologies are routinely carried out on the public without their knowledge or consent

Groups of scientists manipulate, fabricate, or suppress evidence in order to deceive the public

New and advanced technology which would harm current industry is being suppressed

A lot of important information is deliberately concealed from the public out of self-interest

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Measuring sectoral supply and demand shocks during Covid-19[1]

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We measure labor demand and supply shocks at the sector level around the Covid-19 outbreak, by estimating a Bayesian structural vector autoregression on monthly statistics of hours worked and real wages and applying the methodology proposed by Baumeister and Hamilton (2015). Our estimates suggest that two-thirds of the 16.24 percentage point drop in the growth rate of hours worked in April 2020 are attributable to supply. Most sectors were subject to historically large negative labor supply and demand shocks in March and April 2020, but there is substantial heterogeneity in the size of these shocks across sectors. Leisure and Hospitality was particularly affected. We find positive labor demand shocks for sectors such as Retail Trade, and Information in March 2020 that vanish in April 2020. We show that our estimates of supply shocks are correlated with sectoral measures of telework.

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1 Introduction

The on-going COVID-19 outbreak and subsequent health policy response have caused widespread disruption in most economies. On one hand, authorities around the world have enforced containment and mitigation measures that entailed the supervised shutdown of entire sectors of their economies. On the other hand, in face of health safety uncertainty, agents voluntarily self-impose social distancing. There are many aspects that make studying this combined shock interesting. First, its unprecedented and unexpected nature and the fact that it combined features that are traditionally associated with both demand and supply shocks. Second, the fact that its effect across sectors in the economy was extremely heterogeneous, with some industries shutting down almost completely (such as movie theaters), while others potentially benefiting from increased demand (such as general merchandise retailers). For many, it is not clear whether this is mostly a demand or a supply shock.

This note attempts to contribute to answering that question by constructing estimates of labor demand and supply shocks at the sectoral level. We apply the methodology proposed by Baumeister and Hamilton (2015) and use Bayesian structural vector autoregressions (SVAR) to model the joint dynamics of real wages and hours worked for each 2-digit NAICS sector of the US economy, as well as for total private employment. Combined with informative priors on labor demand and supply elasticities, we use sign restrictions to identify and estimate sequences of structural demand and supply shocks. Our latest estimates are for April 2020, the month in which the controlled shutdown of the US economy began.

For April 2020, we find that total private employment was subject to negative supply and demand shocks totaling −16.24 percentage points, with supply accounting for 68.83% of this decrease. This means that total private employment grew by 16.04 percentage points less than its historical average in April 2020 (non-annualized), and that two-thirds of this negative growth was attributed to a negative labor supply shock. While most sectors that we consider were subject to negative supply shocks in this period, there is some heterogeneity in the size of both demand and supply shocks. Leisure and Hospitality was by far the sector subject to a larger disruption (−9.55 pp in March, 59% of which was supply, −63.18 pp in April, 63% of which was supply). The least affected sectors were Utilities, Information, and Financial Activities. In fact, Information experienced positive demand shocks in March (+0.46 pp), and Utilities was the only sector with positive demand shocks in April (+1.173 pp).

Confinement measures such as lockdowns force people to stay at home, which prevents many from being able to perform their jobs (which cannot be done at home). The outbreak itself also induces people to stay at home, regardless of lockdown measures (Baek et al., 2020). Our econometric model captures these situations as negative labor supply shocks. On the other hand, these confinement measures also prevent people from engaging in the consumption of certain goods and services whose enjoyment requires some degree of physical contact. This results in lower product demand for some firms, which results in less labor demand. Additionally, the decline in personal incomes also leads to reductions in expenditure in other goods or services,

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regardless of the associated degree of physical contact. This can also lead to negative labor demand shocks in sectors that are not directly affected by the lockdown. Both of these economic forces are identified as negative labor demand shocks in our model. For that reason, we argue that, while conceptually different, there is a close relationship between "aggregate" demand and supply, and the measures of shocks that we estimate. We validate our shock identification estimates by showing that the estimated (negative) supply shocks in March 2020 and April 2020 are correlated to measures of sectoral exposure to confinement policies, such as the share of jobs that can be done at home in each sector.

Our paper relates to the emerging literature on the economic effects of the COVID-19 outbreak, especially to studies related to the nature of the shocks affecting multi-sector economies.[1] Baqaee and Farhi (2020) study the effects of the COVID-19 crisis in a disaggregated Keynesian model with multiple sectors, factors, and input-output linkages. They find that negative supply shocks are stagflationary and negative demand shocks are deflationary, which serves as the basis for our identification. Similar to us, del Rio-Chanona et al. (2020) perform a sectoral analysis of potential demand and supply shocks in the US economy. Their measure of exposure to supply shocks aggregates a remote labor index across occupations at the sector level, while their exposure to demand shocks is based on Congressional Budget Office estimates. Instead, we jointly measure demand and supply shocks using a unified econometric framework and a single source of data. Guerrieri et al. (2020) show that under certain assumptions in a model with multiple sectors and incomplete markets, supply shocks can have effects that resemble those of demand shocks (what they refer to as "Keynesian supply shocks"). The shocks we estimate are not structural under the lens of their economic model, which means that we cannot disentangle these from other types of demand shocks. Their insights suggest that we may be underestimating the size of supply shocks in our exercise. Finally, there is a new literature embedding epidemiology aspects in standard macroeconomic models, and where epidemics generate reductions in economic activity that would be captured by our framework as negative supply and demand shocks (Eichenbaum et al., 2020).

This note is organized as follows: section 2 describes the econometric framework, section 3 describes the data, section 4 presents the results from our historical decomposition exercise as well as some validation exercises, and section 5 concludes.

2 Methodology

We use the methodology proposed by Baumeister and Hamilton (2015) to identify labor supply and demand shocks in each industry sector $l \in L$. We use a structural vector autoregression (SVAR) to describe the joint dynamics of the growth rate of real wages Δw_t^l and the growth rate of hours worked Δh_t^l in a given sector. Let $\boldsymbol{y}_t^l = (\Delta w_t^l, \Delta h_t^l)$ be the 2×1 vector of observables. Then

[1]Examples include Danieli and Olmstead-Rumsey (2020), Barrot et al. (2020), Bodenstein et al. (2020) and Faria-e-Castro (2020).

the SVAR for sector l takes the form

$$\boldsymbol{A}^l \boldsymbol{y}_t^l = \boldsymbol{B}_0^l + \boldsymbol{B}^l(L)\boldsymbol{y}_{t-1}^l + \boldsymbol{\varepsilon}_t^l, \tag{1}$$

where $\boldsymbol{A}^l$ is a 2×2 matrix describing the contemporaneous relations, $\boldsymbol{B}_0^l$ is a 2×1 vector of constants, $\boldsymbol{B}^l(L) = \boldsymbol{B}_1^l + \boldsymbol{B}_2^l L + \boldsymbol{B}_3^l L^2 + \cdots + \boldsymbol{B}_m^l L^{m-1}$ are the 2×2 matrices associated with each lag of $\boldsymbol{y}_t^l$, and $\boldsymbol{\varepsilon}_t^l$ is a 2×1 vector of structural shocks that are assumed to be i.i.d. $N(0, \boldsymbol{D})$ and mutually uncorrelated ($\boldsymbol{D}$ is diagonal).

Let $\boldsymbol{\varepsilon}_t^l = (\varepsilon_{d,t}^l, \varepsilon_{s,t}^l)$, so that the first equation corresponds to labor demand and the second equation to labor supply. We assume that the contemporaneous relation matrix $\boldsymbol{A}^l$ takes the form

$$\boldsymbol{A}^l = \begin{bmatrix} -\beta^l & 1 \\ -\alpha^l & 1 \end{bmatrix}, \tag{2}$$

where β^l is interpreted as the elasticity of labor demand and α^l as the elasticity of labor supply in sector l. We normalize these parameters so that they are interpreted as elasticities of the growth rate of hours with respect to the growth rate of real wages.

