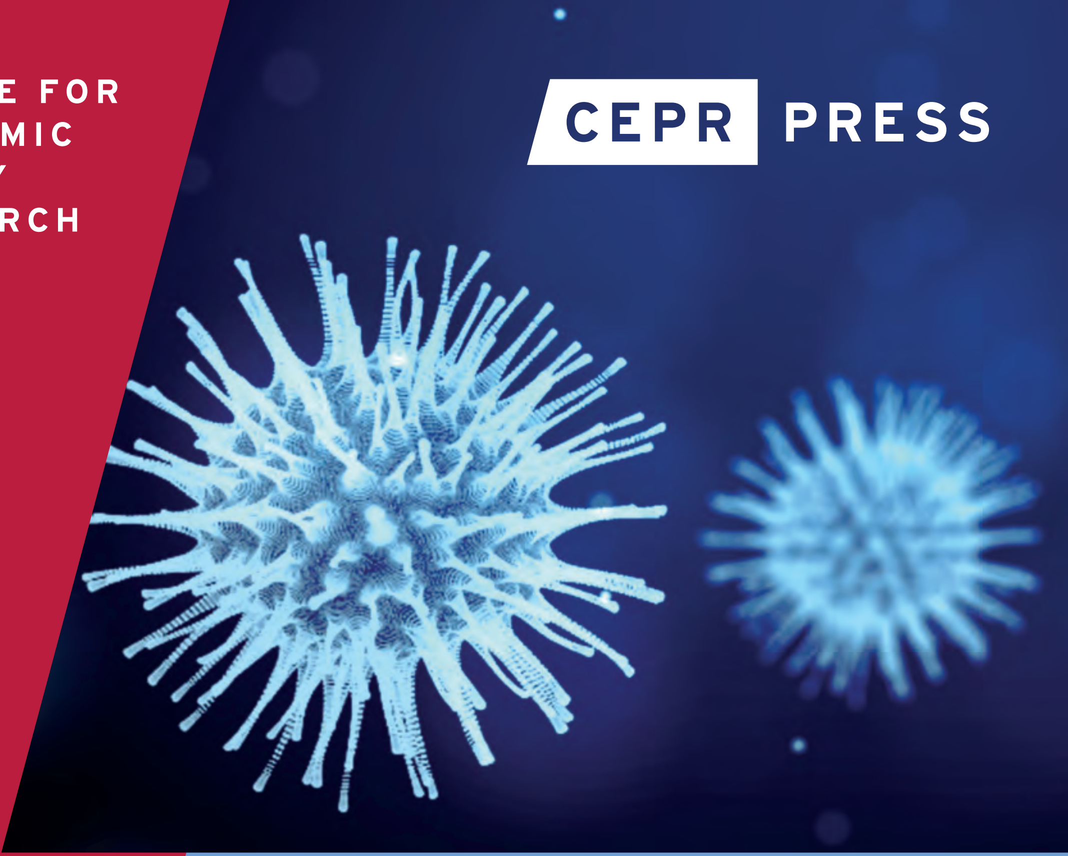
CENTRE FOR ECONOMIC POLICY RESEARCH

CEPR PRESS



COVID ECONOMICS

VETTED AND REAL-TIME PAPERS

ISSUE 28
12 JUNE 2020

EARLY IMPACT ON CONSUMPTION
Lindsay E. Relihan, Marvin M. Ward Jr., Chris W. Wheat and Diana Farrell

WHY ARE STOCK MARKETS DISCONNECTED?
Gunther Capelle-Blancard and Adrien Desroziers

WOMEN'S WORK BEFORE AND DURING COVID-19
Daniela Del Boca, Noemi Oggero, Paola Profeta and Maria Cristina Rossi

MENTAL HEALTH
James Banks and Xiaowei Xu

CONSUMPTION UNDER LOCKDOWN
Bruno P. Carvalho, Susana Peralta and João Pereira dos Santos

REMINDING PEOPLE TO SOCIALLY DISTANCE
Paolo Falco and Sarah Zaccagni

Covid Economics
Vetted and Real-Time Papers

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

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

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

The Centre for Economic Policy Research (CEPR)

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

Editorial Board

Ethics

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

Submission to professional journals

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

American Economic 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

Canadian Journal of 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*.

Covid Economics
Vetted and Real-Time Papers

Issue 28, 12 June 2020

Contents

The early impact of COVID-19 on local commerce: Changes in spend across neighborhoods and online 1
Lindsay E. Relihan, Marvin M. Ward Jr., Chris W. Wheat and Diana Farrell

The stock market is not the economy? Insights from the Covid-19 crisis 29
Gunther Capelle-Blancard and Adrien Desroziers

Women's work, housework and childcare, before and during COVID-19 70
Daniela Del Boca, Noemi Oggero, Paola Profeta and Maria Cristina Rossi

The mental health effects of the first two months of lockdown and social distancing during the Covid-19 pandemic in the UK 91
James Banks and Xiaowei Xu

What and how did people buy during the Great Lockdown? Evidence from electronic payments 119
Bruno P. Carvalho, Susana Peralta and João Pereira dos Santos

Promoting social distancing in a pandemic: Beyond the good intentions 159
Paolo Falco and Sarah Zaccagni

CEPR PRESS

Covid Economics **Issue 28, 12 June 2020**

The early impact of COVID-19 on local commerce: Changes in spend across neighborhoods and online[1]

Lindsay E. Relihan,[2] Marvin M. Ward Jr.,[3] Chris W. Wheat[4] and Diana Farrell[5]

Date submitted: 8 June 2020; Date accepted: 8 June 2020

We document a number of striking features about the initial impact of the pandemic on local commerce across 16 US cities. There are two novel contributions from this analysis: exploration of neighborhood-level effects and shifts between offline and online purchasing channels. In our analysis we use approximately 450 million credit card transactions per month from a rolling sample of 11 million anonymized customers between October 2019 and March 2020. Across the 16 cities we profile, consumers decreased spend on the set of goods and services we define as "local commerce" by 12.8% between March 2019 and March 2020. Growth in all 16 cities was negative. Consumers shifted a substantial share of local commerce spend online, such that year over-year growth in online spend was small, but positive, at 1.5%. With respect to grocery and pharmacy purchases, online spend grew at least three times as fast as offline spend. Overall spend declines were uniform across neighborhoods

1 We thank James Duguid and Bryan Kim for their substantial contributions to the production and analysis of the research presented here. We also thank colleagues at the JPMorgan Chase Institute for their comments and suggestions. This research was made possible by a data-use agreement between Lindsay E. Relihan and the JPMorgan Chase Institute (JPMCI), which has created de-identified data assets that are selectively available to be used for academic research. All statistics from JPMCI data reflect observations based on at least 100 customer accounts with medians reported with small errors to protect privacy where appropriate. The opinions expressed are those of the authors alone and do not represent the views of JPMorgan Chase & Co.
2 Assistant Professor of Real Estate Economic and Finance, London School of Economics & Associate, Urban Programme, Centre for Economic Performance.
3 Research Lead, JPMorgan Chase Institute.
4 Director of Business Research, JPMorgan Chase Institute.
5 President & CEO, JPMorgan Chase Institute.

Covid Economics 28, 12 June 2020: 1-28

of differing median household income, though lower-income neighborhoods experienced the highest proportion of extreme negative declines. We also find evidence that many low-income neighborhoods are increasing spend on online grocery slower than others, but increasing their use of online restaurants the fastest. Consumers in low-income neighborhoods also tend to live farther from the grocery stores at which they shop. Compared to their counterparts in higher-income neighborhoods, consumers in low-income neighborhoods have not been more likely to shop at grocery stores closer to where they live since the onset of the pandemic.

Covid Economics 28, 12 June 2020: 1-28

Covid Economics 28, 12 June 2020: 1-28

1 Introduction

On January 21, 2020 the first case of COVID-19 was diagnosed in Washington state. By May 23, 2020, the case load across the US had grown to over 1.6 million people with nearly 100,000 fatalities. As the virus spread, businesses across the country shuttered their doors to slow contagion, leading to widespread job loss. Between March 14 and May 23, nearly 40 million people filed initial unemployment claims. In the midst of economic calamity, policy leaders at all levels have struggled to understand the scale and scope of the economic shock rippling through the economy. At the federal level, Congress mobilized the largest economic stimulus effort in history, directing trillions of dollars in financial assistance to individuals and businesses. At such great cost, it is imperative this assistance reaches those most in need.

The aim of this research is to use JPMorgan Chase Institute data to understand the impact of the pandemic on the supply and demand of local commerce across US cities.[1] While the scope of the pandemic is global, we experience the impacts locally. Consumers need to be able to acquire critical goods and services where they live. Producers need to be able to service a stable set of consumers, most often those in the same community. Therefore, to understand the strain placed on the local economic ecosystem requires a *place-based* view of local commercial activity that characterizes the *everyday* interplay between consumers and producers in a community.

To bring this interplay into focus, we construct a "local commerce" economic view using a subset of credit card transactions that typify everyday goods and services transacted between local buyers and sellers. This local commerce view differs from other publicly available series because it includes a broader set of goods and services to reflect the modern, more service-based economy.[2] We further restrict to such goods and services that are well represented by card transactions. Such representation is important in studying consumer substitution patterns, such as toward online goods and services. Using these conditions, we define local commerce (LC) to include the following goods and services: clothing, grocery, fuel, general goods, home maintenance goods and services, local leisure goods and services related to arts and sporting activities, pharmacy, personal care and professional consumer services, restaurants, and local private and public ground transportation.[3,4]

The following analysis of LC relies on approximately 450 million credit card transactions

[1]The collection of JPMorgan Chase Institute research related to the impact of COVID-19 can be found here.

[2]This is the case with the Census Monthly Retail Trade Survey, which reports on retail goods and food services. The Bureau of Economic Analysis estimates that consumers spent more than twice as much on services as goods in February 2020.

[3]General goods include department stores, discount stores, large non-specific online retailers, and other miscellaneous retailers like florists and books stores that sell everyday goods. Major categories of personal care services include salons and dry cleaners. Professional consumer services examples include veterinary, legal, and childcare services.

[4]Major categories of goods and services not included in local commerce are automobile-related goods and services, communication services, education services, travel-related leisure, flights, and accommodation.

per month made by a rolling sample of 11 million customer accounts.[5,6] The richness of these transaction-level data allows us to couple attributes of the consumer with those of the establishment at which the purchase was made. This includes information on the distance between the consumer's residence and the establishment's location.[7] These transactions have broad geographic coverage, but we focus on 16 cities with a sufficient number of observations to allow for further detailed analysis at the neighborhood level. After this initial analysis is published, we plan to release a set of online companion resources that enable national and local public policy officials to track the performance of local commerce going forward.

We document a number of striking features from our initial analysis. Across the 16 cities we profile, we measure a 12.8% decline in year-over-year growth in LC spend in March 2020.[8] We also find wide variation in spend growth between and within cities and online versus offline. LC spend across the 16 cities sharply declined in March, regardless of local lockdown or COVID-19 outbreak severity, with declines ranging from 2.8% (Phoenix) to 16.6% (San Francisco). Within and across cities, LC spend declines were relatively uniform across neighborhoods featuring a wide range of household median income. However, a disproportionate share of low-income neighborhoods experienced extreme negative spend declines. Consumers shifted their share of LC spend online by 4.6pp, such that online growth in LC spend was still positive, but just 1.5%. In March, only grocery and pharmacy spend grew relative to the previous year, with extraordinary rates of growth online.

In this initial piece, we provide further detail on changes in spend in consumer food categories: groceries and restaurants. At a high level, in March 2020, overall spend on food decreased between 5.0% for the lowest-income and 8.4% for the fourth-highest income-quintiles. Unsurprisingly, within food, consumers shifted much of their spend toward grocery and away from restaurants. We find proportional changes in food spend allocated to groceries versus restaurants to be relatively even across neighborhoods of all income levels in March 2020. However, neighborhoods with the lowest increases in online grocery spend are more likely to be low-income. Consumers in low-income neighborhoods also tend to live farther from the grocery stores at which they shop. Coupling both

[5]To calculate the measures used in this analysis each month, we select customer credit card accounts with at least 10 transactions in *both* the target month (e.g. February 2020) and same month a year before (e.g. February 2019). This sample selection protocol governs accounts in the analysis through February 2020. In March 2020, in order to reduce measurement error due to unusually high attrition and/or spend reductions, precisely the change we are seeking to explore, we reuse the sample of customer accounts that cleared the screen in February 2020.

[6]In an effort to provide analysis to the public as quickly as possible, we have focused on the use of credit card transactions only. Our typical analysis of LC spend would rely on both credit and debit card transactions. Restricting to credit card users has a material impact on the sample. Credit card holders skew higher income, and according to the Survey of Consumer Finances, credit card holders spend more on basic goods like food. Recent results from Visa also show the recent spend declines have been more severe on credit versus debit cards.

[7]This work is part of broader efforts by other public and private institutions to use proprietary data to provide real-time analysis of the impact of COVID-19. Other examples we are aware of as of this writing include Alexander and Karger (2020); Baker et al. (2020a,b); Chetty et al. (2020) for the US and Carvalho et al. (2020); Chen et al. (2020); Andersen et al. (2020); Chronopoulos et al. (2020) internationally. We show similar high-level findings where there is overlap on US data.

[8]Our LC series typically shows growth rates in the range of 4 percentage points (pp) above the Census Monthly Retail Trade Survey. Month-to-month movement in the two series is highly correlated. The Census survey reports a seasonally adjusted year-over-year decline of 6.2% in March 2020.

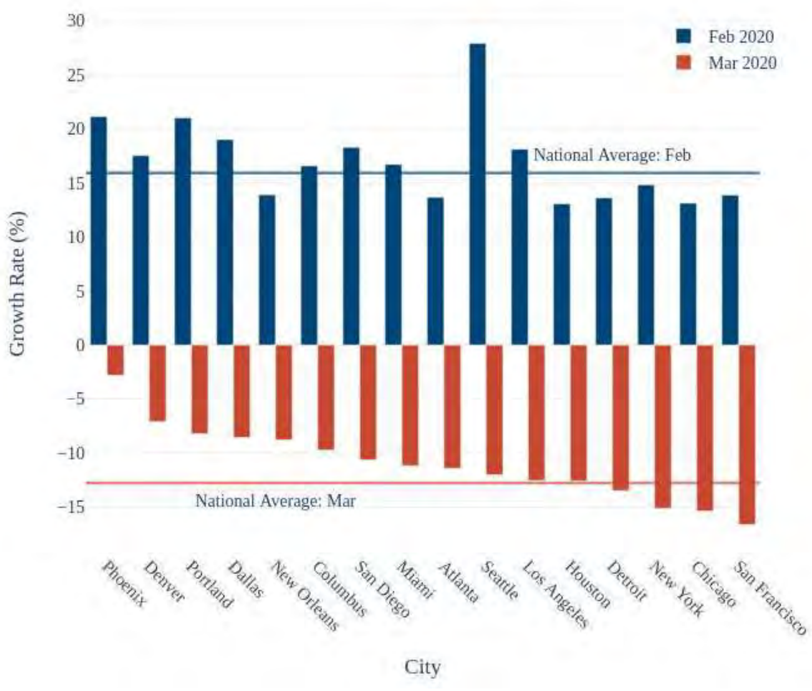
Covid Economics 28, 12 June 2020: 1-28

disadvantages suggests that despite similarity in overall spend patterns on food, consumers living in low-income neighborhoods may be more at risk for COVID-19 when acquiring groceries.

2 Changes in local commerce across cities

The pandemic created severe supply and demand shocks. Many producers are shutdown or serving consumers at a distance, while simultaneously incorporating social distancing guidelines into their production processes. At the same time, consumers have less income to spend on average and are less inclined to physically patronize businesses for fear of contagion. As a consequence, consumers in our cities decreased LC spend by 12.8% between March 2019 and March 2020.

Figure 1: San Francisco, Chicago, New York, and Detroit experienced the sharpest declines in local commerce spend



Note: This figure shows the year-over-year percent change in spend for goods and services included in local commerce for the 16 US cities included in our analysis. The national averages shown are the year-over-year growth in local commerce across all consumers, calculated at 15.9% in February and -12.8% in March 2020. Cities are Core Based Statistical Areas.

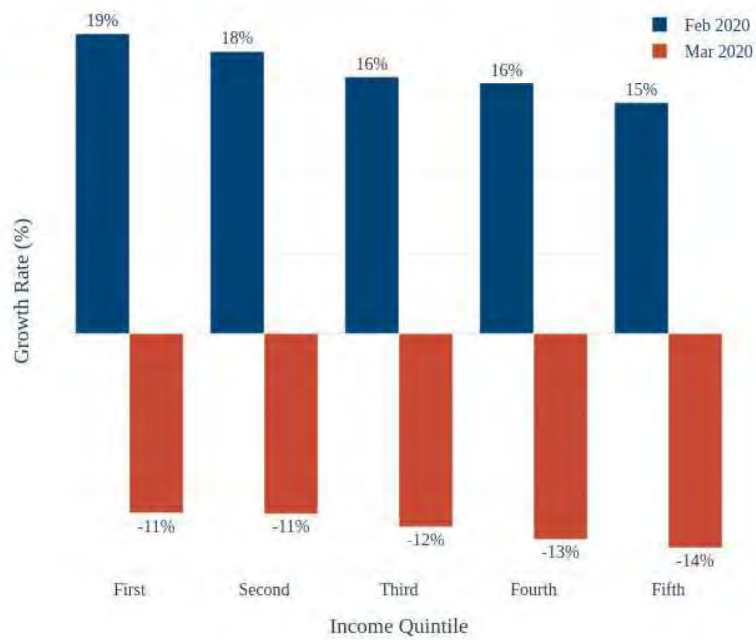
As seen in Figure 1, all 16 cities enjoyed robust LC growth in February 2020; by March, all experienced significant declines. The heaviest decline was in San Francisco (16.6%), the first city

Covid Economics 28, 12 June 2020: 1-28

Covid Economics 28, 12 June 2020: 1-28

with a stay-at-home order starting on March 17. The next heaviest declines were in Chicago, New York, and Detroit: three major cities which, along with New Orleans, have the highest COVID-19 case rates to date. Even cities with limited outbreaks in March experienced high declines.[9] The best performing city in our analysis was Phoenix, where consumer spend still decreased by 2.8%. These results show that, even though the onset of COVID-19 occurred at different times for different cities, consumers across cities pulled back their spend in a narrow time window. The correlated response suggests that consumer sentiment and policy interventions during the pandemic can drive growth outcomes.