Given this, the labor market demand and supply equations in sector l are given by

$$\Delta h_t^l = b_{10}^{d,l} + \beta^l \Delta w_t^l + \sum_{i=1}^{m} b_{11}^{i,d,l} \Delta w_{t-i}^l + \sum_{i=1}^{m} b_{12}^{i,d,l} \Delta h_{t-i}^l + \varepsilon_{d,t}^l \tag{3}$$

$$\Delta h_t^l = b_{20}^{s,l} + \alpha^l \Delta w_t^l + \sum_{i=1}^{m} b_{21}^{i,s,l} \Delta w_{t-i}^l + \sum_{i=1}^{m} b_{22}^{i,s,l} \Delta h_{t-i}^l + \varepsilon_{s,t}^l \tag{4}$$

It is important to emphasize that under this framework, the relative sizes of the impact of supply and demand shocks on equilibrium movements in the growth rate of hours depend crucially on the relative size of demand and supply elasticities. For example, assuming no intercepts and no lags, solving for the growth rates of hours and real wages yields

$$\Delta h_t^l = \left(\frac{1}{1 - \left(\frac{\alpha^l}{\beta^l}\right)^{-1}} \right) \varepsilon_{d,t}^l + \left(\frac{1}{1 - \frac{\alpha^l}{\beta^l}} \right) \varepsilon_{s,t}^l$$

$$\Delta w_t^l = \left(\frac{1/\beta^l}{\frac{\alpha^l}{\beta^l} - 1} \right) \varepsilon_{d,t}^l + \left(\frac{1/\beta^l}{1 - \frac{\alpha^l}{\beta^l}} \right) \varepsilon_{s,t}^l.$$

If we assume that demand is downward sloping and supply is upward sloping we have the standard result that, *ceteris paribus*, a positive shift in the demand curve makes equilibrium hours increase and wage increase, while, *ceteris paribus*, a positive shift in the supply curve makes hours rise and wages fall. That is, if $\beta^l < 0$ and $\alpha^l > 0$, then $\frac{\partial \Delta h_t^l}{\partial \varepsilon_{d,t}^l} > 0$ and $\frac{\partial \Delta h_t^l}{\partial \varepsilon_{s,t}^l} > 0$, while $\frac{\partial \Delta w_t^l}{\partial \varepsilon_{d,t}^l} > 0$ and

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$\frac{\partial \Delta w_t^l}{\partial \varepsilon_{s,t}^l} < 0$. Moreover, note that the relative size effect of supply vs. demand shocks on employment and wages depend on the relative labor demand and supply elasticities $\frac{\alpha^l}{\beta^l}$. The flatter (steeper) is the supply curve relative to the demand curve, the weaker (stronger) is the relative impact a supply shock on hours, and the stronger (weaker) is its impact on real wages.[2]

The reduced-form VAR associated with the SVAR model (1) is given by

$$\boldsymbol{y}_t^l = \Phi_0^l + \Phi^l(L)\boldsymbol{y}_{t-1}^l + \boldsymbol{u}_t^l, \tag{5}$$

where

$$\begin{aligned}
\Phi_0^l &= (\boldsymbol{A}^l)^{-1}\boldsymbol{B}_0^l \\
\Phi^l(L) &= (\boldsymbol{A}^l)^{-1}\boldsymbol{B}^l(L) \\
\boldsymbol{u}_t^l &= (\boldsymbol{A}^l)^{-1}\boldsymbol{\varepsilon}_t^l && (6) \\
E[\boldsymbol{u}_t^l(\boldsymbol{u}_t^l)'] = \Omega &= (\boldsymbol{A}^l)^{-1}\boldsymbol{D}((\boldsymbol{A}^l)^{-1})' && (7)
\end{aligned}$$

We assume that prior beliefs about the values of the structural parameters are represented by a joint density $p(\boldsymbol{A}, \boldsymbol{D}, \boldsymbol{B})$. We then revise these beliefs when confronting them with sectoral data in our sample $\boldsymbol{Y}_T = (\boldsymbol{y}_1, \boldsymbol{y}_2, \cdots, \boldsymbol{y}_T)$. Importantly, Baumeister and Hamilton (2015) show how these beliefs can be updated for any arbitrary prior distribution $p(\boldsymbol{A})$. In principle this prior $p(\boldsymbol{A})$ could incorporate any combination of exclusion restrictions, sign restrictions, and informative prior beliefs about elements of $\boldsymbol{A}$.

Priors Following Baumeister and Hamilton (2015), we use past studies to form informative priors about α^l and β^l. In particular, we impose sign restrictions on sectoral demand and supply elasticities – β^l is negative and α^l is positive – and that they fall somewhere in the range of the literature estimates for the aggregate economy. Lichter et al. (2015), building on information from 151 different studies containing 1334 estimates in total, find that, except for Construction and Manufacturing, the labor demand elasticity does not seem to vary substantially across the remaining sectors we consider. For Construction and Manufacturing, they find a point difference of demand elasticity relative to the aggregate economy of -0.25 and -0.35, respectively. In addition, since the labor supply elasticity should primarily be a function of household behavior, there is no *a priori* reason to believe that it should vary significantly across industries. For that reason, we apply the same prior distribution $p(\boldsymbol{A})$ for all sectors in our sample.

The sign restriction reflects our belief that the labor demand curve should be downward sloping while the supply curve should be upward sloping. However, we do not place a uniform probability on all values that respect these sign restrictions. We assume a truncated Student's t

[2] Uhlig (2017) explicitly lays out all the basic assumptions required for identifying demand and supply shocks. There may be other shocks that shift both demand and supply; our framework is without loss of generality as long as those other shocks do not affect demand and supply in a systematic way.

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distribution for β^l with location parameter -0.6, scale parameter 0.6 and 3 degrees of freedom, so that we place 90% probability on values of β^l being in the range of $[-2.2, -0.1]$. This range reflects the labor demand elasticity estimates found in the micro and macro literatures[3]. In terms of the labor supply elasticity, based on the findings of Chetty et al. (2011), we also use a Student's t distribution for α^l with location parameter -0.6, scale parameter 0.6 and 3 degrees of freedom, so that we place 90% probability on values of α^l being in $[-2.2, -0.1]$ interval. This interval thus includes both the lower estimates reported by microeconometric estimates and by macro estimates when movements in wages are persistent, as well as the high Frisch elasticities reported by macro studies of the business cycle such as Smets and Wouters (2007). Since we use the same prior for both elasticities, we have an implicit prior belief that unit supply and demand shocks have an equal impact on hours.

Next, we define our conditional prior distributions $p(\boldsymbol{D}|\boldsymbol{A})$ and $p(\boldsymbol{B}|\boldsymbol{A}, \boldsymbol{D})$ specifications. For the elements of the diagonal matrix $\boldsymbol{D}$, we assume that their reciprocal (the precision of the structural shocks) follow a gamma distribution with shape parameter κ_i and scale parameter τ_i. We set κ_i to $2, \forall i = \{d, s\}$, which puts a small weight on our prior of just 4 months of data, and set the scale parameter τ_i so that the the prior mean of each element $\frac{\kappa_i}{\tau_i}$ matches the precision of the structural shocks after orthogonalization of univariate autoregressions with 4 lags under $\boldsymbol{A}$. That is, $\tau_i = \kappa_i a_i' \hat{\boldsymbol{S}} a_i$, where $\hat{\boldsymbol{S}}$ is the variance-covariance of the univariate residuals series. With this setting, $p(\boldsymbol{D}|\boldsymbol{A})$ is just the product of the two gamma distributions. Finally, $p(\boldsymbol{B}|\boldsymbol{A}, \boldsymbol{D})$ is set in a way that conforms with the Bayesian VAR Minnesota priors (Doan et al. (1984) and Sims and Zha (1998)) on the reduced-form coefficients Φ. Note that placing a prior on the reduced-form coefficients and conditioning on $\boldsymbol{A}$ implicitly places a prior on $\boldsymbol{B}$ because $\boldsymbol{B} = \boldsymbol{A}\Phi$. Hence the normally distributed coefficients b_i have mean a_i for elements corresponding to own lags and zero to all others. Moreover, our beliefs place a higher degree of certainty that higher lags should be zero. We follow Baumeister and Hamilton (2015) and set the hyperparameter $\lambda_0 = 0.2$ which controls the overall tightness of the prior, $\lambda_1 = 1$ that governs how quickly the prior for lagged coefficients tightens to zero for higher lags, and $\lambda_3 = 100$ which places essentially zero weight on the prior when estimating $\boldsymbol{B}_0$. The joint prior distribution is then given by:

$$p(\boldsymbol{A}, \boldsymbol{D}, \boldsymbol{B}) = p(\boldsymbol{A})p(\boldsymbol{D}|\boldsymbol{A})p(\boldsymbol{B}|\boldsymbol{A}, \boldsymbol{D}) \tag{8}$$

Estimation Based on the Akaike information criterion, we set the number of lags to $m = 4$. We then use Bayesian methods to update our prior beliefs given the data $\boldsymbol{Y}_T$. Baumeister and Hamilton (2015) show that the posterior can be written as

$$p(\boldsymbol{A}, \boldsymbol{D}, \boldsymbol{B}|\boldsymbol{Y}_T) = p(\boldsymbol{A}|\boldsymbol{Y}_T)p(\boldsymbol{D}|\boldsymbol{A}, \boldsymbol{Y}_T)p(\boldsymbol{B}|\boldsymbol{A}, \boldsymbol{D}, \boldsymbol{Y}_T). \tag{9}$$

[3] Hamermesh (1996) provides a survey of microeconometric estimates of labor demand elasticity and finds them to be between -0.15 and -0.75, while Lichter et al. (2015) find that 80% of the estimates are between 0 and -1. Some macro studies such as Akerlof and Dickens (2007) or Galí et al. (2012) find that the labor demand elasticity can be -2.5 or even higher.

The conditional posterior on the structural coefficients $\boldsymbol{B}$ is a multivariate normal density because of natural conjugacy, and the updating follows the standard convex combination of prior means and OLS estimates where the weights are based on the relative precision of the prior mean versus OLS estimates of the reduced-from representation (5) and (7). Also because of natural conjugacy, the conditional posterior $p(\boldsymbol{D}|\boldsymbol{A}, \boldsymbol{Y}_T)$ is also a gamma distribution. Finally, $p(\boldsymbol{A}|\boldsymbol{Y}_T)$ does not have a known distribution and we use a random-walk Metropolis-Hastings algorithm to draw from it.

Identification Note that given (6), structural demand and supply shocks are only set identified, reflecting uncertainty regarding the labor elasticities that can be summarized by $p(\boldsymbol{A}|\boldsymbol{Y}_T)$. We do not impose any long-run restrictions. The final identified set is a function of our specified prior beliefs and data on the growth rates of hours and real wages. It is worth remarking that, as shown by Baumeister and Hamilton (2015), prior beliefs about $\boldsymbol{A}$ will not vanish asymptotically.

3 Data

Our main source of data is the Current Employment Statistics (CES) database from the Bureau of Labor Statistics, from where we obtain monthly real wages and hours worked by sector from March 2006 to April 2020[4]. The CES provides data for 14 main aggregate sectors: total private, mining and logging, construction, manufacturing, wholesale trade, retail trade, transportation and warehousing, utilities, information, financial activities, professional and business services, education and health services, leisure and hospitality, and other services. For each sector, we compute the monthly growth rate for real wages as the log-difference of monthly average hourly earnings of all employees in 1982-1984 dollars. The growth rate of hours worked in a given sector is computed by taking the log-difference of aggregate weekly hours of all employees in that sector. Given the unprecedented nature of the shocks, and as we discuss in more detail in the following section, we estimate the SVAR using data until February 2020 and excluding the last two months in the sample. We use the model estimated until February 2020 to perform a historical decomposition of the shocks in these last two months.

We also rely on the measure constructed by Dingel and Neiman (2020) using survey data from the Occupational Information Network (O*NET) for how feasible it is to perform work at home for each sector.

4 Results

Posteriors Figure 8 in the Appendix plots the prior distribution for the demand α^l and supply β^l elasticities (red line) as well as a histogram of posterior draws (blue bars). For most sectors

[4]Section A in the appendix provides further details on the data and sector classification.

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the beliefs about the elasticities are greatly revised upwards, towards the macro literature estimates. This revision is particularly strong in the Leisure and Hospitality, and Utilities sectors. Likewise, in absolute value the demand elasticities are mostly revised upwards, especially in the Construction and Leisure and Hospitality sectors. Hence, we conclude that our identification of supply and demand shocks is strongly influenced by the data.

Historical Decompositions Figures 9 and 10 perform a historical decomposition of the growth rate of hours by sector, plotting the estimated sequences of demand and supply shocks for each sector back to the beginning of 2006 (without and with the months of March and April 2020, respectively). Figure 1 focuses on Total Private and Leisure and Hospitality. The top panels exclude March and April 2020, which as we will explain, were historically large shocks. These top panels show that the growth rate of hours was subject to large negative shocks both to demand and to supply during the period corresponding to the Great Recession. Consistent with standard narratives, the Great Recession begins with negative demand shocks in late 2007 and early 2008. Starting in late 2008 we also identify large negative labor supply shocks, which is consistent with a large literature on labor markets during this period (Elsby et al., 2010). The bottom panels include March and April 2020, showing that the magnitude of these shocks dwarf anything experienced during the Great Recession (particularly April).

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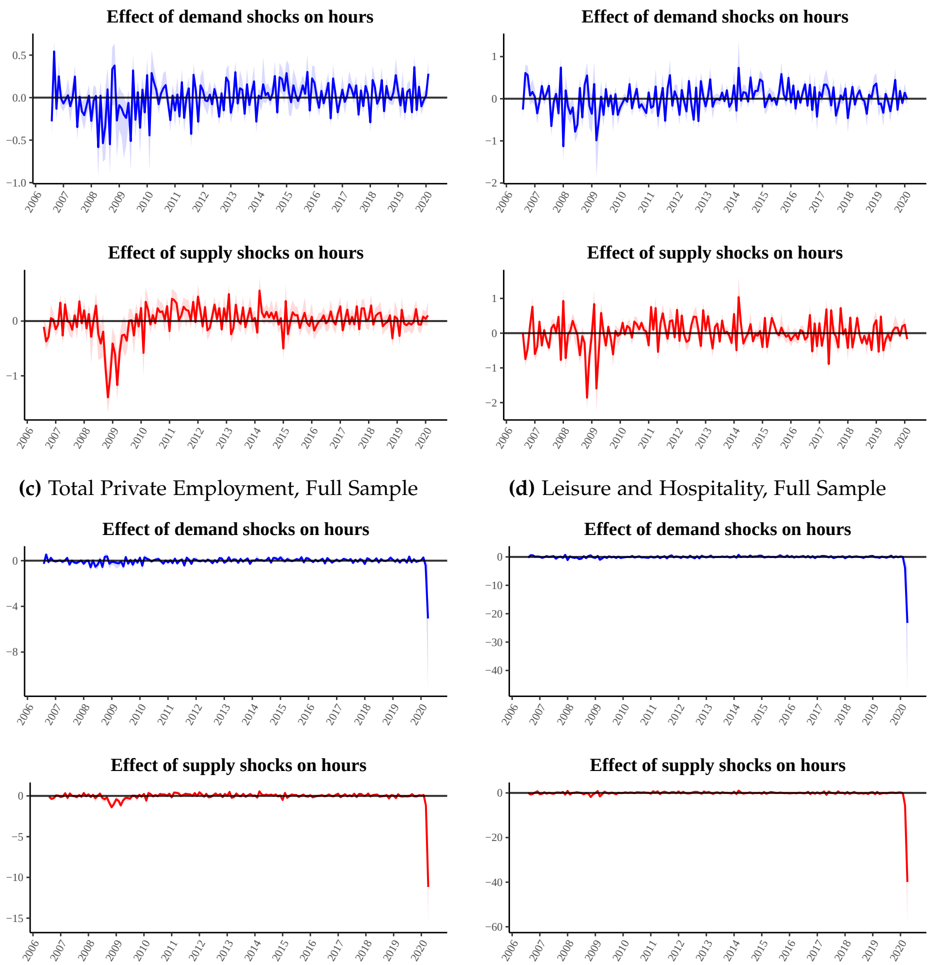
Figure 1: Historical decomposition of the growth rate of hours: Total Private Employment, Leisure and Hospitality