Figure 2: Local commerce spend declines were higher for consumers in high-income neighborhoods



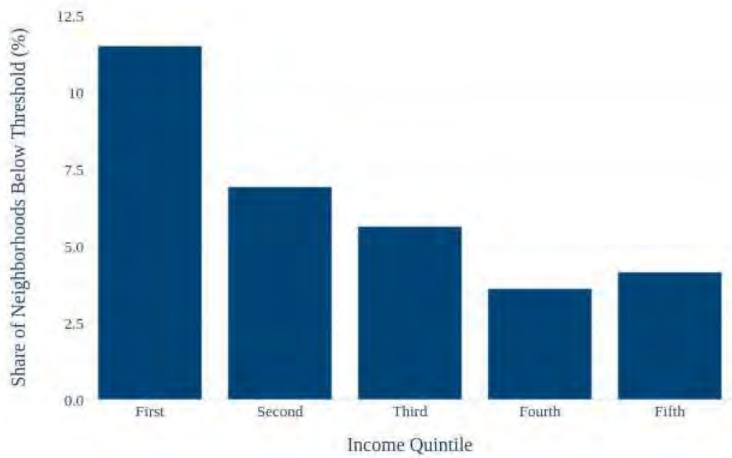
Note: This figure shows the year-over-year percent change in spend for goods and services included in local commerce by consumers' neighborhood income quintile. The income quintile is calculated within city and based on the median household income of the ZIP code as recorded in the American Community Survey 5-year data for 2014-2018.

While these high-level results inform the scale of the current economic crises across the US, policy makers can better direct aid to those most in need with information on how the pandemic is impacting neighborhoods of differing socioeconomic status. To aid this effort, we provide analysis

[9]We note that Houston also shows large declines, but it is unclear whether the bigger driver of this decline was the direct effect of the pandemic or the concurrent economic shock from its link to the oil and gas industry at a time of historically low energy prices.

across neighborhoods by neighborhood income. Throughout the analysis, we use ZIP codes as proxies for neighborhoods. Within each city, we separate neighborhoods into neighborhood income quintiles by city using the neighborhood's median household income as reported in the American Community Survey 5-year data for 2014-2018. Figure 2 shows that all consumers across neighborhood income quintiles increased LC spend in February, and then decreased LC spend in March. High-income neighborhoods experienced the largest contraction in March 2020 at -13.6%.

Figure 3: 11.5% of low-income neighborhoods experienced severe spending declines



Note: This figure shows the share of ZIP codes in an neighborhood income quintile with a greater than one standard deviation fall in year-over-year LC spend (>15.1%) below the average decline in LC spend across all ZIP codes (-9.5%). The income quintile is calculated within city and based on the median household income of the ZIP code as recorded in the American Community Survey 5-year data for 2014-2018.

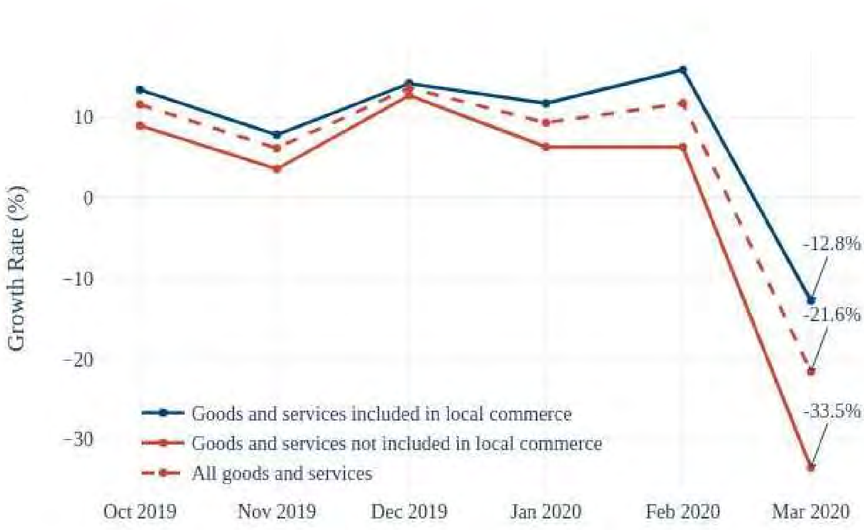
Despite the relative similarity in neighborhood LC spend growth in each quintile, we find that low-income neighborhoods experienced a disproportionate share of extreme spend declines. We define a severe spend decline as a drop of more than one standard deviation (>15.1%) below the average drop across all neighborhoods (-9.5%).[10] As can be seen in Figure 3, 11.5% of the lowest-income neighborhoods, and 6.9% of the neighborhoods in the next highest quintile, are in the severe spend decline category. The fact that low-income neighborhoods were more likely to experience severe declines while high-income neighborhoods had the largest average decline may be a result of differences in the choices available to residents. For example, low-income neighborhoods may be more exposed to job losses while high-income neighborhoods are able to decrease a large share of discretionary spend. We unpack more of the differences across neighborhood income in later sections.

[10]The mean decline in LC spend across all neighborhoods we report was slightly lower than the overall decline in LC spend.

Covid Economics 28, 12 June 2020: 1-28

Covid Economics 28, 12 June 2020: 1-28

Figure 4: Local commerce spend declined less than overall credit card spend in March 2020



Note: This figure shows the year-over-year percent change in spend for goods and services included in local commerce and goods and services not included in commerce spend. Local commerce includes clothing, grocery, fuel, general goods, home maintenance goods and services, local leisure goods and services related to arts and sporting activities, pharmacy, personal care and professional consumer services, restaurants, and local private and public ground transportation. Major categories of goods and services not included in local commerce are automobile-related goods and services, communication services, education services, travel-related leisure, flights, and accommodation.

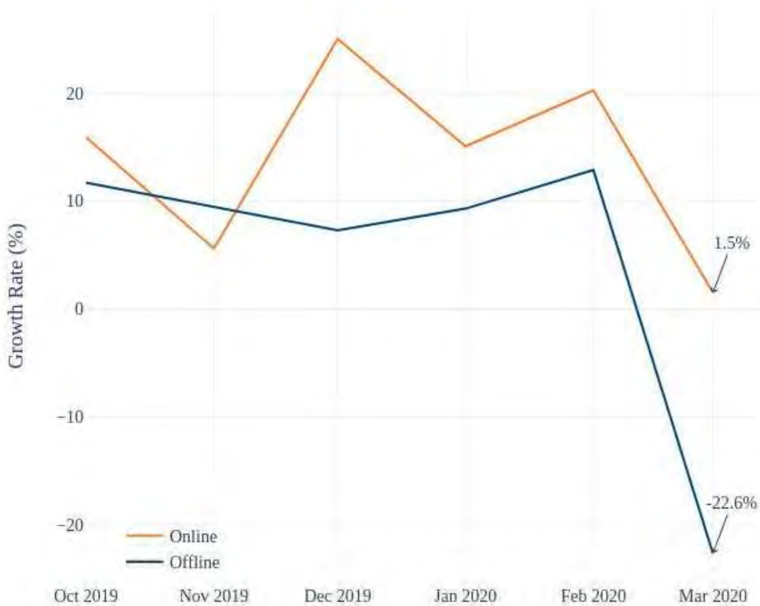
Before further decomposing LC spend changes, we show that LC spend has been more resistant to spend declines than goods and services not included in LC spend. As Figure 4 shows, we find that consumers in our sample responded to the pandemic in March by decreasing their overall spend on goods and services on credit cards by 21.6%. This is an alarming figure for the US economy, in which consumer spend accounts for almost 70% of Gross Domestic Product.[11] Local economies experienced a material contraction overall, but the spending reductions were greater for goods and services consumed primarily away from home. The gap between LC spend growth and non-LC spend growth widened from January to February, with the greatest gap in March. The consistently higher growth in LC spend implies that the LC share of total spend increased as the pandemic worsened. In order to better understand the local economic conditions across the US, we focus on LC spend for the remainder of the analysis.

[11]The US Bureau of Economic Analysis reported Gross Domestic Product was $19.073 trillion in 2019. Of that, Personal Consumption Expenditures accounted for $13.280 trillion

3 Changes in online local commerce

The rise of online commerce over the last three decades has already made deep structural changes in how consumers interact with local producers of goods and services. The pandemic has both accelerated the use of online channels and broadened its use across the population. In efforts to reduce time away from home, we find the online share of LC spend grew from 42.9% in February to 47.5% in March, a difference of 4.6pp. As a result, online LC spend still grew, though at a notably slower pace in March (1.5%) relative to February (20.2%), as can be seen in Figure 5.

Figure 5: Local commerce spend online is still growing in March 2020



Note: This figure shows the year-over-year percent change in LC spend by online and offline channels. Concurrently, the share of LC spend online increased from 42.9% in February to 47.5% in March, a difference of 4.6pp.

We find that the resilience of online LC in March was uneven across cities. For most, online LC spend growth was positive. However, many of the cities with the severest overall spend declines (Chicago, New York, Detroit, and Houston) had declines in both online and offline spend (Figure 6). As expected, every city we observed saw significant declines in offline spend. San Francisco experienced the most significant contraction with a growth rate of -31.0% in offline spend, followed by Seattle (-27.7%), New York (-24.9%), and Los Angeles (-24.5%).

Overall, growth in online commerce did not materially differ by neighborhood income (we find

CEPR PRESS

Figure 6: San Francisco had the largest decline in offline local commerce spend

Note: This figure shows the year-over-year percent change in spend for goods and services included in local commerce by online and offline for the 16 US cities included in our analysis. The national averages shown are the year-over-year growth in local commerce across all consumers in March 2020, calculated at 1.5% for online and -22.8% for offline. A payment is considered to be online if the card was not present at the time of transaction. Cities are Core Based Statistical Areas.

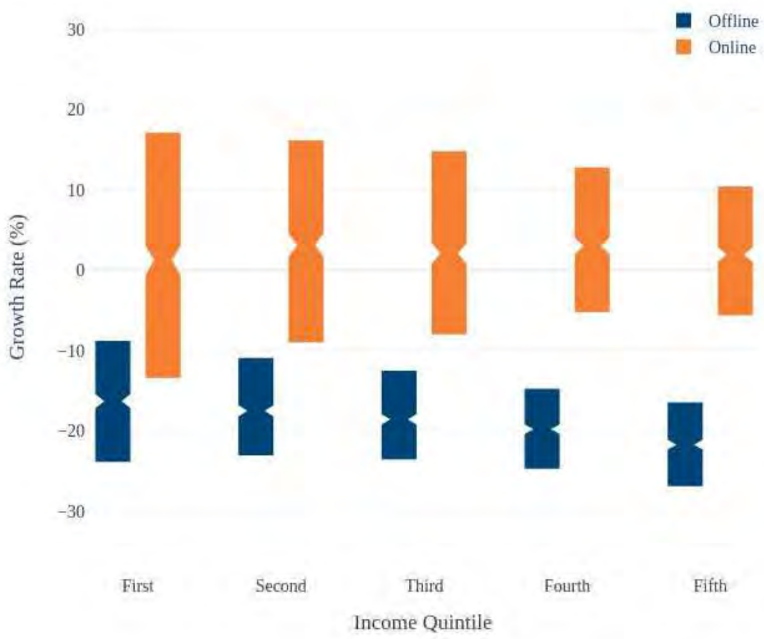
Covid Economics 28, 12 June 2020: 1-28

differences for specific goods and services below). Figure 7 shows the distribution of neighborhood LC spend growth across neighborhood income and online versus offline. In March, we observe sharp contractions in offline spend and increases in online spend across each neighborhood income quintile. Median growth was similar across neighborhood income, though as with overall spend, declines in online spend were more likely in low-income neighborhoods. Furthermore, it is notable that across all neighborhood income quintiles, nearly half of neighborhoods reduced their spend offline *and* online.

4 Changes by product and channel

The LC view captures, by design, the exchange of a subset of goods and services that are well-represented on cards and specific to interactions between local consumers and producers. This

Figure 7: Median growth in online retail was similar across neighborhood income



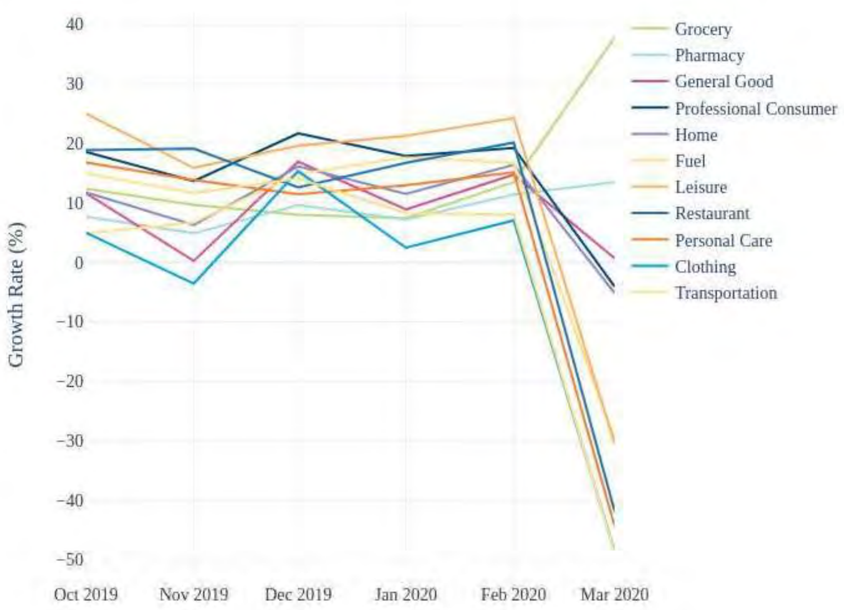
Note: This figure shows the distribution of the year-over-year percent change in local commerce spend by online and offline and neighborhood income quintile. Each box spans the 25th to 75th percentiles of neighborhood growth rates with a notch at the median growth rate. A payment is considered to be online if the card was not present at the time of transaction. The income quintile is calculated within city and based on the median household income of the ZIP code as recorded in the American Community Survey 5-year data for 2014-2018.

Covid Economics 28, 12 June 2020: 1-28

view highlights dynamics in not just the retail goods portion of local economy, but in the consumer services sector as well. Here, we study how the pandemic has changed consumer consumption patterns across the individual goods and services contained in this view. Our results show dramatic shifts in the composition of LC spend for goods and services overall and across online versus offline channels.

As seen in Figure 8, consumers dramatically decreased their consumption of services related to intra-city transportation (e.g. private car service and public transit), clothing, personal care services (e.g. salons and dry cleaners), restaurants, leisure-related arts and sports services, and fuel. By contrast, there was either no change, or limited contraction, in spend related to goods and services one can consume at or close to home. These include home goods and services (e.g. furniture stores, hardware stores, and landscaping services), professional consumer services (e.g. veterinary, legal, and childcare services), and general goods (e.g. department stores, discount stores, large

Figure 8: Only spend at grocery stores and pharmacies increased materially in March 2020



Note: This figure shows the year-over-year percent change in spend in each good and service included in local commerce. Local commerce includes clothing, grocery, fuel, general goods, home maintenance goods and services, local leisure goods and services related to arts and sporting activities, pharmacy, personal care and professional consumer services, restaurants, and local private and public ground transportation.

non-specific online retailers, and other unclassified producers like florists and book stores that we consider to sell everyday goods). Finally, there were two categories that experienced dramatic increases in spend: grocery stores and pharmacies. Figure 9 shows that the share of LC spend at grocery stories and pharmacies grew from 15.6% to 23.9% and from 2.2% to 2.7%, respectively, between February and March 2020. For the remaining LC goods and services, the share declined from 82.2% to 73.4% with the largest decrease in the restaurant share.

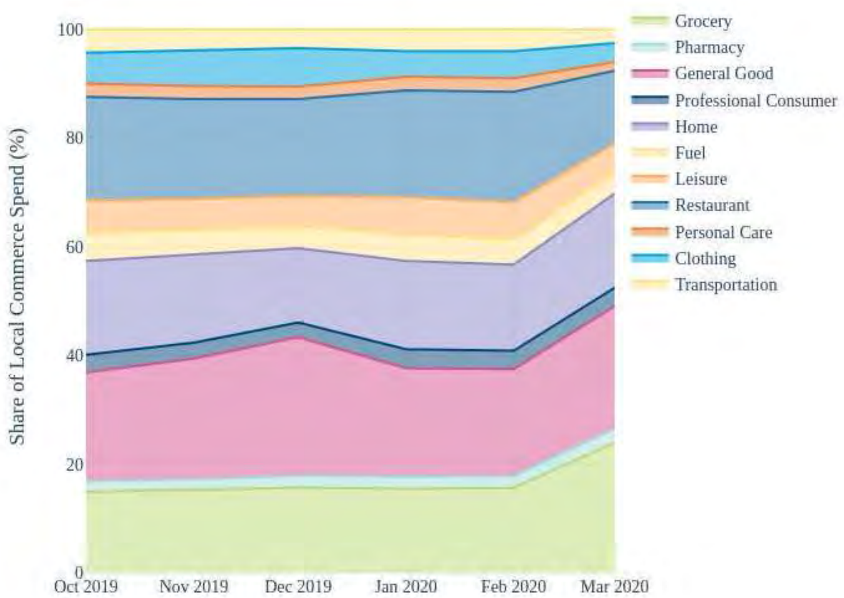
Further decomposing LC spend growth for goods and services purchased online versus offline in March 2020 reveals that the online channel was critical in supporting the acquisition of key goods and services (Figure 10). Online spend on groceries more than doubled, with pharmacies general goods, and restaurants also increasing their online provision substantially. For other goods and services, online provision has not proved a lifeline during the pandemic. Across online and offline channels, personal care services, clothing, and private and public ground transportation have decreased substantially. Declining spend across both channels suggests consumers have far less need for these goods and services when largely confined to the home.