(a) Total Private Employment until February 2020 **(b)** Leisure and Hospitality until February 2020

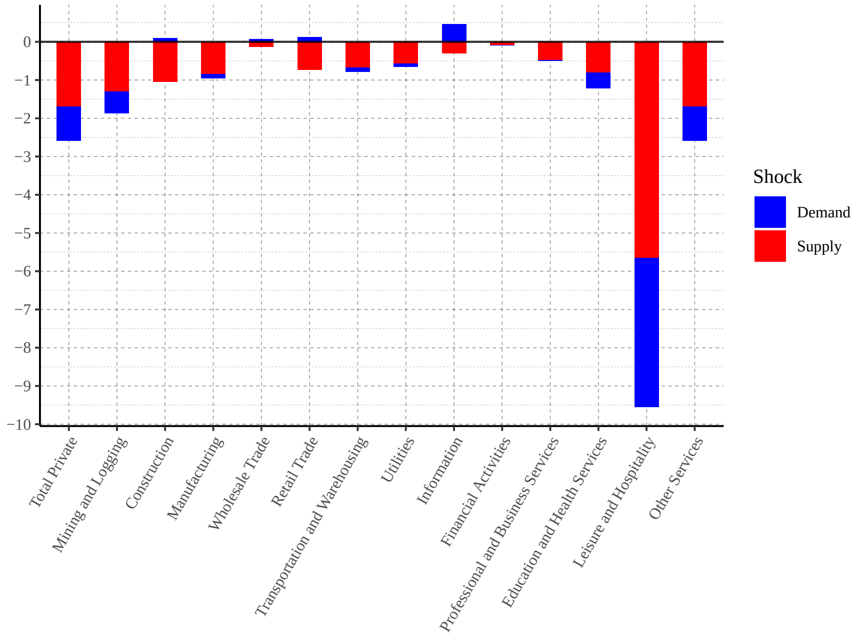
(c) Total Private Employment, Full Sample **(d)** Leisure and Hospitality, Full Sample

4.1 The Great Lockdown: March and April 2020

We now take a closer look at the results for the month of March 2020. Figures 2 and 3 are our main set of results and plot estimated median demand and supply shocks across sectors for the months of March and April, respectively. Tables 1 and 2 report the median values and 95% credible intervals for these shocks. The combined negative effect of supply and demand on the

growth rate of hours for total private employment was −2.59 pp in March and −16.24 in April.[5] Negative supply shocks accounted for 64.8% and 68.8% of these effects, respectively.

Figure 2: Historical decomposition of the growth rate of hours by sector in March 2020



[5] This is the effect on the monthly growth rate, and is not annualized.

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Figure 3: Historical decomposition of the growth rate of hours by sector in April 2020

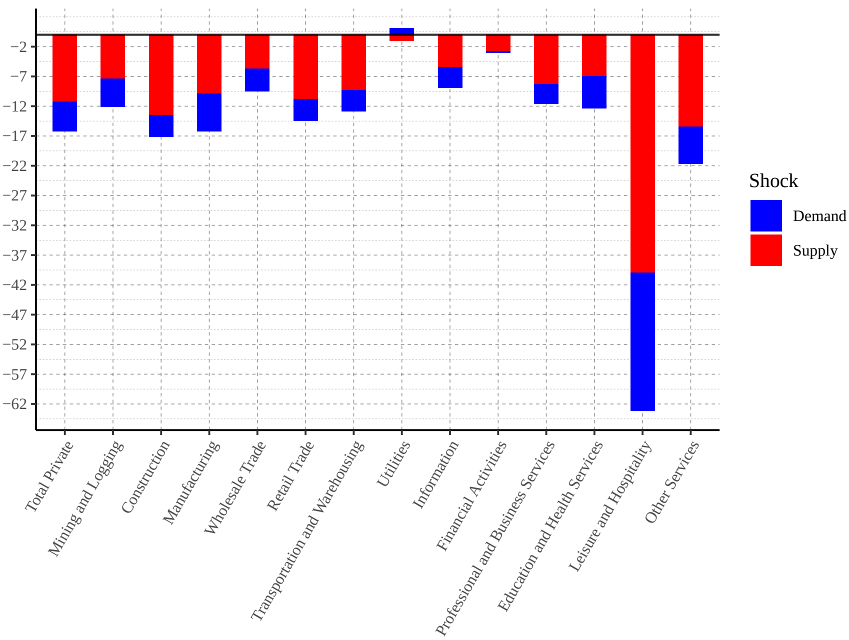

Table 1: Median and 95% credible interval of the effects of demand and supply shocks on the growth rate of hours, March 2020

	Demand			Supply		
Sector	Median	2.5p	97.5p	Median	2.5p	97.5p
Total Private	-0.43	-1.05	-0.02	-1.18	-1.62	-0.56
Mining and Logging	-0.57	-1.44	-0.01	-1.30	-2.14	-0.44
Construction	0.10	-0.37	0.36	-1.05	-1.45	-0.57
Manufacturing	-0.12	-0.64	0.17	-0.83	-1.27	-0.30
Wholesale Trade	0.08	-0.06	0.16	-0.14	-0.29	0.00
Retail Trade	0.12	-0.18	0.38	-0.73	-0.99	-0.43
Transport & Warehousing	-0.12	-0.53	0.12	-0.66	-0.95	-0.27
Utilities	-0.09	-0.55	0.20	-0.57	-0.87	-0.12
Information	0.47	0.26	0.63	-0.30	-0.46	-0.08
Financial Activities	-0.01	-0.12	0.10	-0.07	-0.19	0.03
Prof. and Business Services	-0.01	-0.23	0.07	-0.48	-0.66	-0.24
Education and Health	-0.42	-1.00	0.00	-0.79	-1.22	-0.21
Leisure and Hospitality	-3.91	-7.39	-0.75	-5.64	-8.80	-2.16
Other Services	-0.91	-1.85	-0.13	-1.68	-2.47	-0.74

Table 2: Median and 95% credible interval of the effects of demand and supply shocks on the growth rate of hours, April 2020

	Demand			Supply		
Sector	Median	2.5p	97.5p	Median	2.5p	97.5p
Total Private	-5.06	-11.28	-0.31	-11.18	-15.94	-4.97
Mining and Logging	-4.78	-9.50	-0.84	-7.34	-11.32	-2.62
Construction	-3.65	-12.78	-0.32	-13.47	-16.82	-4.33
Manufacturing	-6.36	-12.93	-1.14	-9.89	-15.13	-3.32
Wholesale Trade	-3.82	-8.23	-0.37	-5.66	-9.10	-1.25
Retail Trade	-3.65	-9.25	-0.04	-10.82	-14.43	-5.23
Transport. & Warehousing	-3.61	-9.06	-0.01	-9.26	-12.85	-3.81
Utilities	1.17	0.41	1.49	-1.08	-1.40	-0.32
Information	-3.51	-6.95	-0.63	-5.39	-8.26	-1.95
Financial Activities	-0.34	-2.00	0.52	-2.72	-3.59	-1.05
Prof. and Business Services	-3.29	-8.05	-0.15	-8.31	-11.44	-3.53
Education and Health	-5.47	-10.77	-0.63	-6.92	-11.76	-1.62
Leisure and Hospitality	-23.26	-46.70	-3.63	-39.92	-59.55	-16.47
Other Services	-6.32	-14.23	-0.48	-15.39	-21.24	-7.47

Figures 2 shows considerable heterogeneity in sectoral exposure to supply and demand shocks. In terms of total exposures, Leisure and Hospitality is the most negatively affected sector, with a combined effect of -9.55 of which 59% is supply. While most sectors receive negative supply shocks, the size of these shocks is very heterogeneous. The least affected sectors are Wholesale Trade (-0.06 pp), Financial Activities (-0.09 pp), and Information (+0.16 pp). Retail Trade, Wholesale Trade, and Construction experience very small positive demand shocks. The most significant demand shock is to Information (+0.46 pp). These results are consistent with the narrative regarding the beginning of the lockdown: high physical-contact services, concentrated on Leisure and Hospitality (and Other Services) experience large negative shocks to both demand and supply. As agents shift their consumption patterns, sectors such as Retail Trade and Wholesale Trade could partly benefit. Finally, the Information sector benefits from a boost of demand as many firms increase their demand for technology services to implement telework arrangements. For comparison, Figure 11 performs the same decomposition but one year earlier, in March 2019, a "normal" period. For March 2019, we find a completely different pattern of shocks, of much smaller magnitudes.

Figure 3 shows the shock decomposition or April, the first full month of lockdown. Note that the scale is very different, reflecting the much larger magnitude of the shocks: Total Private employment receives a combined negative shock of -16.24 pp in the growth rate of hours, of which 68.8% is attributable to supply. Leisure and Hospitality is by far the most affected sector, as before, with a total shock of -63.17 pp of which 63% is supply. This is to be expected for a sector that relies substantially in physical contact-intensive activities. The negative labor supply shock results from lockdown measures that prevent workers from actually going to work, while

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the negative labor demand shock results from consumers not undertaking those activities. It should also be noted that other service sectors such as Education and Health Services or Other Services also experienced negative supply and demand shocks on par with those experienced during the Great Recession, even if those shocks do not look very large when compared to the shocks in other sectors.

Note that, now, essentially all sectors in the economy are negatively affected including sectors that had experienced positive shocks in March (such as Information). The least affected sectors are Utilities (+0.09 pp), Financial Activities (−3.06 pp), and Information (−8.89 pp). As we show in the next section, these are sectors where a high percentage of jobs can be done at home. The supply/demand composition is overall similar across sectors. The sectors where demand was more relevant were Manufacturing (40%), Information (40%) and Education and Health Services (45%). This is consistent with the idea that even sectors that are not necessarily exposed to the lockdown measures can be affected by a fall in aggregate demand.

Decomposition by Subsector Figure 4 performs the same decomposition for selected subsectors in March 2020.[6] It clearly shows the shifting of consumption patterns in the early stages of the lockdown: Food services and drinking places, and Acommodation experienced large negative supply and demand shocks. In the case of Food services and drinking places, the demand shock was larger than the supply shock. As people switched their food consumption patterns, Food and Beverage sectors experienced a positive demand shock, while Food manufacturing experienced very small shocks. Also note that Air Transportation seems to have experienced positive demand and supply shocks, as the collapse in passenger air travel was not yet visible in the March BLS statistics.

[6] April 2020 data for subsectors was not yet available at the time this draft was written.

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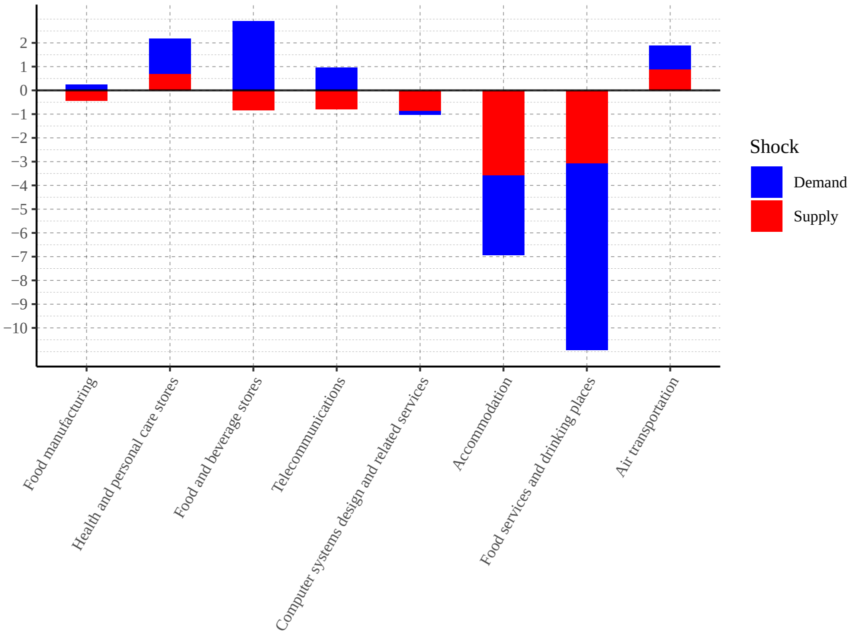
Figure 4: Historical decomposition of the growth rate of hours for selected subsectors in March 2020



4.2 Challenges posed by COVID-19

The sheer size of shocks during the COVID-19 pandemic can pose challenges to our exercise for a number of reasons. First, it can threaten the assumption of Gaussian errors that is essential for constructing the likelihood function. Second, it can make the residuals non-stationary, thus rendering the Wold decomposition invalid. Third, it can put into question the assumption of linearity due to either a structural break or because large shifts in supply and demand curves may push them into a region where their elasticities are no longer constant.

We address the first and second concerns by estimating the model excluding the COVID-19 periods (March and April 2020). The third issue, regarding linearity, is harder to address. We choose to treat the unknown nonlinear mechanics as unknown at the moment and hence as part of the shock. Moreover, identifying the structural break or nonlinear structure is impossible given the size of the sample during the COVID-19 period. We attempt to assuage concerns regarding this third aspect by performing a validation exercise, in which we argue that our identified shock series correlate with externally measured series such as a telework index.

One challenge to our identification assumptions (that is not directly related to the econometric model per se) is related to composition effects and heterogeneous exposure of occupations to the demand and supply shocks. A situation where a negative labor demand shock leads to the

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destruction of mostly low wage jobs is consistent with a fall in the number of hours and an increase in the average real wage, which could be captured as a supply shock.[7] The only way to address this issue is to control for wage heterogeneity across sectors, which we partly do by separately estimating shocks for different sectors.

Finally, the CES data for March and April is only preliminary at the moment and the BLS has reported that data collection during these months for the CES surveys was impacted by the coronavirus. We can expect data for these months to be revised in the future and we will update our estimates as data gets revised.