Covid Economics 28, 12 June 2020: 1-28

CEPR PRESS

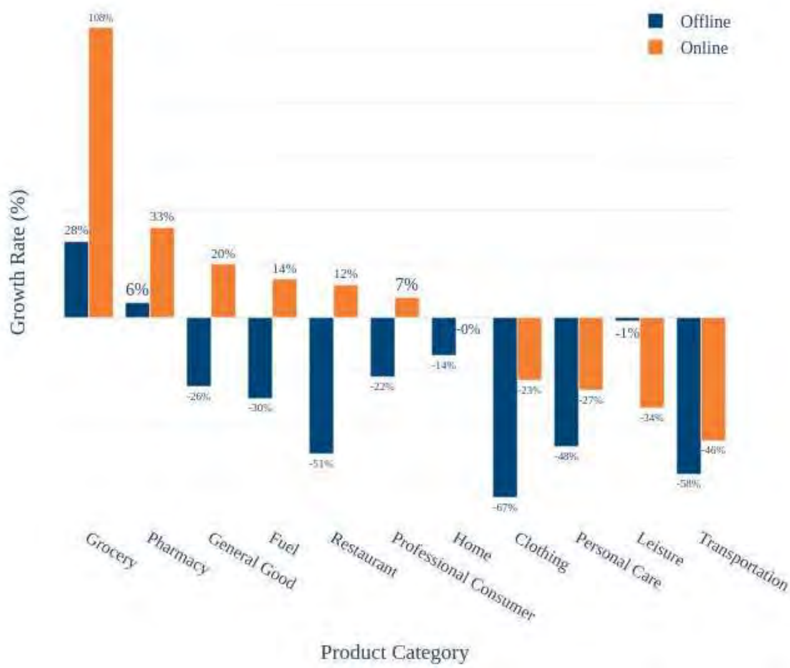
Covid Economics 28, 12 June 2020: 1-28

Figure 9: Grocery stores and pharmacies grew to 26.6% of local commerce spend in March 2020



Note: This figure shows the spend share of each good and service included in local commerce. Local commerce includes clothing, grocery, fuel, general goods, home maintenance goods and services, local leisure goods and services related to arts and sporting activities, pharmacy, personal care and professional consumer services, restaurants, and local private and public ground transportation.

Figure 10: Online spend on groceries more than doubled



Note: This figure shows the year-over-year percent change in spend for goods and services included in local commerce by online and offline for the goods and services in local commerce. Local commerce includes clothing, grocery, fuel, general goods, home maintenance goods and services, local leisure goods and services related to arts and sporting activities, pharmacy, personal care and professional consumer services, restaurants, and local private and public ground transportation. A payment is considered to be online if the card was not present at the time of transaction.

Covid Economics 28, 12 June 2020: 1-28

Covid Economics 28, 12 June 2020: 1-28

5 Changes in food spend and distance

In this final section, we focus on food spend at groceries and restaurants as one way to examine the impact of the pandemic on the well-being of residents across neighborhoods. We find that in March 2020, residents across neighborhoods largely reduced spend on food at similar rates and allocated similar proportions of total LC spend to food. However, we find differences in the use of online food channels across neighborhoods. Consumers increased their spend on online groceries and restaurants across the board, but consumers in lower-income neighborhoods were less likely to increase online grocery spend and more likely to increase online restaurant spend. Variation in increases in grocery spend is also much wider across cities online than offline, suggesting that the existing infrastructure for online groceries is a potential impediment for rapid expansion in access to online groceries. A small pilot program by the US Department of Agriculture was widely expanded in March to allow use of Supplemental Nutrition Assistance Program (SNAP) benefits for online grocery purchases.[12] Efforts like these to increase the use of online groceries may be hampered by supply constraints in the short-term.

In addition to spend, we study the offline physical accessibility of grocery stores in a neighborhood. To do so, we measure the distances between consumers' home neighborhoods and the grocery stores at which they transact, then calculate the median distance of those transactions for each consumer neighborhood.[13] We find that consumers in low-income neighborhoods are more likely to live farther from their chosen grocery stores. Moreover, during the pandemic, median distances dropped the most for consumers in high-income neighborhoods. Our results by channel and median distance show that despite consistent shifts in grocery spend across neighborhoods of different economic means, consumers in many low-income neighborhoods are not accessing groceries from nearby stores or increasing their online grocery purchases to the same extent as their counterparts in high-income neighborhoods. Both elements increase time away from home, and therefore increase the risk of contagion associated with simply buying food.

Finally, *we find that city-specific dynamics can deviate from broad patterns observed across cities*, which suggests that our within-city results are particularly useful for local policy makers.[14] To highlight our within-city results, we use New York City as an example. As with other cities, lower-income neighborhoods had higher growth in offline grocery spend and higher-income neighborhoods had higher growth in online grocery spend. However, unlike other cities, the cross-quintile pattern in median retail distance is somewhat U-shaped insofar as consumers in both low- and high-income neighborhoods tend to live relatively close to their chosen grocery stores.

[12] Current details of the program and availability can be found on the USDA website.

[13] We only have information on the ZIP code of the consumers' home location and the ZIP code of the establishment at which they transaction. Therefore, we calculate distances between ZIP code centroids.

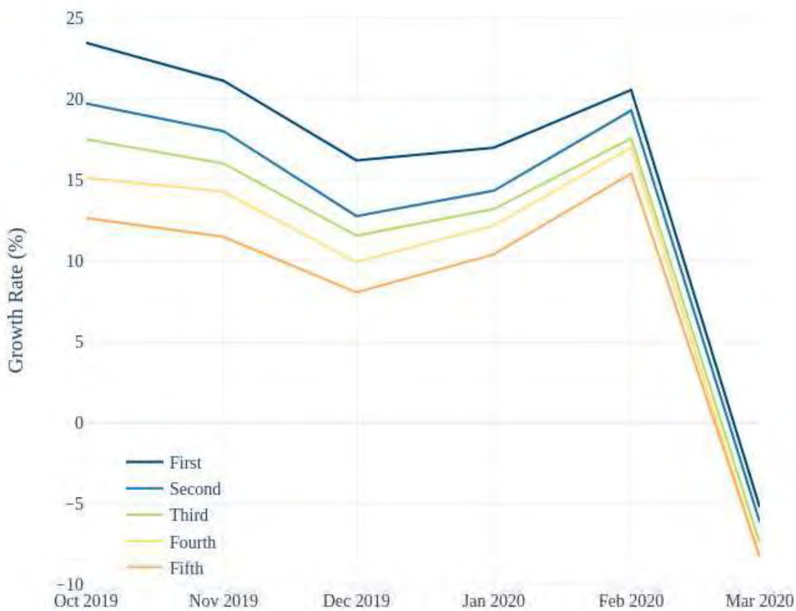
[14] Our forthcoming companion figure and data resources contain details on these results specific to each city.

CEPR PRESS

5.1 Changes in spend within food and online

Consumers across neighborhoods are changing their total spend on food in similar ways, but the slower increase in the use of online groceries in many low-income neighborhoods suggests differential access to a key low-risk food channel during the pandemic. Overall spending on food declined by 5.0% for the lowest-income quintile and 8.4% for the fourth-highest-income quintile in March, despite high rates of growth on groceries (Figure 11). The greater decline for higher-income neighborhoods is driven by a slightly higher shift away from restaurants. We find that changes in spend shares were largely even for groceries and restaurants across consumers by neighborhood income quintile. Figure 12 shows that in February, total grocery and restaurant spend as a share of LC spend was about 16% and 20%, respectively, across neighborhoods. In March, all consumers reallocated toward grocery such that grocery and restaurants spend shares were about 24% and 13%, respectively. Average reallocation within both food categories toward online was also relatively uniform across neighborhood income.

Figure 11: Overall spend on food declined at least 5.0% in all neighborhoods



Note: This figure shows the year-over-year percent change in overall food spend by consumers' neighborhood income quintile. The income quintile is calculated within city and based on the median household income of the ZIP code as recorded in the American Community Survey 5-year data for 2014-2018.

However, examining the distribution of growth rates in online groceries by neighborhood income

Figure 12: Food spend shifted toward groceries and online across neighborhood income

Note: This figure shows the spend share for grocery stores and restaurants, split by online and offline channels. A payment is considered to be online if the card was not present at the time of transaction.

shows that individual neighborhood experiences can be quite different from the national average (Figure 13 (a)). Lower-income neighborhoods are less likely overall to increase online grocery spending as quickly as higher-income neighborhoods. The neighborhoods with the 25th percentile growth rate in the first and second quintiles experienced online grocery spend growth rates that were 12.6pp and 17.4pp below the corresponding growth rate for the 25th percentile neighborhood in the fifth quintile (54.6%). Interestingly, we find there are a subset of neighborhoods in the first income quintile with particularly high growth in online spend on groceries. This may reflect the effects of the new SNAP pilot program in March.[15] Otherwise, the 25th, 50th, and 75th percentile of the distribution in each of the other neighborhood income quintiles rises with income, as expected.[16]

At the same time, low-income neighborhoods are increasing their online restaurant spend faster than high-income neighborhoods at each point of the neighborhood growth distribution (Figure 13 (b)). The median growth rate for first quintile neighborhoods was 24.4%, while the growth rate for the fifth quintile was just 12.1%. Furthermore, the lowest-income quintile is the only one in which online restaurant spend increased in more than three-quarters of neighborhoods. Differential access to groceries versus restaurants in low- versus high-income neighborhoods, both online and offline, may be part of the explanation for these differences.

[15]Although SNAP transactions themselves do not appear in our data, the effects of the program could lead to expanded availability and awareness of the program in low-income neighborhoods such that there is an increase in online grocery spending in the set of transactions that we do observe.

[16]Previous research shows that higher-income households spend more on online groceries. See Farrell et al. (2018) and Relihan (2017).

Covid Economics 28, 12 June 2020: 1-28

We also find that the increase in online grocery use was substantially higher in cities where the online share of groceries was already high before the pandemic. Figure 14 (a) shows that offline grocery growth in March was between 17.4% (San Francisco) and 32.9% (Miami), a relatively tight range. However, as shown in 14 (b), the range for online grocery growth in March was very wide, from 28.7% (Houston) to 194.4% (San Francisco). The cities with the 4 highest rates of growth in online grocery in March were also those cities with the highest share of grocery spend online in February (San Francisco had the highest share in February, at 20.7% of total grocery spend). This suggests that the ability to shift grocery spend online was in large part determined by the existing market size and infrastructure for grocery delivery. Online grocery platforms, much more than other online goods and services, have large fixed costs to delivering in a city that limit their ability to expand.[17] Though online groceries are clearly trying to increase capacity, these fixed costs are likely to constrain expansion of this service in many areas in the short run.

5.2 Changes in neighborhood median retail distance to groceries

The distance between consumers and the establishments they visit is another important, non-monetary dimension of accessibility to retail goods, particularly now when travel outside the home is higher risk.[18] In our previous work, we explored the variation in this distance to illuminate local patterns of disparity across consumers within a city that could not be easily identified with available economic data.[19] Our median distance measure accords with intuition insofar as distances are lower in downtown areas and more dense retail areas. It also tends to move slowly across years, because residents and establishments move in and out of neighborhoods at low rates.[20]

Of deep concern in general, and during the pandemic in particular, is the median retail distance for groceries.[21] In Figure 15(a), we observe that while in March 2019 consumers in the median high-income neighborhood traveled virtually the same distance to grocery stores as consumers in the median low-income neighborhood, there were far more high-income neighborhoods that featured shorter distances than low-income neighborhoods. In other words, consumers in high-income neighborhoods were more likely to travel shorter distances for access to groceries than their low-income counterparts. In March 2020, the median distances for grocery fell for all quintiles, but they fell the farthest for consumers in the highest-income neighborhoods while consumers in the lowest-income neighborhoods experienced little change (Figure 15 (b)). We also note that for the fourth and fifth quintile neighborhoods, the 25th percentile distances dropped by 1.1 and 1.0 miles, respectively. Corresponding distributional shifts for the remaining quintiles were also

[17] This is discussed at greater length in Relihan (2017).

[18] To reiterate, we measure retail accessibility by the median ZIP code centroid to centroid distance between the consumers in a ZIP code and the within-city brick-and-mortar establishments at which they transact.

[19] See Farrell et al. (2017) for previous retail distance analysis on New York City and Detroit by the JPMorgan Chase Institute.

[20] We do see, however, notable seasonal variation as consumers make different choices about which businesses to patronize over the course of a year.

[21] Our work specific to median distance between consumers and grocery stores is closely related to the food desert literature. See Handbury et al. (2016) for one recent example.

Covid Economics 28, 12 June 2020: 1-28

negative, but much more modest. Combined with our results by channel, the disparity in distance changes suggests that many lower income neighborhoods are likely not accessing online groceries and nearby grocery stores to the same extent as consumers in high-income neighborhoods. This wedge in physical access to safer grocery channels is widening during the pandemic.

5.3 Results specific to New York City

In this section, we examine the within-city spend patterns between neighborhoods of different median household income in the New York City metropolitan area. These within-city patterns for New York may be instructive for dense neighborhoods as well as those hit hard by the crisis. To anchor the discussion, Figure 16 displays the location of neighborhoods in different median household income quintiles. Manhattan south of Harlem, Westchester bordering Connecticut, and eastern parts of Long Island are some areas with high concentrations of high-income neighborhoods. Upper Manhattan, the Bronx, Brooklyn, Queens, and Newark in New Jersey have higher concentrations of low-income neighborhoods.

The correspondence between neighborhood income and increases in spend on offline versus online groceries is evident in our neighborhood spend maps (Figure 17). Offline grocery growth is more concentrated downtown, especially in those areas, like Harlem and into the Bronx, with higher concentrations of low-income neighborhoods. The highest growth rates for online grocery are in the wealthier neighborhoods of Manhattan, Westchester, and eastern Long Island.

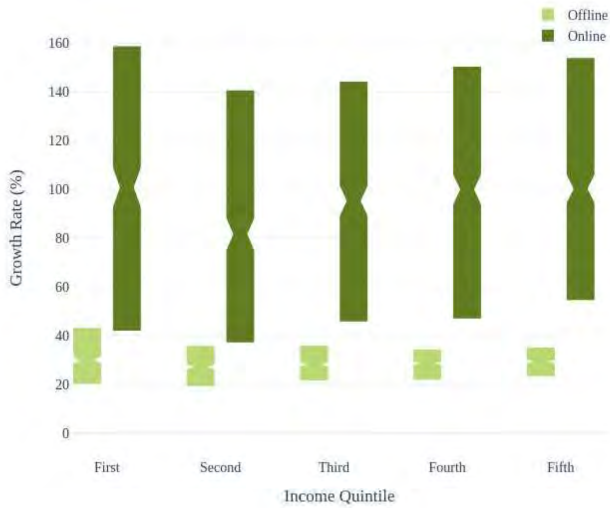
We also find that in contrast to most other cities, median retail distance for groceries across neighborhood income in New York City is somewhat U-shaped (Figure 18 (a)). In both March 2019 and March 2020, the consumers in the lowest-income neighborhoods lived the closest to their chosen grocery stores. In March 2020, distances dropped for the median neighborhood in all quintiles, with the largest median drops in the second and third income quintiles, at 0.3 miles less for each. (Figure 18 (b)). Thus, physical access to offline groceries, as measured by median retail distance, was notably different in New York than it was across all cities. Coupled with the spatial disparities in the growth of online grocery spend, these results suggest that consumers along the income distribution are reducing grocery store travel through different means in New York City – high-income neighborhoods focused more on online groceries and low-income neighborhoods focused more on grocery spend offline close to home.

Covid Economics 28, 12 June 2020: 1-28

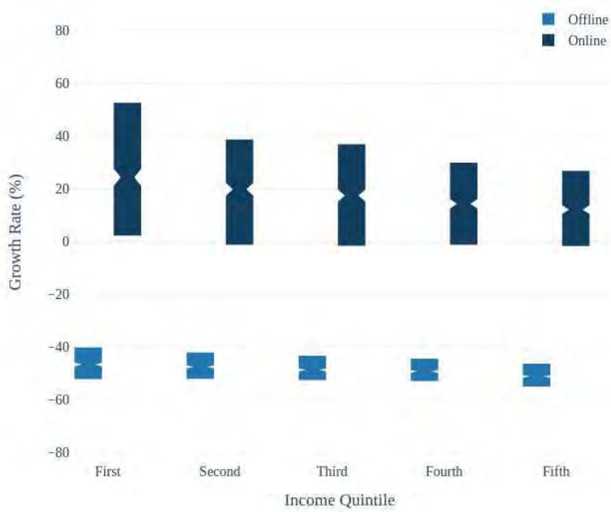
CEPR PRESS

Figure 13: Consumers are differentially increasing spend on online groceries and restaurants

(a) Grocery



(b) Restaurant

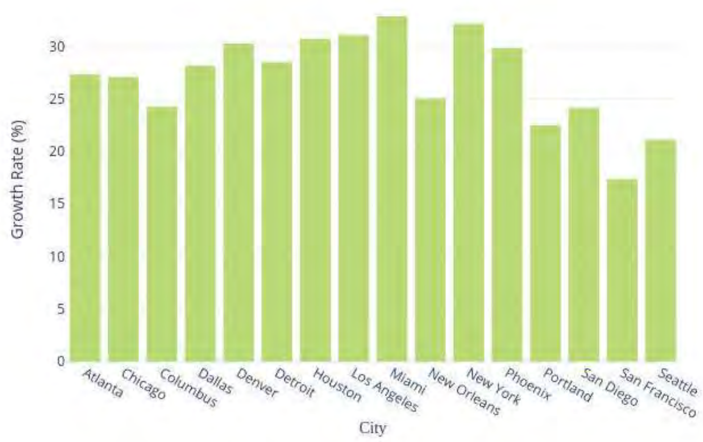


Note: This figure shows the distributions of the year-over-year percent change in grocery and restaurant spend by online and offline for each of the ZIP codes in our sample by income quintile of the ZIP code. Each box spans the 25th to 75th percentiles of neighborhood growth rates with a notch at the median growth rate. A payment is considered to be online if the card was not present at the time of transaction. The income quintile is calculated within city and based on the median household income of the ZIP code as recorded in the American Community Survey 5-year data for 2014-2018.

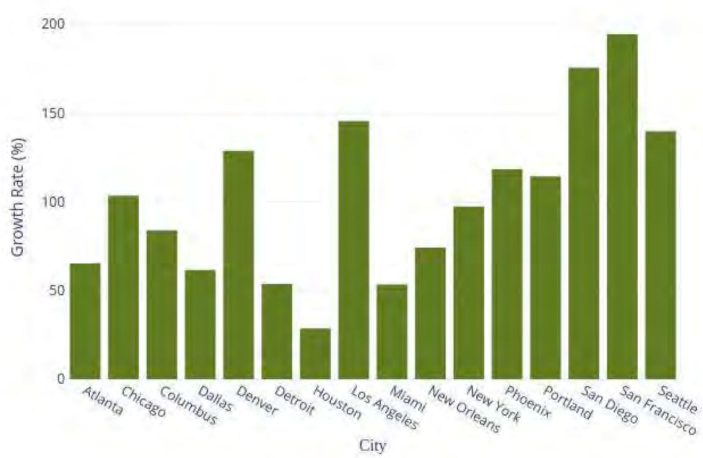
Covid Economics 28, 12 June 2020: 1-28

Figure 14: Across cities there are wider differences in online than offline spend growth

(a) Offline Grocery



(b) Online Grocery



Note: This figure shows the year-over-year percent change in spend on grocery across cities by offline and online channel. A payment is considered to be online if the card was not present at the time of transaction.

Covid Economics 28, 12 June 2020: 1-28

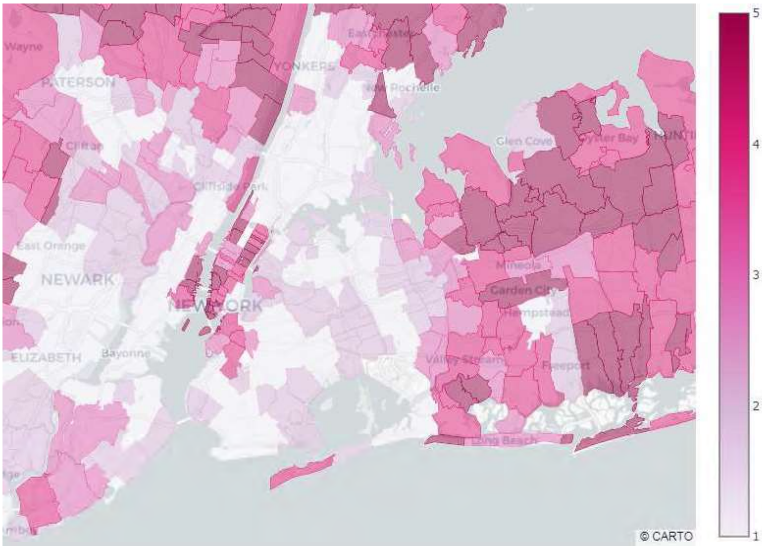
Covid Economics 28, 12 June 2020: 1-28

Figure 15: Grocery store median distance was more likely to fall in high-income neighborhoods

Note: This figure shows the distribution of median retail distance for grocery purchases for each of the ZIP codes in our sample by income quintile of the ZIP code for February and March 2020. Each box spans the 25th to 75th percentiles of neighborhood retail distance with a notch at the median retail distance. The income quintile is calculated within city and based on the median household income of the ZIP code as recorded in the American Community Survey 5-year data for 2014-2018.

Covid Economics 28, 12 June 2020: 1-28

Figure 16: NYC metro area neighborhoods by median household income quintile

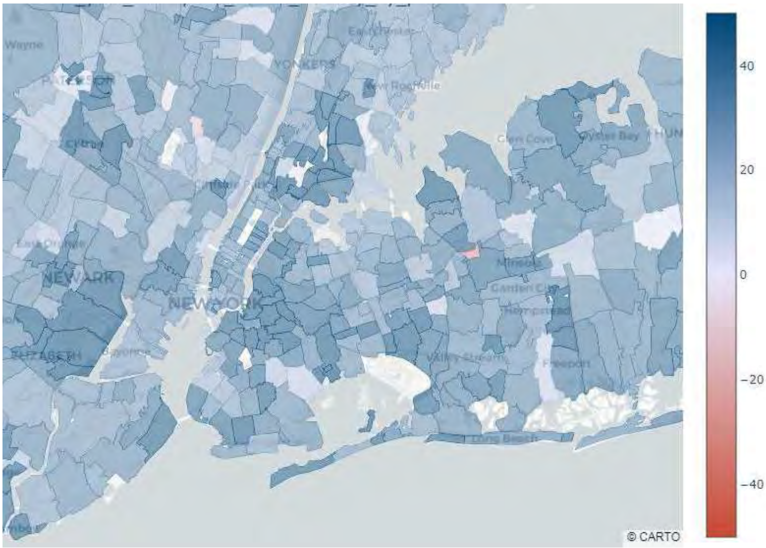


Note: This figure shows the spatial distribution of median household income by ZIP code in the New York City metropolitan area, colored by the quintile of the ZIP code. The income quintile is calculated within city and based on the median household income of the ZIP code as recorded in the American Community Survey 5-year data for 2014-2018.

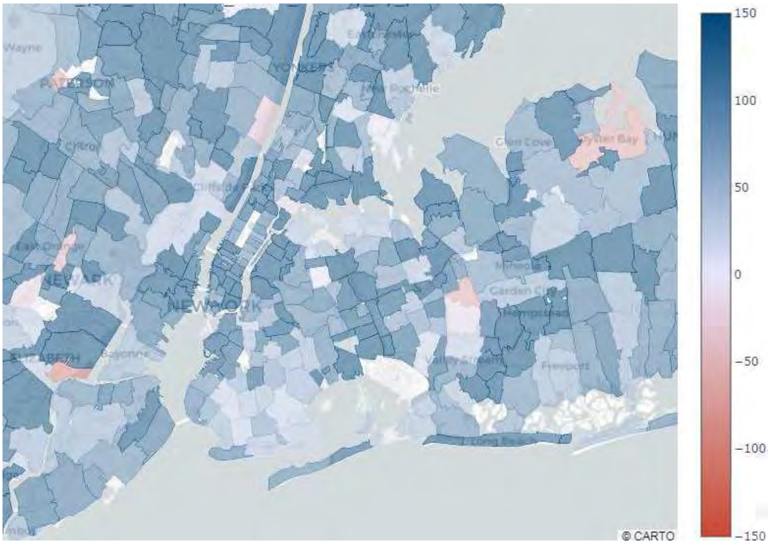
Covid Economics 28, 12 June 2020: 1-28

Figure 17: NYC metro area offline and online grocery spend shows differential growth across neighborhoods

(a) Offline



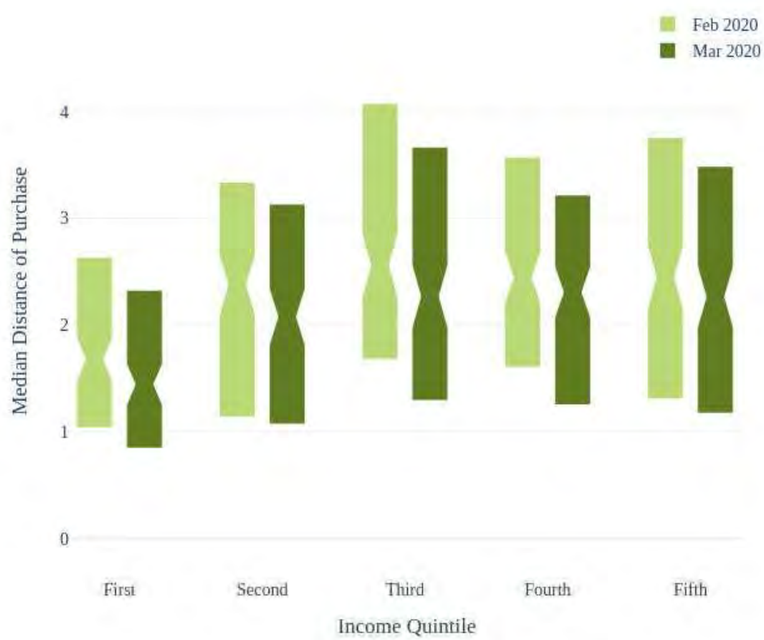
(a) Online



Note: This figure shows the spatial distribution of year-over-year changes in grocery spend, by online/offline channel and ZIP code in New York City, colored by the growth rate. A payment is considered to be online if the card was not present at the time of transaction.

CEPR PRESS

Figure 18: NYC metro area grocery store median distance improved in middle income neighborhoods



Note: This figure shows the distribution of median retail distance for grocery purchases for each of the ZIP codes in New York City by income quintile of the ZIP code. Each box spans the 25th to 75th percentiles of neighborhood retail distance with a notch at the median retail distance. The income quintile is calculated within city and based on the median household income of the ZIP code as recorded in the American Community Survey 5-year data for 2014-2018.

Covid Economics 28, 12 June 2020: 1-28

6 Discussion

The research presented here is a first effort at using a uniquely large and granular transaction-based dataset to understand the initial impact of the pandemic on local commerce across neighborhoods and online. This piece and the forthcoming companion online resources will provide measurement and analysis of impacts that local decision makers can use in their ongoing efforts to support local economies.

For our study, we create a measure of local commerce comprised of a subset of goods and services that characterize the everyday purchases of buyers and sellers in the same geographic market. We show that across the 16 cities we profile, local commerce declined 12.8%. Declines began in March in each city regardless of local pandemic-related conditions. The uniformity in timing suggests consumer confidence about safety and broader economic conditions was important in the initial decline. They are likely to also be important factors that impact the success of reduced restrictions in spurring returns to growth. Furthermore, the decline in spend on local commerce was smaller than the 33.5% decline for other goods and services purchased on credit cards. This result is in line with local goods and services consumed near home being more robust to the current economic shock, unlike services such as flights and accommodation. Of course, these other services, while less likely to be consumed by local residents, are vitally important to local economies. They often provide a valuable source of tax revenue for local governments and support tourism-dependent cities. A return to greater spend in these categories will be an important turning point in any recovery.

We also find that the initial economic impact of the pandemic on local commerce has been harder on lower-income neighborhoods in several important ways. First, they were much more likely to experience extreme negative spending declines – about 1 in 9 neighborhoods in the first income quintile experienced local commerce spend declines in excess of one standard deviation over the neighborhood mean in March 2020 (more than a -24.6% decline). Safe access to groceries was also more difficult for many lower-income neighborhoods. Consumers in those neighborhoods were less able to expand their access to online groceries in many cases and were unable to substantially shift their spend to more local grocery stores to the same extent as consumers in higher-income neighborhoods. These are stark disparities that emerged before the vast majority of recent job losses. It is likely that differences have continued to widen.

Finally, our work shows that the initial shift of local commerce online has been limited to a smaller subset of of local commerce goods and services. In addition to groceries, pharmacies, general goods producers, and restaurants have been lifted by their ability to transact online. As online goods and services that are easier to consume at home, this is in-line with other home-favored consumption patterns. In many cases, constraints on the physical infrastructure for delivering online goods have likely limited the extent to which consumers would have preferred to move online. As this infrastructure improves, further shifts online are possible even as many local lockdown restrictions are eased. Some spend shifted online due to the pandemic may also become permanent as consumers are introduced to new online products and new shopping behaviors become ingrained.

Covid Economics 28, 12 June 2020: 1-28

For restaurants, one of the largest and most severely impacted industries, the shift online was smaller than that for groceries. Unlike groceries, restaurant meals purchased online require coordination between the offline producer and online service provider. This dependency is creating conflict over online restaurant revenues and spurring calls to cap restaurant delivery fees. Such caps may limit the shift of restaurant meals online.

Future work will continue to track these and other emerging trends as the pandemic's economic impacts and policy makers' responses enter new phases. That work will also move beyond the descriptive to separate out the causal impacts of specific interventions and the mechanisms underlying consumer substitution patterns offline and online. The data resources developed for this analysis will also be an ideal resource for understanding the new local commerce landscape that emerges from the crisis.

Covid Economics 28, 12 June 2020: 1-28

References

Alexander, Diane and Ezra Karger, "Do Stay-at-Home Orders Cause People to stay at Home? Effects of Stay-at-Home Orders on Consumer Behavior," Working Paper No. WP-2020-12, Federal Reserve Bank of Chicago 2020.

Andersen, Asger Lau, Emil Toft Hansen, Niels Johannesen, and Adam Sheridan, "Consumer Responses to the COVID-19 Crises: Evidence from Bank Account Transaction Data," Working Paper 2020.

Baker, Scott R., R.A. Farrokhnia, Steffen Meyer, Michaela Pagel, and Constantine Yannelis, "How Does Household Spending Respond to an Epidemic? Consumption During the 2020 COVID-19 Pandemic," *Covid Economics*, 2020, (18), 73–108.

_ , _ , _ , _ , and _ , "Income, Liquidity, and the Consumption Response to the 2020 Economic Stimulus Payments," Working Paper No. 27097, National Bureau of Economic Research 2020.

Carvalho, Vasco M, Juan Ramon Garcia, Stephen Hansen, Alvaro Ortiz, Tomasa Rodrigo, Sevi Rodriguez Mora, , and Pep Ruiz, "Tracking the COVID-19 Crisis with High-resolution transaction data," Discussion Paper No. DP14642, Centre for Economic Policy Research 2020.

Chen, Haiqiang, Wenlan Qian, and Qiang Wen, "The Imapact of the COVID-19 Pandemic on Consumption: Learning from High Frequency Transaction Data," Working Paper 2020.

Chetty, Raj, John N. Friedman, Nathaniel Hendren, and Michael Stepner, "Real-Time Economics: A New Platform to Track the Impacts of COVID-19 on People, Businesses, and Communities Using Private Sector Data," Working Paper, Opportunity Insights 2020.

Chronopoulos, Dimitris K., Marcel Lukas, and John O. S. Wilson, "Consumer Spending Responses to the COVID-19 Pandemic: An Assessment of Great Britain," Working Paper 2020.

Farrell, Diana, Lindsay Relihan, and Marvin Ward, "Going the distance: big data on resident access to everyday goods," Report, JPMorgan Chase Institute Report 2017.

_ , _ , and _ , "Shopping Near and Far: Local Commerce in the Digital Age," Report, JPMorgan Chase Institute Report 2018.

Handbury, Jessie, Ilya Rahkovsky, and Molly Schnell, "Is the Focus on Food Deserts Fruitless? Retail Access and Food Purchases Across the Socioeconomic Spectrum," Working Paper No. 21126, National Bureau of Economic Research 2016.

Relihan, Lindsay E., "Is Online Retail Killing Coffee Shops? Estimating the Winners and Losers of Online Retail using Customer Transaction Microdata," Working Paper 2017.

CEPR PRESS

The stock market is not the economy? Insights from the Covid-19 crisis[1]

Gunther Capelle-Blancard[2] and Adrien Desroziers[3]

Date submitted: 4 June 2020; Date accepted: 10 June 2020

Covid Economics 28, 12 June 2020: 29-69

During the COVID-19 crisis, while the world economy suffered the worst crisis since the Great Depression, the reactions of stock markets have raised concerns. Several economists (including some Nobel laureates) have seen these reactions as evidence that stock markets are not fully efficient, while others have emphasized the difficulty of assessing the dramatic flow of information about the pandemic and its economic consequences. In this paper, we assess how stock markets have integrated public information about the COVID-19, the subsequent lockdowns and the policy reactions. Although the COVID-19 shock has been global, not all countries have been impacted in the same way, and they have not reacted in the same way. We take advantage of this strong heterogeneity. We consider a panel of 74 countries with daily information about the health and economic crisis, from January to April 2020. Stock market reaction can be summarized as follows. 1) Stock markets initially ignored the pandemic (until Feb. 21), before reacted strongly to the growing number of infected people (Feb. 23 to Mar. 20), while volatility surged and concerns about the pandemic arose; following the intervention of central banks (Mar. 23 to Apr. 30), however, shareholders no longer seemed troubled by news of the health crisis, as prices rebound all around the world. 2) Country-specific characteristics appear to have had no influence on stock market response. 3) Investors were sensitive to the number of COVID-19 cases in neighbouring and wealthy

1 The authors thank Anne-Laure Delatte, Thomas Renault, Jérôme Valette, Urszula Szczerbowicz, and Alliance Sorbonne Webinar participants, for their help and fruitful comments. We also thank Jesse Grabowski for excellent research assistance

2 Université Paris 1 Panthéon-Sorbonne (Centre d'Economie de la Sorbonne) and Paris School of Business.
3 Université Paris 1 Panthéon-Sorbonne (Centre d'Economie de la Sorbonne).

countries. 4) Credit facilities and government guarantees, lower policy interest rates, and lockdown measures mitigated the decline in domestic stock prices. Overall, these results suggest that stock markets have been less sensitive to each country' macroeconomic fundamentals prior the crisis, than to their short-term reaction during the crisis. However, our selected variables explain only a small part of the stock market variations, so it is hard to deny that the link between stock price movements and fundamentals have been anything other than loose.