4.3 Validating the Results: share of jobs that can be performed from home by sector

If confinement measures are empirically meaningful for labor supply, we should expect that the labor supply shocks we identify be positively correlated with the possibility for workers to perform their tasks from home. In Figure 5 we plot our estimated supply shocks (y-axis) for April against the share of jobs that can be done at home by sector (x-axis). Panel (a) confirms that to be the case. Leisure and Hospitality, the sector with the smallest share of jobs that can be performed from home, was precisely the sector that was hit the hardest by a negative labor supply shock. Sectors where such share is higher endured smaller labor supply shocks, such as Financial activities, and Information. Despite the small number of observations, the relationship is statistically significant at the 5% level ($p-val = 0.043$) and the share of workers that can perform their job at home per sector explains more than half of the variation ($R^2 = 0.57$). Note also that this relationship is robust to excluding the Labor and Hospitality sector from the analysis (see panel (c), where we remove this sector). Panel (b) shows that there is also some correlation between the share of jobs that can be done at home and the estimated demand shock in March 2020, but panel (d) shows that this correlation vanishes once we remove Labor and Hospitality.

Furthermore, the relationship between this measure and the supply shocks is consistently stronger than that with demand shocks, even when we remove Leisure and Hospitality (which experienced both the largest demand and the largest supply shock during this period).

We repeat the analysis for April 2020 (see figure 6). As expected, the linear impact of the share of jobs that can be performed from home is now almost one order of magnitude larger (3.9 vs 27) as confinement measures were now in full effect; the correlation is even more significant and so is the share of variation explained.

We perform another validation exercise by performing the same comparison but with supply shocks a year earlier, in March and April of 2019. Figure 7 shows that the statistically significant and positive correlation vanishes when this measure is compared to supply shocks estimated during a "normal" period.

[7] Mongey et al. (2020) document that workers predicted to be employed in low work-from-home jobs tend to have lower income and experienced greater declines in employment according to the March 2020 CPS.

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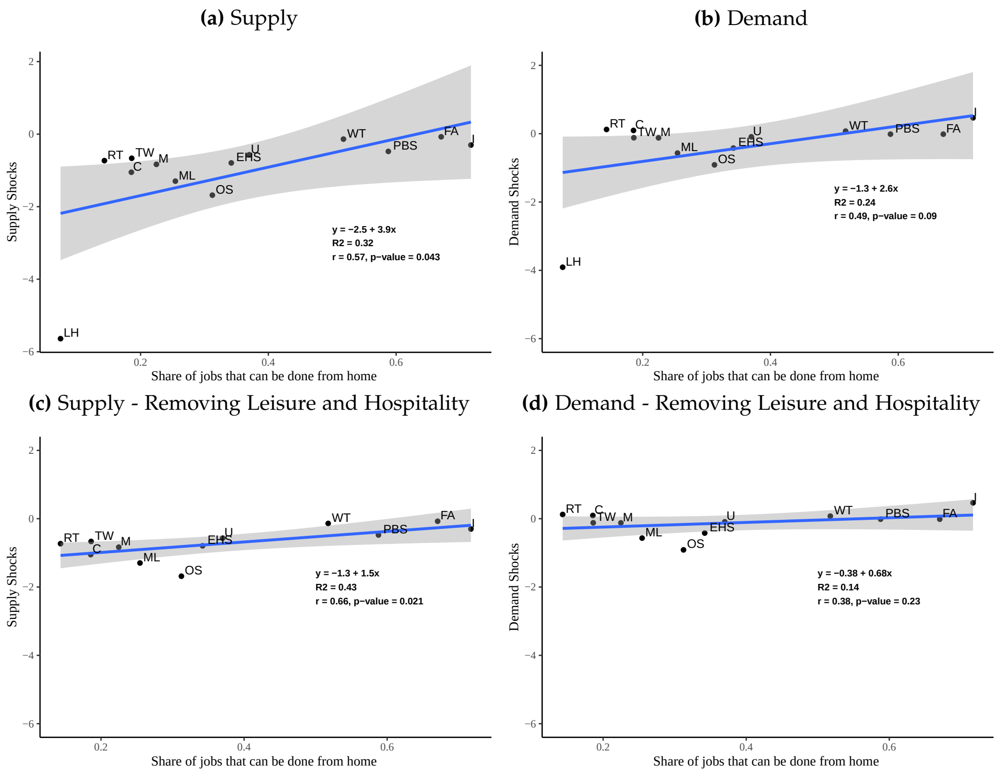
Figure 5: Correlation between sectoral shocks in March 2020 and sectoral share of jobs that can be done at home



ML: Minning and logging; **C**: Construction;**M**: Manufacturing; **WT**: Wholesale trade; **RT**: Retail trade; **TW**: Transportation and warehousing; **U**: Utilities; **I**: Information; **FA**: Financial activities; **PBS**: Professional and business services; **EHS**: Education and health services; **LH**: Leisure and hospitality; **OS**: Other services. Grey bands represent 95% confidence intervals.

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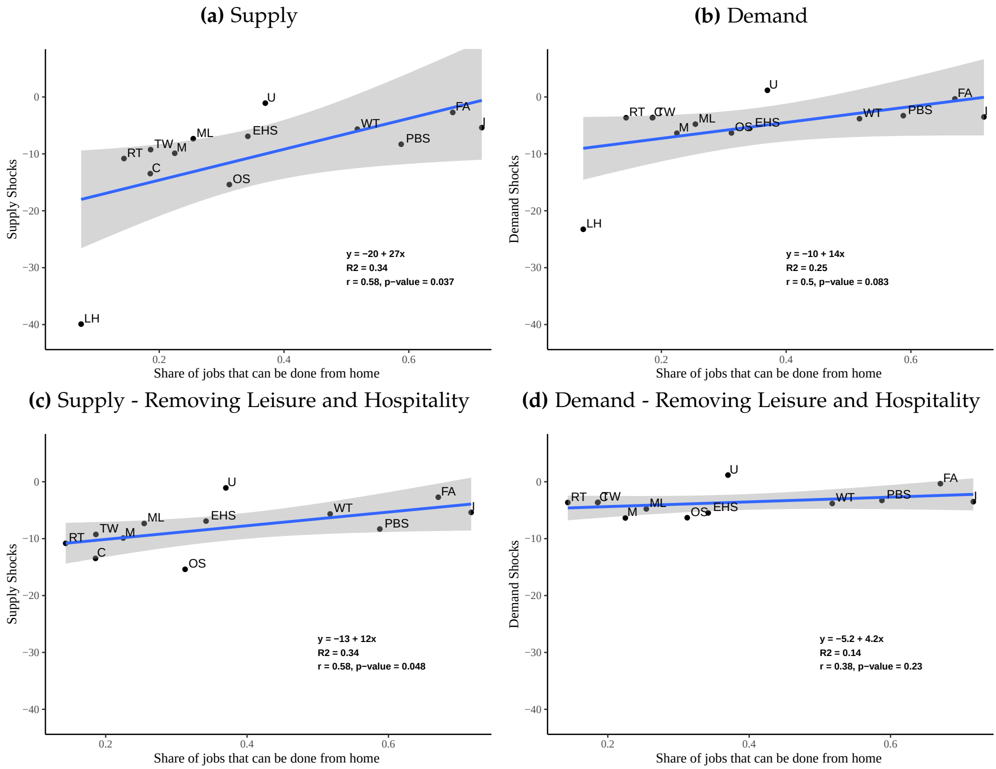
Figure 6: Correlation between sectoral shocks in April 2020 and sectoral share of jobs that can be done at home