Covid Economics 28, 12 June 2020: 29-69

Covid Economics 28, 12 June 2020: 29-69

THE STOCK MARKET IS NOT THE ECONOMY? INSIGHTS FROM THE COVID-19 CRISIS

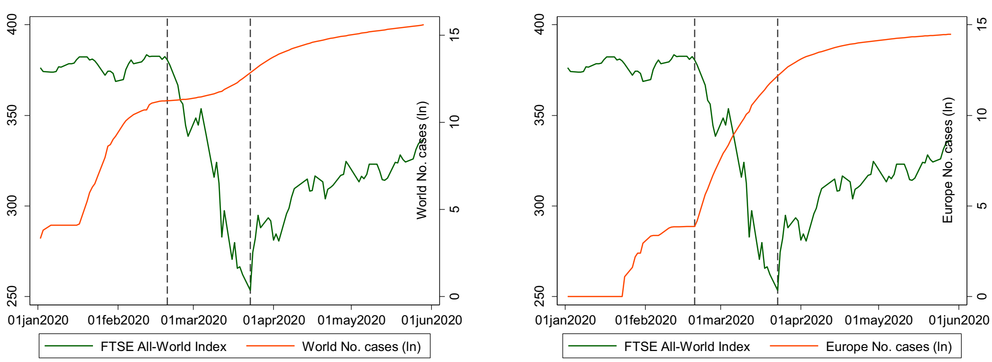
1. Introduction

Is anything weird about the stock market behaviour in the time of COVID-19? As the world economy suffered from the worst crisis since the Great Depression (Gopinath, 2020), the reactions of stock markets raised questions. As shown in Figure 1, it is difficult to see any relationship between the health crisis and the reactions of stock markets. First, shareholders seem to have remained completely insensitive to the skyrocketing increase in the number of COVID-19 cases and deaths. Second, from February 19 to March 23, when the crisis spread to Europe, stock markets plummeted by unprecedented proportions. Third, while the United States was being hit hard, stock prices rebounded strongly with the intervention of the Fed. To what extent could this overall reaction of the stock markets, often at odds with the COVID-19 pandemic, be explained by fundamentals?

Figure 1. The reaction of the stock market during the COVID-19 crisis

1a. World

1b. Europe



Note: The figure 1 shows the FTSE All-World Index (left scale) and the total number of reported COVID-19 cases (in log, right scale) reported in the World (1a) or in Europe (1b) from January 1, 2020 to June 1, 2020. The vertical lines correspond to February 20 and March 23 respectively. Sources: JHU and Reuters. Authors' computation.

In one of his influential *New York Times* columns, Paul Krugman said out loud what many people were thinking (Krugman, 2020). Given the huge discrepancy between the worsening health situation and stock prices, there was cause for genuine concerns about what was going on. Krugman's statement was direct: *"What's bad for America is sometimes good for the market (...). Whenever you consider the economic implications of stock prices, you want to remember three rules. First, the stock market is not the economy. Second, the stock market is not the economy. Third, the stock market is not the economy (...). The relationship between stock performance – largely driven by the oscillation between greed and fear – and real economic growth has always been somewhere between loose and nonexistent"*. Krugman's column not only calls into question the relationship between stock markets and the economy, but actually challenges the Efficient Market Hypothesis (EMH). The no less famous Burton Malkiel and Robert Shiller have also discussed the seemingly odd behaviour of stock markets in the face of the COVID-19 (Malkiel and Shiller, 2020). According to Malkiel, the alleged stock market irrationality is only "*apparent*". Malkiel readily admits that investor might under- or over-react to news, especially when they are so difficult to interpret. He contends that the *"EMH does not imply that prices will always be 'correct'"* and claims that the COVID-19 crisis does not *"impl[y] that markets are inefficient"* inasmuch as there are no arbitrage opportunities, and stock markets remain extraordinarily hard to beat. Shiller is more nuanced and considers *"that the [EMH], and the random walk theory are half-truths (...) Speculative prices may indeed statistically resemble a random walk, but they are not so tied to genuine information (...). The contagious stories about the coronavirus had their own internal dynamics only loosely related to the information about the actual truth"*. Which of these masterminds in economics is closest to the truth? It is, of course, impossible to settle this matter definitively. However, the exceptional – and sadly dramatic – COVID-19 crisis gives us the opportunity to take a fresh look at, and to gain new insights into the long-standing EHM debate.

What new insights on stock markets behaviour can be drawn from the COVID-19 crisis? This debate is of special importance. Indeed, as stressed by Rajan (2015), it is essential to be concerned about what the general public thinks about finance. All the more since the COVID-19 put to the test science and experts (Aksoy et al., 2020), without sparing economists.

There is a fast growing literature looking at the responses of stock markets to the COVID-19 pandemic that is already giving insights into this issue. While the evolution of stock markets during the pandemic might look random, irrational, or even insane at first glance, on closer inspection it becomes clear that they did not react blindly. First, the rebound dates precisely to the moment when monetary authorities, led by the US Federal Reserve, announced the implementation of a vast

Covid Economics 28, 12 June 2020: 29-69

stimulus plan to tackle the crises (Haddad et al., 2020).[1] Second, several studies have shown that stock markets were effective in discounting the most exposed companies: those who were more financially fragile, subject to the disruption of international value chains, or vulnerable in terms of corporate social responsibility (e.g. Alburque et al., 2020; Ding et al., 2020; Fahlenbrach et al., 2020, Ramelli and Wagner, 2020). Moreover, it seems that stock market losses are related to analyst forecast revisions, at least in the medium term (Landier and Thesmar, 2020). In relation to these papers, we take a macroeconomic perspective. Indeed, the above-mentioned studies provide valuable information[2], but some questions remain open.

How have stock markets worldwide reacted to the COVID-19 pandemic? How to explain differences in response between countries? Are these differences in stock market response across countries related to macroeconomic or institutional characteristics, and if so, which ones? Are these differences due to the way governments have handled the pandemic? How stock markets have reacted to lockdowns and domestic economic policies countrywide to flatten the curve of infection and the curve of recession (Gourinchas, 2020)?

It is important to note that although the COVID-19 shock has been global, not all countries have been impacted in the same way, and they have not reacted in the same way. This heterogeneity relates to several aspects: i) the exposure to the COVID-19, ii) the health and economic situation of each country before the COVID-19 pandemic and their capacity to manage a crisis, iii) the effective responses of governments to curb the spread of the virus and to reduce its economic impact. Of course, many of these aspects interact with each other. Some figures can help to grasp this large heterogeneity. Countries have not been equally hit by the COVID-19, and not at the same time. For instance, while COVID-19 cases have been confirmed in China at the very beginning of 2020, the virus reached several countries (Ireland, New Zealand, etc.) only two months later. Then, the path of the pandemic has not been similar in all countries. As of end of April 2020, the number of COVID-19 confirmed cases per inhabitant, varies from less than 0.01% (Argentina, Japan, etc.) to more than 0.3% (Spain, the US, etc.). National strategies aiming at control and mitigate the pandemic (containment, quarantine, contact tracing, face masks distribution, etc.) were very diverse from one country to another, with quite varying degrees of success. Considering only the containment measures, half of humanity was on lockdown in early April 2020, with some countries having strict measures (e.g. Taiwan), while others have taken a more flexible attitude (e.g. Brazil, Sweden). These differences in strategy have given rise to lively debates, which are far from over.

Covid Economics 28, 12 June 2020: 29-69

[1] See also https://www.brookings.edu/research/fed-response-to-covid19/.
[2] A brief survey is provided hereafter.

Our objective is not to assess the effectiveness of these different strategies, but how all these have been priced by investors. The answer is definitely not obvious. Indeed, there is no direct evidence of a relationship between the number of COVID-19 cases and the performance of the stock markets. First, let us consider several countries with a similar number of cases *ex post* (as of end of April 2020). For a given number of COVID-19 cases, whatever the reason, we can observe strong discrepancies in stock markets response. For instance, Switzerland or the United States record a very high number of COVID-19 cases per inhabitant (above 0.3%), but their stock markets are doing rather well, with a drop of only 11% over the period January-April 2020. Conversely, in Spain or Italy for instance, with a similar relative number of cases, the stock index dropped by more than 30%. Second, let us consider several countries which are expected to share a lot of cultural, institutional and economic similarities *ex ante* (prior 2020). For instance, if we look at Scandinavian countries, there are also large discrepancies in stock market reaction: Iceland (0.5%) has recorded twice as many cases per inhabitant as Sweden (0.2), which itself has had twice as many cases as Finland (0.1); yet stock markets have dropped by 13%, 12%, 15% and 1% respectively. What meaning can we give to these stock price movements which are different to explain from one country to another?

In this paper, we assess how stock markets have integrated public information about the COVID-19 pandemic and the subsequent lockdowns. We take advantage of the strong heterogeneity across countries, and we aim to explain the difference in stock markets response by the situation in each country *before* the crisis, and by the economic policies and containment measures implemented *during* the crisis. We consider a panel of 74 countries from January to April 2020 which might be divided into four phases: Incubation, Outbreak, Fear, and Rebound[3]. For each country, we collected daily data about stock index prices, global market sentiment and volatility, the number of COVID-19 cumulative cases and deaths, government measures taken in response to the outbreak, and various indicators of mobility (or lack thereof). We pay special attention to cross-sectional and temporal dependencies by using a conservative approach with time and country fixed effects. In addition to our main findings, several robustness checks are conducted, including limiting our sample period to February and March (the Outbreak and Fever phases), consideration of global time-varying explanatory variables, adjustment of domestic stock returns to account for the performance of the world index, and use of Driscoll-Kraay (1998) standard errors.

Three main findings about stock market reactions during the COVID-19 pandemic arise from this study. First, after initially ignoring the pandemic (until Feb. 21), stock markets reacted strongly to the increase in the number of infected people in each country (Feb. 23 to Mar. 20), while volatility

[3] Most studies (in the drafts available at the time of writing) stop at the end of March and ignore the rebound.

Covid Economics 28, 12 June 2020: 29-69

surged and concerns about the pandemic grew. Following the intervention of central banks (Mar. 23 to Apr. 30), however, shareholders no longer seemed troubled by news of the health crisis, as prices rebound all around the world. Second, country-specific characteristics appear to have had no influence on stock market responses. Shareholders do not react differently whether the country is more or less wealthy, indebted, open to international tourism, whether it has a population at-risk, a previous experience of a pandemic or more state power. Third, investors were sensitive to the number of COVID-19 cases in neighbouring and wealthy countries. Fourth, credit facilities and government guarantees, lower policy interest rates, and lockdown measures mitigated the decline in stock prices. Overall, these results suggest that stock markets have been less sensitive to each country' macroeconomic fundamentals prior the crisis, than to their short-term reaction during the crisis. All these results are robust to alternative specifications, including the inclusion of day fixed effects, use of either the number of cases or the number or deaths, as well as various methods of controlling for cross-sectional dependencies. However, as our selected variables explain only a small part of the stock market variations, it would be unwise to pretend that the stock markets have fully integrated all available information.

The remainder of the paper is organized as follows. First, we review the (preliminary) evidence about how stock markets reacted to COVID-19. Second, we present our data, we document stock market behaviour during the COVID-19 crisis, and describe our methodology, while paying special attention to cross-sectional dependencies. Third, we provide our results. We conclude with a brief discussion.

2. COVID-19 related empirical studies

In the face of the COVID-19 pandemic, there has been an intense response from the scientific community, which quickly set to understanding the many aspects of the crisis, including its economic impact.[4] There is no doubt that COVID-19 will leave deep scars on the economy (Baldwin and di Mauro, 2020, Bénassy-Quéré and di Mauro, 2020). Preliminary investigations into the COVID-19 pandemic and the associated lockdowns report vast costs (Barro et al., 2020; Coibion et al., 2020a) and welfare effects (Hamermesh, 2020; Pindyck, 2020), a huge impact on labor markets in the short term (Coibion et al., 2020b; Lozano Rojas et al. 2020) and likely in the long term (Barrero et al., 2020; Gregory et al., 2020), in particular for the most vulnerable (Alstadsæter et al., 2020; Montenovo et al., 2020). In addition, macro-policy responses attempting

[4] See https://cepr.org/content/covid-19 or https://www.nber.org/wp_covid19_rco_05112020.html. See also Dixit (2020) for an (hilarious) assessment.

to mitigate the pandemic will likely also result in large shocks (Eichenbaum et al., 2020; Gourinchas, 2020). Jordà et al. (2020) consider twelve previous pandemics from the 14th century onwards and find that macroeconomics effects persist for about forty years.

All of these effects also have obvious impacts on the financial health of companies. Hassan et al. (2020) use transcripts of quarterly earnings conference calls held by more than ten thousand publicly listed firms up to March 2020 to investigate which implications of the COVID-19 crisis companies were most worried about. The authors found companies' concerns were related to the collapse of demand, uncertainty, disorder of supply chains, and to a lesser extent capacity reductions, closures, and employee welfare, while financing did not seem to be a matter of great concern. Moreover, they identify companies that expect opportunities in new or disrupted markets related to the pandemic. Other research has emphasised how the crisis disproportionally affects the smaller businesses (Bartik et al., 2020). Haddad et al. (2020) focus on the disruption in the US debt market during the COVID-19 crisis and trace the recovery once the Fed purchased corporate bonds.

How have stock markets reacted to the COVID-19 pandemic, the lockdown, their effects on demand and supply, and the economic policies implemented to mitigate the crisis? A first set of papers focus on the US, and seek to characterize the general dynamics of stock prices in the crisis period. Baker et al. (2020) run a text-based analysis from major US newspapers to compare equity market volatility during the COVID-19 crisis with that of previous epidemics (H5N1 in 1997-98, SARS in 2003, H1N1 in 2009, MERS/Ebola in 2014-15), as well as with volatility during large historical financial crashes (October 1929, the Great Depression in 1933, Black Monday in 1987, and the Subprime crisis in 2008). Overall, they confirm the unprecedented impact of the COVID-19 pandemic on US stock markets. Gormsen and Koijen (2020) investigate dividend futures and show that the drop in stock prices is due both to changes in investors' expectations and changes in discount rates.[5] Giglio et al. (2020) survey retail investors in February, March and April 2020 and show that they turned more pessimistic in the short run, but not in the long run.

A second group of studies examine the impact of the crisis at the firm level. Companies differ greatly according not only sector by sector, but also in their individual organization, financial structure, opportunities, suppliers, risk and so on. Ramelli and Wagner (2020) provide a comprehensive analysis of the daily abnormal stock returns for the Russell 3000 constituents between January 2, 2020 to March 20, 2020. They show first strong differences between industries: Telecom services performed relatively well, while energy and consumer services were among the

[5] Baig et al. (2020) consider the constituent stocks of the S&P 500 index between January 13 and April 17 and examine the impact of the crisis on market volatility and illiquidity. They consider, as potential determinants, the number of cases and deaths, and various proxies for the severity of the pandemic: a worldwide sentiment index (RavenPack), a stringency index of the government response (Oxford Covid-19 Government Response Tracker), and an index of mobility in the US (Apple). All these variables, in level and independently, have a positive and significant impact.

biggest losers. They also show that, within industries, more negative abnormal returns were associated with higher foreign exposure, especially with China. Landier and Thesmar (2020) examine US firm-level analyst forecasts and find that their downward revisions are consistent with the observed negative stock return over the whole period between January and May 2020, but not with the maximum drop within this period, which would suggest overreaction during the Fever phase. Ding et al. (2020) analyze 6,000 firms across 56 countries in the first quarter of 2020. They find that weekly raw returns have been less negative for firms with stronger pre-2020 finances (more cash, less debt, and larger profits), less exposure to the pandemic through global supply chains and customer locations, more CSR activities, less entrenched executives, and larger non-financial corporate ownership. Fahlenbrach et al. (2020) also consider the relationship between corporate characteristics and stock price reactions. They consider about two thousands US firms in February and March 2020 and show that firms with less financial flexibility experienced worse stock returns until March 23 and benefited more from the stimulus on March 24. Albuquerque et al. (2020) and Garel and Petit-Romec (2020a,b) find that better ESG ratings mitigated the stock price decrease. Eldar and Wittry (2020) investigate the use of "poison pill" anti-takeover devices by about fifty US firms from March 2 to April 23, 2020. They show that highly exposed firms to take-over (low liquidity and high leverage) have suffered a steeper price decline before taking the pill but have benefited a significant increase following adoption. Heyden and Heyden (2020) run an event study to capture the stock market reaction following key events. They consider a sample of 867 firms from the US and Europe, from January 20 to March 26, 2020. They show that shareholders reacted significantly to the announcement of the first COVID-19 related deaths, but not to the first cases. Moreover, while announcement of fiscal policies caused negative abnormal returns, they found that the market declines were reduced by announcement of expansive monetary policy.

A third group of papers examine cross-country effects and assess the relationship between measures of the pandemic's severity and aggregate stock market returns. Alfaro et al. (2020) compare the impact of the SARS outbreak in Hong Kong from January 1 to July 11, 2003 with the COVID-19 pandemic in the US from January 22 to March 27, 2020. They model cumulative infections as exponential or logistic[6], and show that *unanticipated* changes in the number of cases forecast stock returns. Ru et al. (2020) consider 65 countries, focusing on two specific periods: the initial outbreak in China (Jan. 20 to Jan. 31, 2020) and the global outbreak (Feb. 21 to Mar. 5, 2020). They show that stock markets reacted more quickly and strongly in countries that previously suffered from the 2003 SARS epidemic. Gerding et al. (2020) consider nearly thirty thousand firms in more than one hundred countries from January 2 to April 7, and show that stock price reactions were stronger in countries with higher debt-to-GDP ratio. Asharaf (2020), using a sample of 64 countries between

[6] See, for instance, Fernández-Villaverde and Jones (2020) for a more sophisticated epidemiological model.

January 22 and April 17, suggests stock markets reacted more strongly to the growth in confirmed cases rather than those of deaths, but only during the early days of the pandemic in each country. He also suggest that the effects were short-term, however, and only persisted for 40 to 60 days.[7] Crose et al. (2020) look at stock returns around announcement with intraday data and show that news about COVID-19 from Twitter has a significant impact on stock returns.

Overall, it might appear that stock markets integrated new information, at least partially, about Covid-19 into prices as the EMH predicts. Indeed, most of the intuitions one might have about differential impact between companies, sectors, and countries are seemingly confirmed. Nevertheless, several issues still remain. Papers which used firm-level data are very useful for assessing relative valuation of firms, but they do not tell us anything about global changes of the stock market, the fall and the rebound. Moreover, all these papers rely on different specifications, and it is not clear whether they are robust to, i) the choice of the period, and the inclusion of the rebound phase, ii) the method of computing returns (raw *versus* market-adjusted), and iii) the metric used to measure the pandemic (deaths *versus* cases, new *versus* cumulative figures). Finally, albeit statistically significant, the effects put forward so far explain only a small part of the stock market variations.

3. Data and methodology

The urgency of the COVID-19 crisis has made an unprecedented amount data available in record time. This large quantity, however, allows for a wide range of heterogeneous specifications, and researchers must be extremely careful that their results are not wholly conditional on using one specific time period, sample, or measure. In particular, we should pay special attention to cross-sectional and temporal dependencies, lest we risk finding spurious results. In this spirit, we first begin by carefully presenting our selected data so as to not jump into a race for p-hacking. Second, we present some stylized facts about the stock markets response to the COVID-19 pandemic and formulate some testable hypothesis. Finally, we detail our methodology, using a conservative approach with time and country fixed effects, and present several robustness tests.

[7] Alber (2020) and Ozili and Arun (2020) also provided preliminary analysis of the relationship between the Covid-19 and stock index returns in a small subset of countries. However, they do not consider risk-adjusted return and it is not clear whether they control for country and/or day fixed effects, which casts doubt on their identification strategy. Another paper, albeit with a different method, is Wang and Enilov (2020) consider the G7 countries from February 17 to April 9, 2020 and show that the number of Covid-19 cases Granger-caused stock market returns for Canada, France, Germany, Italy, and the US, but not for Japan and the UK.

Covid Economics 28, 12 June 2020: 29-69

3.1. Data

To assess the impact of the COVID-19 pandemic on stock markets, we have collected data for 74 countries between January 2nd to April 30th, 2020. In this section, we motivate and describe our difference sources. All databases used are public. Table 1 presents some descriptive statistics.[8]

Countries. While first studies on the COVID-19 have mainly focused on the US (Ramelli, and Wagner, 2020; Takahshi and Yamada, 2020; Eldar and Wittry, 2020), we gather data on a broader set of 74 countries to provide an effective assessment of the world situation.

Stock returns. For each country, we have collected daily closing prices for each country's major stock index from Reuters. We also use the FTSE All-World index to capture the global stock market dynamic. In the core estimations, we consider daily log-returns, but in some specifications we use instead daily adjusted log-returns. Adjusted returns are computed as the difference between the observable stock index return and its value predicted using the extended CAPM, for which parameters were estimated over the period January 2019 to April 2020.

As shown in Table 1, the daily average return is -0.24%, with a minimum of -18% and a maximum of +13%, which show the very high variability of prices over this period, despite the general decline.

Period. Ramelli and Wagner (2020) distinguish three sub-periods of the pandemic: *Incubation* from January 2, with the first announcements of pneumonia cases in Wuhan and the closing of a Seafood Wholesale Market, to January 17; *Outbreak* from January 20, when Chinese authorities confirmed the transmission of the virus between humans and the WHO published its first report on the epidemic, to February 21; *Fever* from February 24, with the announcement of the lockdown in Italy, to March 20 (their last observation). In this paper, we extend the period and add a fourth phase: the *Rebound* from March 23, the date of Fed intervention, to April 30. At the time of writing, many of the papers reviewed above are limited to the February-March period, and therefore exclude the market rebound in April.

COVID. Multiple databases were set up to assess the spread of COVID-19 within and between countries. We consider the Coronavirus COVID-19 Global Cases Database managed by Dong, Du and Gardner (2020) at the John Hopkins University (JHU), which seems to be the most reliable source.[9]

[8] The Online Appendix provides detail on the sources (Table A), the computation of the variables (Table B), the list of countries with their summary statistics (Table C) and the matrix of correlations (Table D).

[9] The JHU database is completed with data from Owid-COVID when needed (in particular the latter provides information from January 1, 2020).

Our main variable of interest is the daily log-growth for each country *i* at time *t*, $COVID_{i,t}$, defined as follow[10]:

$$COVID_{i,t} = ln(1 + cumulative\ cases_{i,t}) - ln\ (1 + cumulative\ cases_{i,t-1})$$

In Table 1, the daily average growth is +7%.

We also consider the path of the COVID-19 pandemic at the global and regional level. To do so, we consider the following variables for each country:

$$COVID\ Region\ _{i,t} = ln\left(1 + \sum\nolimits_{j\in(Wld\ni i)} cumulative\ cases_{j,t}\right) - ln\ \left(1 + \sum\nolimits_{j\in(Wld\ni i)} cumulative\ cases_{j,t-1}\right)$$

$$COVID\ RoW\ _{i,t} = ln\left(1 + \sum\nolimits_{j\in(Reg\ni i)} cumulative\ cases_{j,t}\right) - ln\ \left(1 + \sum\nolimits_{j\in(Reg\ni i)} cumulative\ cases_{j,t-1}\right)$$

where *Wld* denotes the countries in the world (188 in the JHU database) and Reg_i the region (Africa, Asia, Europe, Latin America, North America, Oceania) to which country *i* belongs.

Following Ding et al. (2020), we chose the number of cumulative cases to proxy the spread of the crisis, but our results are not different when the number of cumulative deaths are used instead (albeit it reduces the variability of the variable *COVID*, with more zeros at the beginning of the period).

General attention to COVID-19 and market sentiment. To gauge the level public attention toward the COVID-19 pandemic, we use Google Trends. Google Trends is widely used by scholars for studying the spread of epidemics, nowcasting, and a means of assessing market sentiment. Google Trends provide time-series and cross-section data of terms used by users of Google's web search platform. The queries are normalized to equal 100 for the highest volume during the period for each country. We selected the terms "COVID-19" and "Coronavirus", because it is very unlikely that there will be any spelling differences throughout languages, allowing us a daily, country-specific, and cross-country comparable variable.[11] From January 1 to April 30, 2020, we found that in most countries in our sample these terms have been among the most searched for.

We also rely on the VIX index, which represents the market's expectation of 30-day forward-looking volatility. The VIX index is computed by the CBOE as the implied volatility of the S&P 500 index options over the next 30 calendar days. This index is well-known among financial practitioners as a proxy of fear and stress in the market. In addition, we consider the Infectious

[10] Because the number of cases is often known after the stock market closed, we match stock returns at time *t* with COVID data at time *t*–1. For weekends and holidays we divided the log-growth of COVID cumulative cases by *n*, the numbers of calendar days between two non-consecutive business days.

[11] First epicenter of the COVID-19 pandemics, the Chinese have also reached this maximum threshold on the Google platform. Because Google is not so commonly used in the country, however, the time-series distribution is not smooth. We considered correcting this using the main Chinese search engine, Baidu, but it is only accessible to Chinese speakers.

Covid Economics 28, 12 June 2020: 29-69

Disease Equity Market Volatility tracker (IDEMV) provided by Baker et al. (2020). IDEMV is computed as the overall Equity Market Volatility (EMV) tracker, which reflects the frequency of articles about stock market volatility in leading U.S. newspapers, multiplied by the share of those articles that contain words related to diseases or epidemics.

Macroeconomic and institutional variables. We control for country characteristics using pre-2020 figures such as their GDP per capita, the percentage of the population over 65 years old, health expenditure (as % of GDP), the unemployment rate (in % of labour force), the percentage of urban population over total population, general level of government debt (as % of GDP), stock market capitalisation (as % of GDP), and tourism receipts (as % of total exports). For each country, we use the latest observations available from the World Bank database. Specific country characteristics are not time-varying in our sample period, and we examine their interaction with *COVID*.

Policy Interventions. For interest rates, we gathered daily policy rates for each country from the BIS database. For other kinds of policy intervention, we rely on the COVID-19 Response Tracker (CFRT) provided by the Yale Program on Financial Stability (YPFS), which collects economic policy responses from official government websites around the world. We consider five categories of announcements: asset purchases, government credit guarantees or facilities for nonfinancial firms, support to the financial system, tax reduction and public spending increase, changes in bank supervisory rules, and swap lines.

Lockdown. To measure lockdown initiatives, we use the Stringency index provided by the Oxford COVID-19 Government Response Tracker. The index is computed as the average of nine sub-indexes, each ranging from 0 (the least stringent) to 100 (the most stringent) responses. The index takes into account external and internal movement restrictions, fiscal support, and even measures supporting the healthcare system. In addition, we use Apple and Google mobility trackers to assess citizen mobility, as quarantines and social distancing policies have reduced all forms of travel, whether for business or personal reasons.[12] These indices provides us different methods of assessing internal travels restrictions. For example, Google Mobility compares the change in daily trips of users who have activated their location history relative to the median number of trips made by users during a pre-lockdown control period, between January 3 and February 6, 2020. Apple's Mobility compares the volume of its users' travel searches on its map app to a benchmark volume on January 13, 2020. These searches are divided into three categories: public transport, car, and walking.

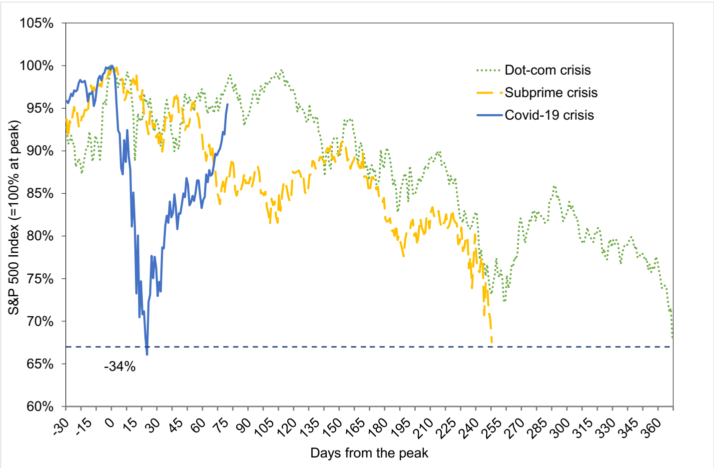
[12] We also attempted to use the registered number of flights worldwide provided by FlightRadar24, or data from Citymapper or Opentable (which provides the number of reservations accepted by restaurants) but the country coverage is not sufficient.

3.2. Stylized facts and testable assumptions

The S&P 500 stock index reached an all-time record high on February 19th, 2020, despite the fact that terrible news of the COVID-19 pandemic had already been pouring in for nearly a month.[13] In particular, as early as January 30th, the World Health Organization (WHO) had declared a "*public health emergency of international concern*". On the day of the US stock market peak, the number of confirmed cases in the world had already exceeded 75,000, with more than 2,000 reported deaths. Then, on March 23rd, the S&P 500 fell by 34% compared to its peak. The fall in prices was extremely rapid.

Figure 2 compares this fall in prices to other recent stock market crashes. In March 2020, it took only one month for the S&P 500 to lose one-third of its value, while it took one year for the subprime crisis to decline the same amount, and one year and half for the dotcom bust. In the wake of this historical decline, however, the stock market rebound strongly. As of June 8th, the S&P 500 is off by only 5% from its peak, putting it back to the same level as January 2019. In most countries, In Europe, stock index patterns were similar, even if the rebound is not always as strong as in the U.S.[14]

Figure 2. The US stock market in times of crisis



Note: Figure 2 compares the drop of the S&P 500 Index during the dot-com crisis (which peaked on March 24, 2000), the subprime crisis (peaked on Oct. 9, 2007) and the COVID-19 crisis (peaked on Feb. 19, 2020). Authors' computation.

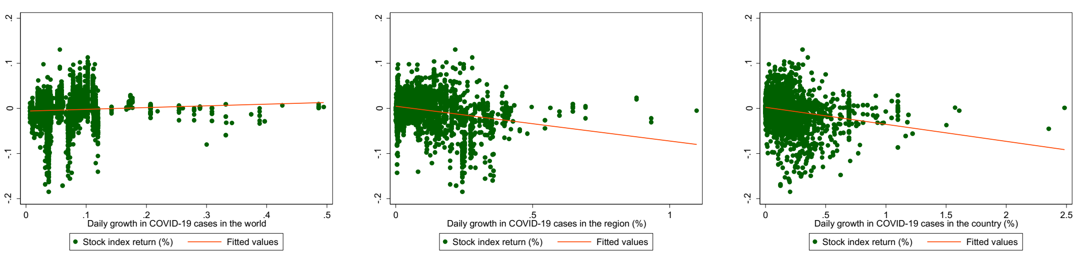
[13] For a timeline, see https://www.nytimes.com/article/coronavirus-timeline.html?searchResultPosition=1
[14] See the Online Appendix.

Stock markets seem to have poorly anticipated the economic consequence of the COVID-19 pandemic, albeit they were not the only ones to have underestimated its effects. In hindsight, given the winds of panic that gripped the world at the end of February, it is unsurprising that stock markets fell so much. What remains striking is the massive rebound that followed, while with stay-at-home orders proliferated everywhere, cases climbed to over three million, and deaths rose to over 200,000 worldwide. That being said, it is difficult to assess investor behaviour in absolute terms, so in this paper we take a somewhat less ambitious approach. Our aim, then, is to examine whether investors' reaction is explainable by economic fundamentals by looking not at their reaction in absolute terms, but by comparing stock price movements across countries and attributing them to differences between countries.

By casting the problem in terms of economic fundamentals across countries, several testable hypothesis present themselves. First, we can hypothesize that stock markets reacted more strongly in countries where the pandemic spread more rapidly.[15] Figure 3 shows correlations between the performance of the country's stock market index and the rate of spread of the pandemics, measuring as daily growth in the number of COVID-19 cases at the world level, the regional level or country level. At first glance, there seems to be a slight negative correlation in this dimension.

Figure 3. Daily stock index returns and COVID-19 cases

3a) World 3b) Europe 3c) Domestic



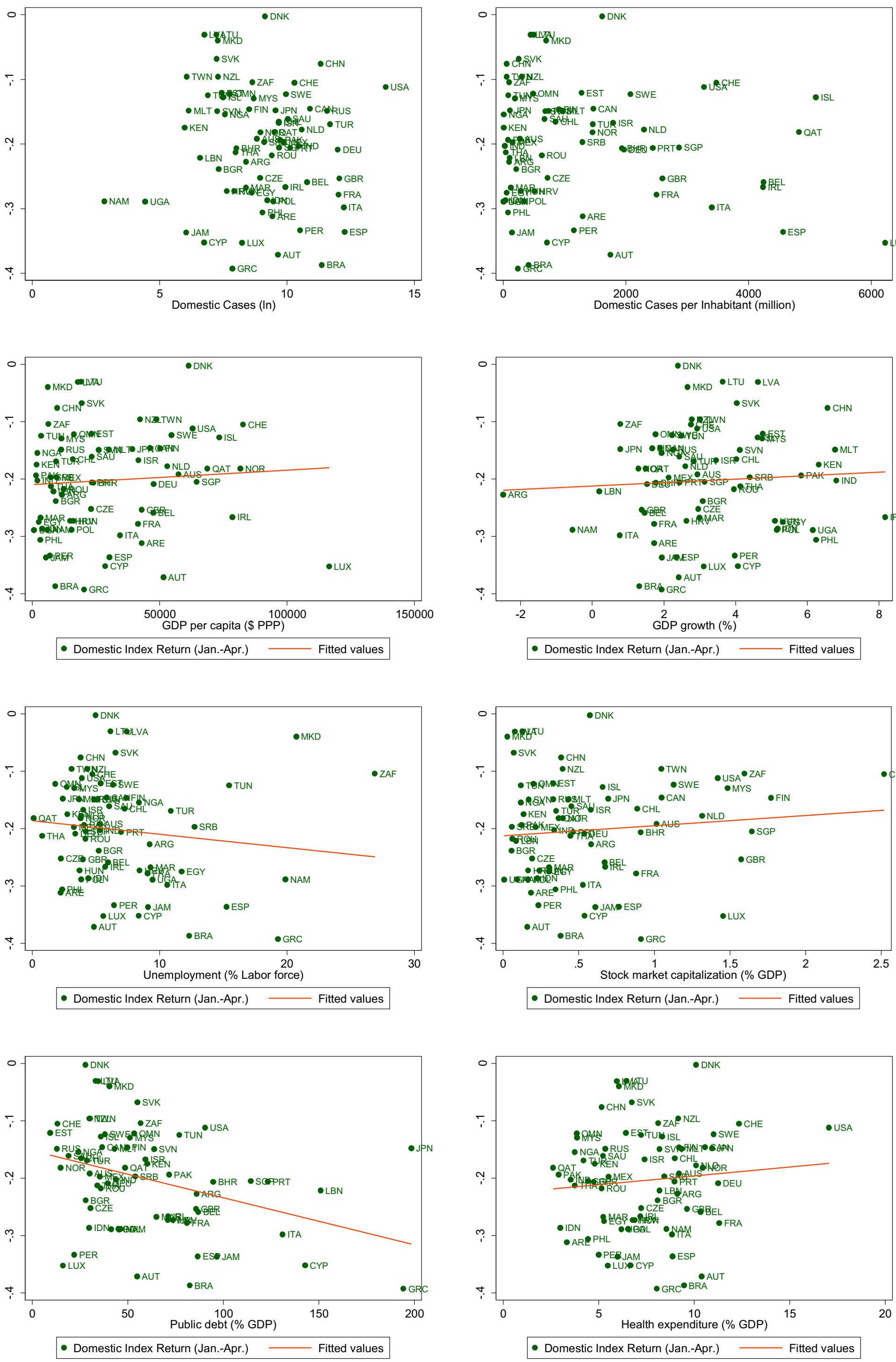
Note: Figure 3 provides several scatter plots of daily domestic index returns and the daily growth in the number of COVID-19 cases reported in the World (2a), in the region (2b) or in each country (2c). Sources: JHU and Reuters. Sample: 74 countries from January 1, 2020 to May 1, 2020. Authors' computation.