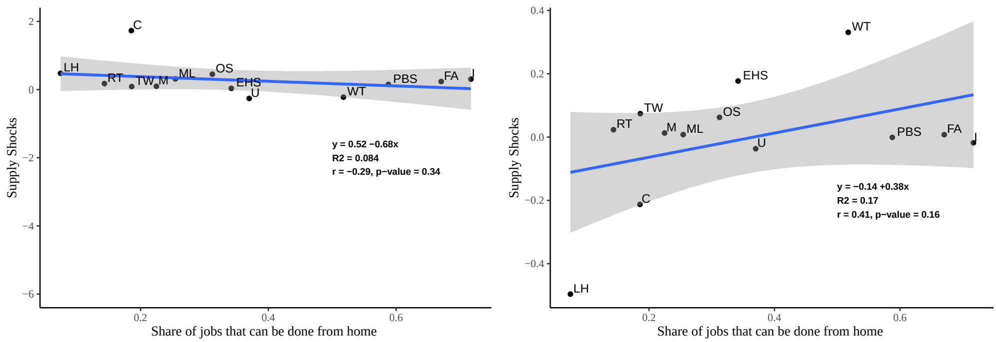
ML: Minning and logging; **C**: Construction;**M**: Manufacturing; **WT**: Wholesale trade; **RT**: Retail trade; **TW**: Transportation and warehousing; **U**: Utilities; **I**: Information; **FA**: Financial activities; **PBS**: Professional and business services; **EHS**: Education and health services; **LH**: Leisure and hospitality; **OS**: Other services. Grey bands represent 95% confidence intervals.

5 Discussion

In this note, we estimated Bayesian SVARs on the growth rates of hours worked and real wages for each major sector of the US economy. Our identification strategy, based on sign restrictions and informative priors, allowed us to estimate sequences of labor supply and demand shocks for each sector. Focusing on the on-going COVID-19 outbreak, we found that two-thirds of the fall in the growth rate of hours worked in March and April 2020 could be attributed to negative labor supply shocks. Most NAICS-2 sectors were subject to negative labor supply and demand shocks. One sector in particular – Leisure and Hospitality – was subject to historically large negative supply and demand shocks. Other sectors, such as Information and Retail Trade, experienced negligible supply shocks and, in some cases, positive demand shocks. We showed

Figure 7: Supply Shocks in 2019 vs. Share of jobs that can be done from home

(a) March 2019 **(b)** April 2019



ML: Minning and logging; **C**: Construction;**M**: Manufacturing; **WT**: Wholesale trade; **RT**: Retail trade; **TW**: Transportation and warehousing; **U**: Utilities; **I**: Information; **FA**: Financial activities; **PBS**: Professional and business services; **EHS**: Education and health services; **LH**: Leisure and hospitality; **OS**: Other services. Grey bands represent 95% confidence intervals.

that the size of our estimated supply shocks correlates positively with other measures, such as the fraction of jobs in each sector that can be performed from home.

This piece of research is work in progress, and we expect to update it as more BLS data becomes available in the coming months. We believe that identifying the nature of the shocks that hit each sector is relevant for the design of policy interventions: while negative labor demand and supply shocks arising from social distancing and other confinement measures are a feature of the public health policy response, the resulting fall in aggregate income can cause demand to be inefficiently low in other sectors (Guerrieri et al., 2020; Faria-e-Castro, 2020), which is something that could be addressed with targeted fiscal or credit policies, for example. We hope to address these topics in future iterations of this note.

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Appendix

A Data sources and sectors classification

We use the Current Employment Statistics (CES) database from the Bureau of Labor Statistics (BLS) to obtain monthly average hourly earnings of all employees in 1982-1984 dollars (CES code: 13) and aggregate weekly hours of all employees (CES code: 56). The data starts in March 2006 and goes until April 2020, and all series are seasonally adjusted. Table 3 lists all used CES industry classifications as well as the associated NAICS codes.

Table 3: CES industry classification

Sector	BLS Code	NAICS Code
Total private	05000000	-
Mining and logging	10000000	11-21
Construction	20000000	23
Manufacturing	30000000	31-33
Wholesale trade	41420000	42
Retail trade	42000000	44-45
Transportation and warehousing	43000000	48-49
Utilities	44220000	22
Information	50000000	51
Financial activities	55000000	52-53
Professional and business services	60000000	54-56
Education and health services	65000000	61-62
Leisure and hospitality	70000000	71-72
Other services	80000000	81

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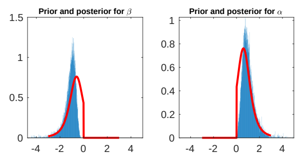
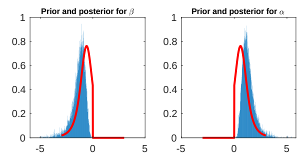
B Additional figures

Figure 8: Prior and posterior distribution of labor demand and supply elasticities by sector

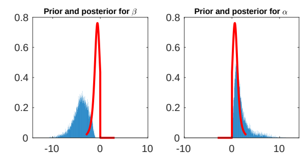
(a) Total Private



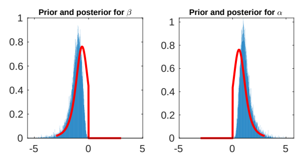
(b) Mining and Logging



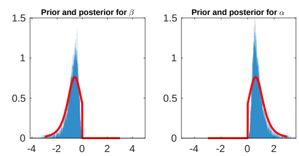
(c) Construction



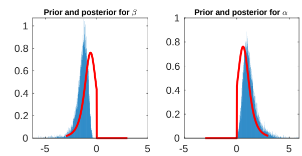
(d) Manufacturing



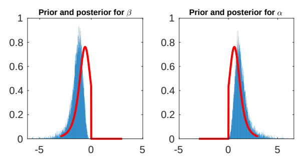
(e) Wholesale Trade



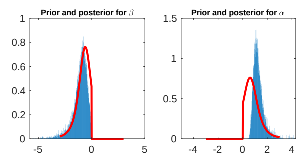
(f) Retail Trade



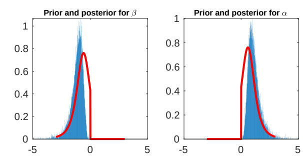
(g) Transportation and Warehousing



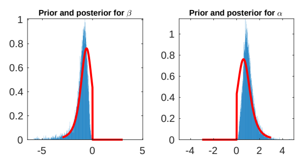
(h) Utilities



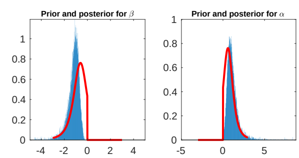
(i) Information



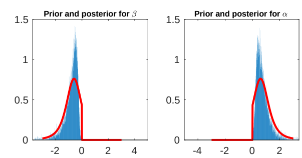
(j) Financial Activities



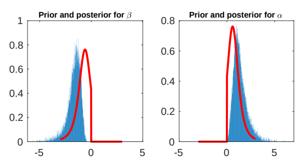
(k) Professional and Business Services



(l) Education and Health Services



(m) Leisure and Hospitality



(n) Other Services

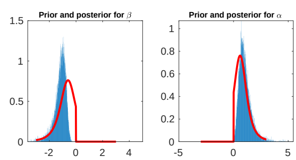


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Figure 9: Historical decomposition of the growth rate of hours by sector, excluding March and April 2020