[15] On the contrary, one can think that investors were more distracted and, consequently, not very sensitive to country specific news (Ehrmann and Jansen, 2020).

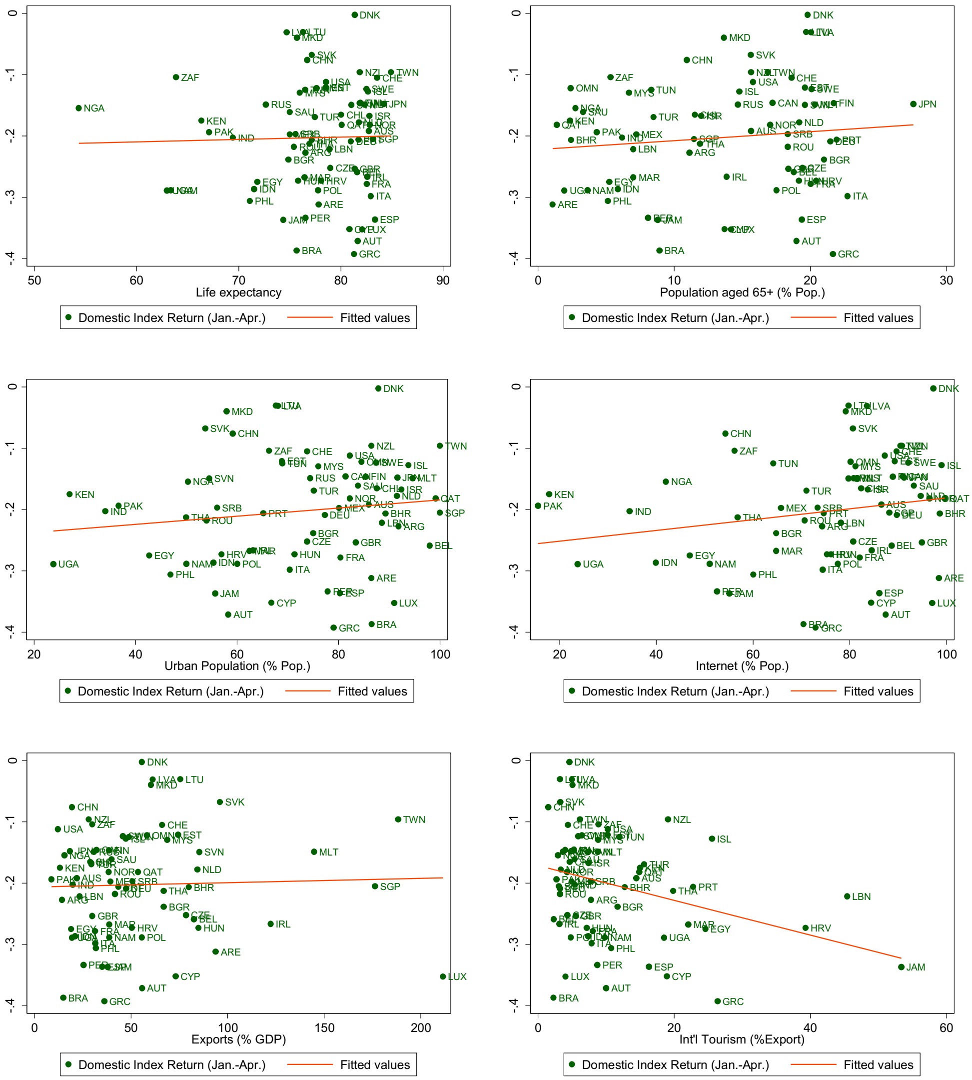
Second, we can hypothesize that stock markets reacted more strongly in countries which were more susceptible to a potential pandemic, either due to structural economic fragility or exposure to transmission vectors. Figure 4 presents scatter plots between the stock index returns over the crisis period (January to April) and various prior-2020 macroeconomic and institutional variables chosen to capture potential fragility or vulnerability. The usual suspects are: GDP per capita, GDP growth, unemployment, stock market capitalization-to-GDP, public debt-to-GDP, health expenditures-to-GDP, life expectancy, percentage of population aged 65 or over, percentage of urban population, access to internet, exports-to-GDP, and international tourism-to-GDP. Countries whose fiscal response would be constrained by poverty or debt might be thought to be more susceptible to a pandemic. Similarly, countries with more at-risk populations, concentrated in big cities or with large older, at-risk populations, might also be more susceptible. The COVID-19 having disrupted value chains and inhibited international mobility, countries with more international trade and tourism likely might have been more impacted. These international activities also represent potential vectors of entry and spread of the pandemic. On the positive side, it is easy to see how a better health care system would make a country more resilient. Moreover, a larger stock market is often seen as a resilience factor. Finally, internet access is included as a proxy of ease of remote working, a post-COVID phenomenon essential for keeping economies running during lockdowns.[16]

[16] See Dingel and Neiman (2020) for an analysis of the share of jobs that can be done at home.

Figure 4. Domestic index returns in time of COVID-19



Covid Economics 28, 12 June 2020: 29-69

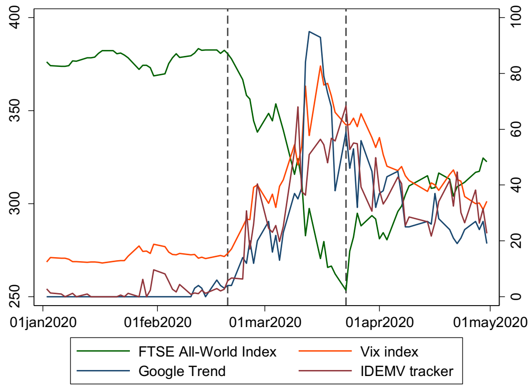


Note: The figure 4 provides several scatter plots showing domestic index returns over the 4 first months of 2020 and selected variables of structural and institutional resilience to pandemic (prior-2020). Sources: World Bank and Reuters. Sample: 74 countries from January 1, 2020 to May 1, 2020. Authors' computation.

Covid Economics 28, 12 June 2020: 29-69

Third, it is likely that investors were not only sensitive to the raw reality of the COVID-19's figures, but also to the prevailing general attention towards the pandemic in each country. As shown in Figure 5, the VIX index reached all-time highs at 82.69 (Table 1) during the Fever phase, with a new all-time largest close-to-close point increase (+24.86). Similarly, albeit not necessarily at the same time, the Infectious Disease EMV tracker and the number of web search worldwide as reported by Google Trends also reach a peak.

Figure 5. General attention, volatility, market sentiment and FTSE All-World index in time of COVID-19

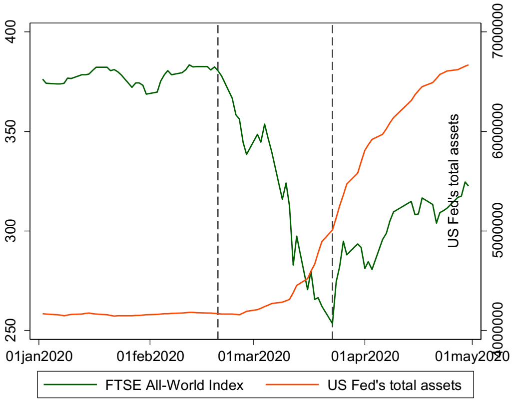


Note: This figure shows the FTSE All-Word Index, the VIX index, Google Trends (worldwide) and IDEMV tracker from January 1, 2020 to May 1, 2020. The vertical lines correspond to the stock market peak (February 20) and bottom (March 23). Authors' computation.

Fourth, investors were also very sensitive to announcements made by public authorities, especially central banks. It is clear that the rebound owes a lot to the intervention of the US Federal reserve.[17] Figure 6 show the spectacular growth in Fed's total assets, but the main other central banks (the Bank of England, the Bank of Japan, and the European Central Bank) have acted similarly. In addition, most of the governments have launched specific economic policy to tackle the economic downturn and "flatten the recession curve" (Gourinchas, 2020).

[17] See Cieslak and Vissing-Jorgensen (2020) for an investigation of the Fed's reaction to market declines in the last decades (including the COVID-19).

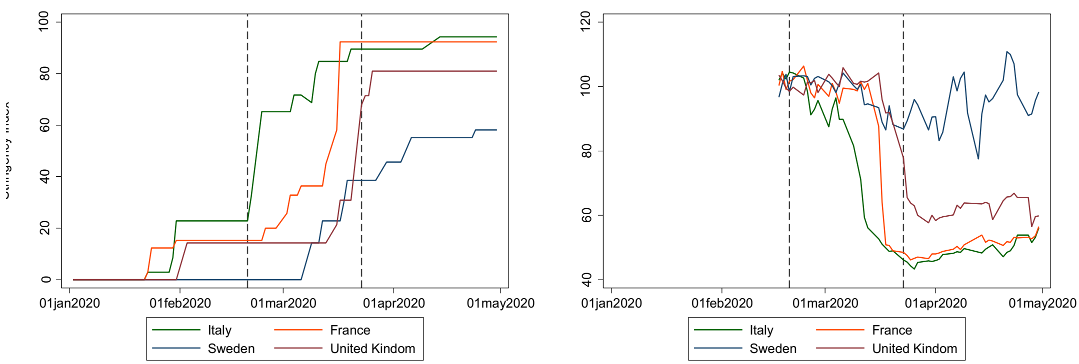
Figure 6. US Fed's total assets and FTSE All-World index in time of COVID-19



Note: This figure shows the FTSE All –Word Index and the total assets of the US Federal reserve from January 1, 2020 to May 1, 2020. The vertical lines correspond to the stock market peak (February 20) and bottom (March 23). Authors' computation.

Fifth, the lockdown may have had an effect on the response of stock markets. The primary strategies to deal with outbreak are containment and mitigation ("*flattening the curve*"). Most countries have taken action in this direction, but some have also played the (controversial) strategy of herd immunity. Figure 7 compares the severity of containment in selected European countries, and shows their impact on people's observed mobility. While the first one indicates *de jure* measures of containment, the last one represents *de facto* changes in mobility (Chen el al. 2020).

Figure 7. Lockdown and mobility in time of COVID-19



Note: This figure shows the Stringency index (Oxford COVID-19 Government Response Tracker, OxCGRT) and the Google mobility index for a sample of European countries from January 1, 2020 to May 1, 2020. The vertical lines correspond to the stock market peak (February 20) and bottom (March 23). Authors' computation.

3.3. Methodology

To capture the shareholders reaction to the COVID-19 pandemic, we use as a baseline the following model:

$$R_{i,t} = \alpha + \beta * COVID_{i,t} + \gamma * GoogleTrend_{i,t} + \delta \times \Phi_{i,t} + \mu_i + \mu_t + \varepsilon_{i,t} \qquad (1)$$

where, the dependent variable, R_{it} is the closing price of the daily (raw) stock index return of country *i* at time *t* from January 2 to April 30, 2020. $COVID_{it}$ is the daily (avg) ln-growth rate of COVID-19 cases. $GoogleTrend_{it}$ is the search interest related to the COVID-19. $COVID_{it}$ and $GoogleTrend_{it}$ form our basic model, accounting for both the spread of the pandemic and a measure of public perception about the spread. We complement this benchmark specification with $\Phi_{i,t}$, a $k \times 1$ vector of independent variables. These additional explanatory variables are grouped into four categories: country's institutional and macroeconomic characteristics, measures of global networks and supply chains, policy initiatives, and measures of lockdown.[18] Most of the variables are time-varying and country specific, but we also include an array of interaction terms between pre-pandemic country traits and *COVID*. For each category of explanatory variables, a regression was run including only that category and omitting the other three. Finally, a regression including selected variables from all four categories was run. In the core analyses, we also include both country (μ_i) and day (μ_t) fixed effects to control for any time-invariant country traits or for any time-varying factors common to all countries.

In some specifications, we omit day fixed effects to attempt to assess how global events or announcements may have influenced stock prices during the COVID-19 pandemic. Then, the model becomes:

$$R_{i,t} = \alpha + \beta * Covid_{i,t} + \gamma * GoogleTrend_{i,t} + \delta \times \Phi_{i,t} + \mu_i + \rho \times \Omega_t + \varepsilon_{i,t} \qquad (2)$$

where we have substituted the day fixed effect μ_t by Ω_t a 4×1 vector of covariates shared by all countries, including the daily FTSE All-World index return, the VIX index, the growth of the infectious disease equity market volatility (IDEMV) tracker, and the growth of the US Fed's total assets. Total Fed assets is added in order to account for the impact of expansionary monetary policy, and the Fed was chosen because of the leadership role they play in shaping central bank policies around the world. While very similar to equation (1), this specification

[18] All the variables are detailed in the Online Appendix.

Covid Economics 28, 12 June 2020: 29-69

Covid Economics 28, 12 June 2020: 29-69

provides controls for both stock market correlations in the time dimension and captures cross-sectional dependencies.

In the core analysis, Equations (1) and (2) are estimated using ordinary least squares (OLS), with robust standard errors.

To test the robustness of our results and ensure our findings are not conditional on the specific choices of data and time period we made, several additional variants are considered. A) We consider adjusted returns instead of raw returns as the dependant variable to rule out any remaining correlation between stock markets. B) We consider the model without day fixed effects, as described in Equation (2). C) We limit our sample period to the Outbreak and Fever phases, ignoring the Incubation and Rebound phases, as in Ding et al. (2020). D) We estimate Equation (1) with Driscoll-Kraay (1998) standard errors to further correct for cross-sectional dependence.

4. Empirical results

We first present our benchmark specification with only the growth in the domestic number of COVID-19 cases and the intensity of searches relating to the COVID-19 pandemic on Google, with country and day fixed effects. We also present results omitting day fixed effects but including global factors (world return, volatility, general attention and central bank intervention) to assess the impact of global trends. Then we successively consider the influence of the four categories of variables individually. Next, we include all control variables simultaneously. Finally, we discuss our robustness tests.

4.1. Stock index returns in response to the COVID-19 pandemic

As a benchmark, and for the sake of comparison with other studies, we begin by assessing the relationship between stock index returns and the growth in the number of COVID-19 cases without considering any additional explanatory variables. Table 2, column 1 presents results from such a baseline regression, both with day fixed effects (2a) and without day fixed effects but with global factors (2b).

As shown in Table 2, *COVID* enters negatively and significantly in most specifications, suggesting that stock market performance is strongly and negatively correlated with country exposure to the pandemic. The results hold whether or not day fixed effects are included. In

Table 2a, column 1, the coefficient associated with *COVID* is equal to –0.69 and it is significant at the 1% level, which mean that investors responded more strongly to countries where the pandemic spread more rapidly. In addition, the coefficient associated with *GoogleTrend* is also negative (–0.39) and significant at the 1% level, suggesting that the stock market reacts negatively when public concerns about the COVID-19 are greater. This result is consistent with Croce et al. (2020) who underline the importance of social networks in the spread of the panic.

Table 2 also shows that these relationships were much stronger during the Fever phase. When we estimate the model on sub-periods (column 2-4), the variables *COVID* and *GoogleTrend* are negative only for a sample restricted to the Fever phase (sub-period from Feb. 24 to March 20, 2020). During the Incubation, Outbreak, and Rebound phases, countries more affected by the pandemic did not experience greater changes in stock market indexes than others. The result is the same when we interact *COVID* with indicator variables corresponding to each phase (column 5): the only significant interaction is with the Fever phase.

We also interact the variable *COVID* with different proxies of public attention or sentiment in the face of the pandemic. We consider three alternatives computed first separately (columns 6-8) then jointly (column 9): stock market volatility, as measured by the VIX index, public attention about COVID-19, as measured by Google Trends, and newspaper-based uncertainty about infectious disease, as measured by the IDEMV tracker. These three variables are expressed as daily growth rates. When we include the interaction between *COVID* and *gVix* or *gIDEMV*, the variable *COVID* is no longer significant, but the interaction term is negative and significant at the 1% level. It means that stock markets react negatively to the growth in the number of COVID-19 cases, but only after volatility had already surged and the pandemic had become a growing concern.

In Table 2b. we run the same nine specifications without day fixed effects. This allows us to add the world stock index return, VIX index, and IDEMV tracker to capture cross-sectional dependencies and account for stock-market interconnectivity. Obviously, the coefficient associated with *World return* is positive and strongly significant, with a beta between 0.45 and 0.66. We might have also expected a negative relationship between *VIX* and stock index returns, but the relationship is barely significant. Interestingly, the *gIDEMV* is negative and significant, which provides evidence that the general uncertainty about the pandemic fuelled the decrease in stock returns.