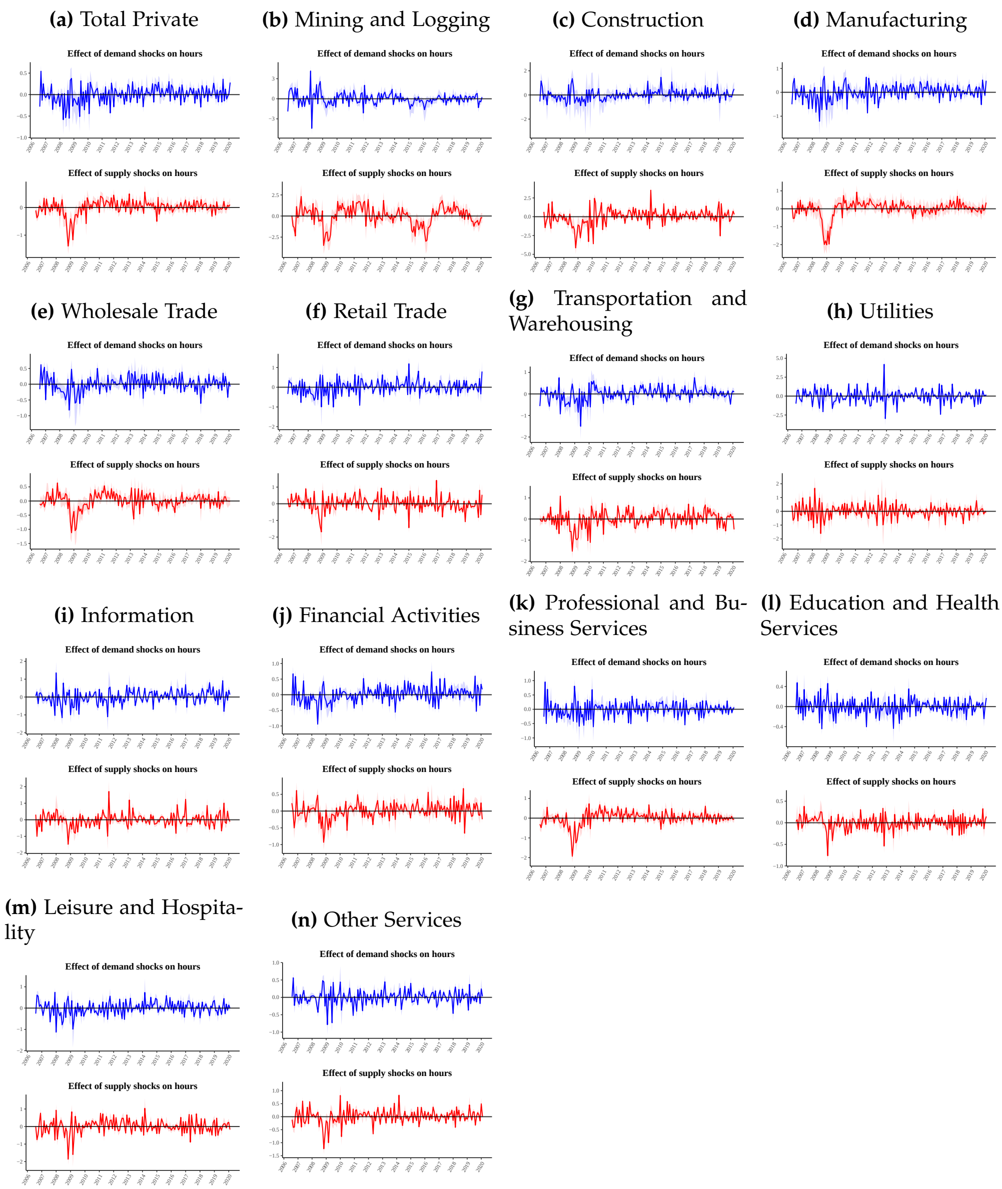
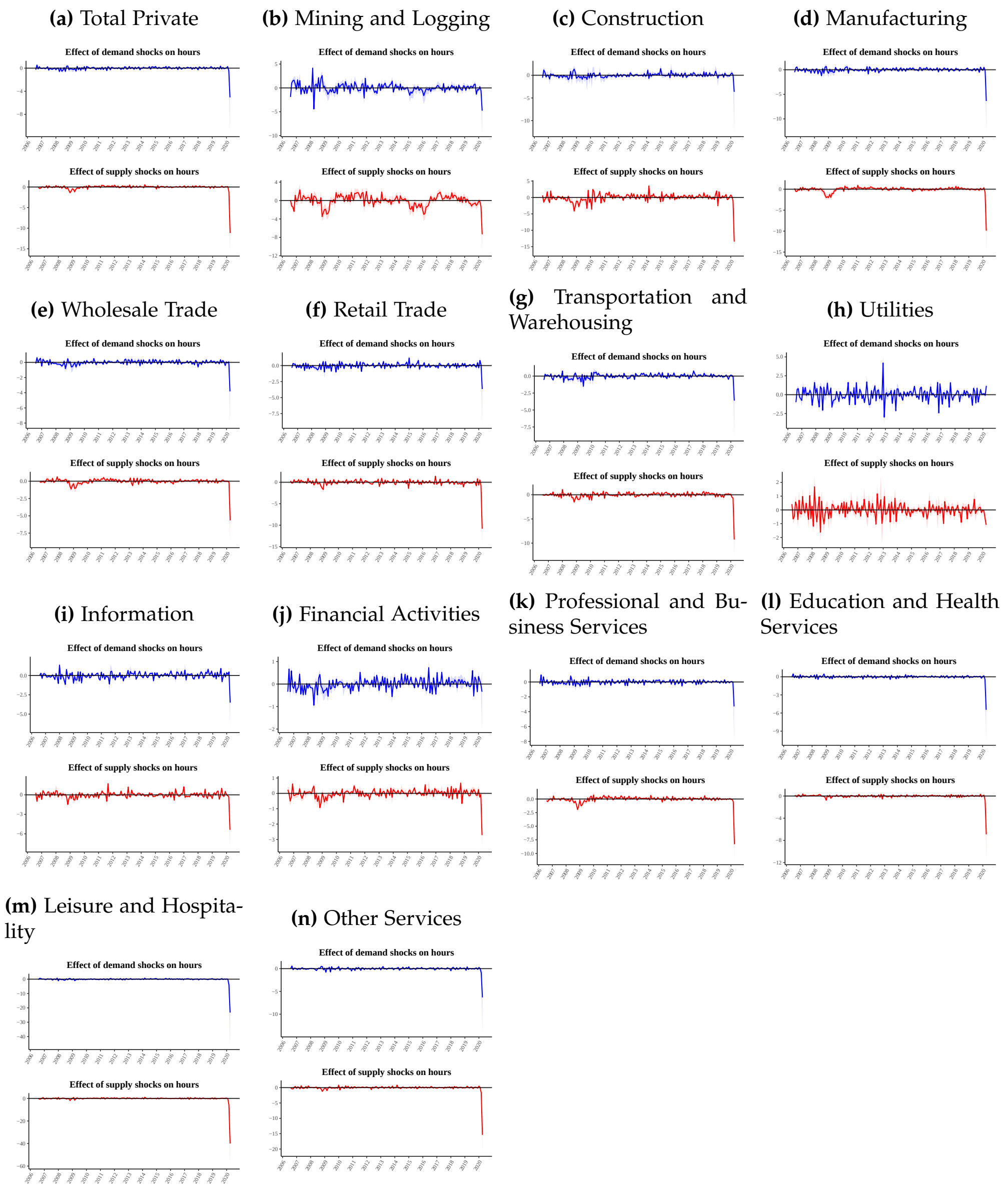


Figure 10: Historical decomposition of the growth rate of hours by sector, full sample



(a) Total Private **(b)** Mining and Logging **(c)** Construction **(d)** Manufacturing

(e) Wholesale Trade **(f)** Retail Trade **(g)** Transportation and Warehousing **(h)** Utilities

(i) Information **(j)** Financial Activities **(k)** Professional and Business Services **(l)** Education and Health Services

(m) Leisure and Hospitality **(n)** Other Services

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Figure 11: Historical decomposition of the growth rate of hours across sectors, March 2019