Covid Economics 28, 12 June 2020: 29-69

Moreover, by omitting day fixed effect while adding variables capturing interconnectivity between stock markets, we can examine some time-varying determinants that may have had a global impact for all countries. The prime suspect is clearly the intervention of the US Federal reserve, which is proxied by the daily average growth of total assets, *gFED*. In all specifications (excluding sub-samples), the associated coefficient is positive and significant at the 1% level, which confirms the impact of action by monetary authorities.[19]

Otherwise, our previous findings all remain valid when day fixed effects are removed[20]: stock market returns are negatively correlated with exposure to the pandemic (the coefficient associated to *COVID* is –0.96 in column 1), but the negative impact is limited to the Fever phase (column 2-5), or when accompanied by a surge in volatility, or wide-spread concern about the pandemic (column 6-9).

Moving forward, we will consider the entire sample period (Jan.-Apr. 2020), including the Rebound phase, in our analysis. Results restricted to the Fever phase are available in the Online Appendix. Furthermore, we will only consider models with day fixed effects in the rest of the analysis, because results using either fixed effects or time-series variables were extremely similar. Nevertheless, all results without fixed effects are available in the Online Appendix.

4.2. Country characteristics

Table 3 provides estimates with several country specific factors added to the benchmark model. The benchmark model itself is presented again in column 1 for ease of comparison. The country specific variables are considered in interaction with the variable *COVID*. Column 2 presents a model following Ding et al. (2020) that includes GDP per capita (*GDP_capita*), GDP growth (*GDP_growth*), the percentage of population aged above 65 among the total population (*Popu_65above*), as well dummy variables coding a country's legal origin: French (*fr*), German (*ge*) or Scandinavian (*sc*), with Anglo-Saxon common law as the baseline (column 2). We also consider, in columns 3-8, a series of additional economic variables (*Eco*): health expenditure to GDP (in %), the share of unemployment in the total population (in %), the debt to GDP ratio (in %), the stock market capitalization to GDP ratio or the share

[19] We also considered the growth of the balance sheet of the ECB and the results are the same.
[20] The only differences is that *gIDEMV* is significant instead of *GoogleTrend*, which is however negative and significant in interaction with *Covid*.

of tourism receipts in total exports (in %).[21] Lastly, in column 9, like Ru et al. (2020), we have also used a dummy to check whether countries previously affected by the SARS pandemic were more affected than those that were not.[22]

Overall, our previous results hold. *COVID* and/or *GoogleTrend* are negative and significant in most models. Unfortunately, we fail to highlight any genuine differences in response between countries. Thus, it is not clear whether stock markets in richer economies[23], younger countries, more indebted countries, countries most open to international tourism, countries with larger and more resilient stock exchanges, with more state power or countries that have experienced the SARS pandemic have reacted differently to the COVID-19.

4.3. Global networks and supply chain

Table 4 examines how countries' exposure to COVID-19 through their neighbours and trade partners affect stock index returns. In addition to the benchmark model with *COVID* and *GoogleTrend* (column 1), we add the growth in the number of COVID-19 cases in the rest of the world (column 2, *COVID RoW*) and the growth in the number of COVID-19 cases in the region (column 3, *COVID Region*) to which the country belongs: Africa, Asia, Europe, Latin America, or North America. We then take a bilateral approach, and consider the relationships between each country and each other country in the world. To do so, we draw on the literature in geographic economics and the gravity model: for each country *i*, we weighted the number of COVID-19 cases in the rest of the world (countries *j*) by the geographical distance between *i* and *j* (column 4, *COVID RoW*Dist.*) and by the GDP of *j* (column 5, *COVID RoW*GDP*). We also consider the influence of international supply chains on stock index returns in response to the COVID-19 pandemic: we weighted the growth in the number of COVID-19 cases in *j* by the exports (in % of GDP) of *i* towards *j* (column 6, *COVID RoW*Export*) or the imports (in % of GDP) of *i* from *j* (column 7, *COVID RoW*Import*).[24] Finally, all the variables are included simultaneously (column 8).

[21] We also tested for other country's traits (Internet access, Life expectancy, or Tax revenue), but the results (not tabulated but available on request) are not significant.
[22] We alternatively consider the number of SARS case or death, or a dummy variable, but it does not change the results.
[23] If we restrict to the Fever period, Covid interacted with *GDP_capita* or *GDP_growth* are significant at the 10% level as in Ding et al. (2020). See the Online Appendix.
[24] We also considered bilateral trade (exports or imports) according to level of processing (primary goods, basic and manufacturing goods, intermediate goods, equipment goods, mixed products, and consumption goods). The results are not significant – See Online Appendix. For the role of global supply chains in the COVID-19 pandemic, see Bonadio et al. (2020).

Covid Economics 28, 12 June 2020: 29-69

The global nature of the COVID-19 pandemic means that stock markets might have responded not only to the worsening domestic health situation, but also to the situation in the rest of the world. Our results show that the reality is more nuanced: the world dynamic of the pandemic did not impact stock markets. Our previous results showed that stock markets largely ignored the pandemic while it was confined to in China during the Outbreak phase, and the fact that *COVID RoW* is not significant is consistent with this observation. However, investors did not overlook what was happening in neighbouring countries, as *COVID Region* is significant at the 1% level in both models, with the magnitude of its coefficient close to that of the coefficient associated with the growth in the number of cases at the domestic level. If we consider the interactions with traditional gravity variables, we find no effect of distance, but a strong effect of GDP. This means that the growth in the number of cases worldwide had an effect on stock markets, but only when the cases were in rich countries. Again, this is consistent with the analysis of the stylized facts depicted in Figure 1a-b.

While one might have expected the breakdown of international value chains to influence the stock market's response to COVID-19, when growth in the number of cases worldwide is weighted by bilateral trade (exports or imports), the resulting interaction terms are not significant. Our analysis does not confirm the results of Ding et al. (2020) on this topic, but this is probably related to the fact that countries differ much less in their trade relations with foreign countries than do companies.

4.4. Policy interventions

Table 5 focuses on the impact of policy interventions on stock market returns during the COVID-19 crisis. Most observers have attributed the market rebound to massive intervention by monetary authorities, particularly the Fed. Central banks have played a critical role in preserving the economy by implementing a range of measures: policy rate cuts, liquidity supports, swap lines, and asset purchase schemes (quantitative easing). The challenge is that most of these policies are difficult to quantify at the country level. Beginning from benchmark model with *COVID* and *GoogleTrend* (column 1), we first introduce the change in key interest rates by central banks (column 2, *Δ Interest Rate*). Then, we rely on the data from the Yale Program on Financial Stability which collect most of the policy announcements made by the governments worldwide during the crisis. Using this data, we consider a number of daily country-specific indicator variables. We group these economic policy announcements

Covid Economics 28, 12 June 2020: 29-69

according to the following categories: asset purchases (*YPT Asset purchases*), government credit guarantees or facilities for nonfinancial firms (*YPT Credit guarantees*), support to the financial system (*YPT Financial system*), tax reduction and public spending increase (*YPT Fiscal stimulus*), changes in bank supervisory rules (*YPT Macroprudential*), and swap lines (*YPT Swap lines*). We include these daily announcements with (column 3) or without (column 4) change in the policy rate.

There is little doubt that the Fed's intervention on March 23, 2020 was a decisive moment to curb the economic impact of the crisis (Haddad et al., 2020), but we do not test its impact here. Indeed, it is important to recall that we only consider country-specific announcements, while the Fed intervention has an impact that goes far beyond the US.[25] With this caveat in mind, announcements at the country level related to asset purchases did not impact stock returns. Similarly, we do not find any particular effect associated with the announcement of fiscal policies[26], macroprudential policies, or policies in favour of the financial system. In contrast, *ΔInterest Rate* is negative and significant in the presence of all other policy variables, meaning that the decrease in domestic interest rate increased stock market indices. Finally, the economic policy measure that seems to have had the greatest effect on stock markets is domestic support for nonfinancial firms in the form of loans guarantees.

4.5. Lockdown

Table 6 shows the impact of the lockdown on stock market returns during the COVID-19. In addition to the benchmark (column 1), the three main variables that together proxy for the effects of lockdown policies are *Stringency* from Oxford COVID-19 Government Response Tracker (column 2), as well as *Apple mobility* (column 3) and *Google mobility* (column 4). Obviously, these variables are strongly correlated, so we estimate regressions of stock index returns on each variable separately. All three variables are measured daily.

Whatever variable is considered, lockdowns are found to have mitigated the impact of the COVID-19 crisis on stock markets. The coefficient associated with *Stringency* is positive and significant, meaning that stronger *de jure* restrictions imposed in each country are associated with a smaller decrease in returns. Conversely, the coefficient associated with *Apple mobility*

[25] The specific interventions of the main central banks (Bank of Japan, Bank of England, European Central Bank) would deserve further investigations.
[26] This result does not support Heyden and Heyden (2020), who find that announcement of fiscal policies have caused negative abnormal returns. See also Klose and Tillmann (2020).

and *Google mobility* are negative and significant, showing that *de facto* restrictions on mobility are also seen by investors as a solution to the spread of the crisis.

4.6. Robustness

In Table 7, we consider a model of all explanatory variables simultaneously: pre-2020 country traits, global networks, policy interventions, and lockdown initiatives. As this represents a large number of potential variables, we take only those variables which were significant in the regressions for each category (Tables 3-6). In addition to the benchmark model (columns 1-3), we include estimations with adjusted returns as dependant variable (columns 4-6) and without day fixed effect to take into account time-varying global trends (columns 7-9).

Overall, our main messages hold, regardless of the specification. The coefficient associated with key variables *COVID* and *Google Trend* are negative and significant, except in the presence of an interaction term that captures the domestic evolution of the COVID-19 pandemic. In the specifications without day fixed effects, the coefficient associated with the world stock index return (*Wld. Return*) is positive and significant and the one associated with *VIX* is negative and significant, as expected. No less surprisingly, the exceptional monetary policy conducted by the US Federal reserve has greatly contributed to supporting stock markets worldwide, with the coefficient associated with *gFED* strongly positive and significant. The path of the pandemic in neighbouring countries (*COVID Region*) is also significant only when raw returns are considered. Domestic policies aiming to support nonfinancial corporations through government-guaranteed loans (*YPT Credit guarantees*), and cuts in domestic interest rates (*Δ Interest rate*) both had a positive and a significant impact no matter the specification. The effect of lockdown measures has also been positive, but to a lesser extent: the coefficient associated with *Stringency* is positive, while the one associated with *Apple mobility* is negative and significant, except when we consider adjusted return.

It can be noted that the adjusted R^2 varies little with the inclusion of any of the variables under consideration.[27] Thus, it seems that our explanatory variables explain very little of the variation in the performance of stock market indices, which are essentially captured by time and country fixed effects.

[27] This is also the case in Ding et al. (2020) with an Adj. R^2 between 0.46 and 0.54.

Covid Economics 28, 12 June 2020: 29-69

Moreover, in addition to OLS with robust standard errors, we also considered Driscoll-Kraay standard errors. Though the results are not tabulated, we re-estimated all the tables and found little to no change in the results. These tables (available on request) are qualitatively the same.

5. Conclusion

Since at least Isaac Newton[28], stock price movements have never ceased to surprise, not just the general public, but also some of the most successful economists. The collapse of stock prices around the world at the time of the COVID-19 crisis, as well as the extraordinary rebound that followed the Fed's intervention, has been no exception. This immediately sparked controversy.

Do stock markets incorporate all available information? Actually, we can see the glass half-full or half-empty. Admittedly, there is no evidence of arbitrage opportunities and it appears that the evolution of stock markets during the COVID-19 pandemic is not completely accidental. In particular, our study suggests that it was not the situation of countries before the crisis that influenced the reaction of stock markets, but rather the health policies implemented during the crisis to limit the transmission of the virus and the macroeconomic policies aiming to support companies. In this regard, our study is consistent with the results obtained by similar studies (Ding et al., 2020; Fahlenbrach et al., 2020; Gormsen and Koijen, 2020; Haddad et al., 2020; Heyden and Heyden, 2020; Landier and Thesmar, 2020; Ramelli and Wagner, 2020), even though some of the effects mentioned in these studies may not appear to be significant.

Possible extensions could include a better understanding of the investors reaction to central bank actions at the domestic level. It would also be interesting to examine stock prices in relation to trading volumes, or other microstructure-based indicators, including high frequency variables. The period could also be extended to include May 2020, with a gradual return to normality in many countries, and during which several fiscal stimulus packages have been announced. Whatever, it is still very difficult to report on the overall evolution of stock markets that might been largely driven by narratives and subject to over-reaction.[29] Indeed, fundamentals seem to explain a very small part of the stock market variations. Just like

[28] After the stock market turmoil consecutive to the South Sea Bubble, the genius scientist was said to have remarked: "*I can calculate the motions of the heavenly bodies, but not the madness of people*" (Kindleberger, 2005, p. 41).
[29] See for instance Piccoli et al. (2017) for overreaction of stock markets to extreme events.

Covid Economics 28, 12 June 2020: 29-69

Krugman and Shiller have claimed, it is hard to deny that the link between stock price movements and fundamentals have been anything other than loose. Our article only scratches the surface of this issue, which should be the subject of promising future studies.

References

Aksoy, C.G., Eichengren, B., and Saka O. (2020), Revenge of the Experts: Will COVID-19 Renew or Diminish Public Trust in Education? LSE Systemic Risk Centre Discussion Paper No. 96.

Alber, N., (2020), The effect of the Coronavirus Spread on stock markets: the case of the worst 6 countries, SSRN 3578080.

Albuquerque, R.A., Koskinen, Y., Yang, S., and Zhang, C. (2020), Love in the Time of COVID-19: The Resiliency of Environmental and Social Stocks, SSRN 3583611.

Alstadsæter, A., Bratsberg, B., Eielsen, G., Kopczuk, W., Markussen, S., Raaum, O., and Røed, K. (2020), The First Weeks of the Coronavirus Crisis: Who Got Hit, When and Why? Evidence from Norway, NBER Working Paper No. 27131.

Bartik, A.W., Bertrand, M., Cullen, Z.B., Glaeser, E. L., Luca, M., and Stanton, C.T. (2020), How are small businesses adjusting to COVID-19? early evidence from a survey, NBER Working Paper No. 26989.

Baker, S.R., Bloom, N., Davis, S.J., Kost, K., Sammon, M., and Viratyosin, T. (2020), The unprecedented stock market reaction to COVID-19, NBER Working Paper No. 26945.

Baldwin, R., and Weder di Mauro, B. (eds) (2020), Economics in the time of COVID-19: A new eBook, CEPR Press.

Benassy-Quere, A., and Weder di Mauro, B. (eds) (2020), Europe in the time of COVID-19, a VoxEU eBook, CEPR Press.

Barrero, J.M., Bloom, N., and Davis, S.J. (2020), COVID-19 Is Also a Reallocation Shock, NBER Working Paper No. 27137.

Barro, R.J., Ursua, J.F., and Weng, J. (2020), The coronavirus and the greatinfluenza pandemic: Lessons from the “spanish flu” for the coronavirus’s potential effectson mortality and economic activity. NBER Working Paper No. 26866.

Bonadio, B., Huo Z., Levchenko A.A. and Pandalai-Nayar N. (2020), Global Supply Chains in the Pandemic, CEPR Discussion Paper 14766.

Caballero, R.J., and Simsek, A. (2020), A Model of Asset Price Spirals and Aggregate Demand Amplification of a COVID-19 Shock, NBER Working Paper No. 27044.

Chen, S., Igan, D., Pierri, N., and Presbitero, A.F. (2020), Tracking the Economic Impact of COVID-19 and Mitigation Policies in Europe and the United States, IMF Special Series on COVID-19.

Cieslak, A. and Vissing-Jorgensen, A., (2020), The Economics of the Fed Put, NBER Working Paper No. 26894.

Coibion, O., Gorodnichenko Y., and Weber M. (2020a), The Cost of the COVID-19 Crisis: Lockdowns, Macroeconomic Expectations, and Consumer Spending, BFI Working Paper 2020-60.

Coibion, O., Gorodnichenko Y., and Weber M. (2020b), Labor Markets During the COVID-19 Crisis: A Preliminary View, NBER Working Paper No. 27017.

Ding, W., Levine, R., Lin, C., and Xie, W. (2020), Corporate Immunity to the COVID-19 Pandemic, NBER Working Paper No. 27055.

Dingel, J.I. and B Neiman (2020), How many jobs can be done at home?, NBER Working Paper No. 26948.

Dixit, A. (2020), R0 for COVID-19 research: An early estimate and policy implications, Princeton University, mimeo.

Dong, E., Du, H., and Gardner, L. (2020), An interactive web-based dashboard to track COVID-19 in real time, The Lancet Infectious Diseases.

Driscoll, J.C., and Kraay, A.C. (1998), Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data, Review of Economics and Statistics, 80: 549–560.

Ehrmann, M., and Jansen, D.-J. (2020), Stock Return Comovement When Investors are Distracted: More, and More Homogeneous. CEPR Discussion Paper No. DP14713.

Fahlenbrach, R., Rageth, K., and Stulz, R.M. (2020), How Valuable is Financial Flexibility when Revenue Stops? Evidence from the COVID-19 Crisis, NBER Working Papers 27106.

Fernández-Villaverde, J., and Jones, C.I. (2020), Estimating and Simulating a SIRD Model of COVID-19 for Many Countries, States, and Cities, NBER Working Paper No. 27128.

Garel, A., and Petit-Romec, A. (2020a), Investor Rewards to Environmental Responsibility: Evidence from the COVID-19 crisis, Working paper.

Garel, A., and Petit-Romec, A. (2020b), The Resilience of French Companies to the COVID-19 Crisis, Working paper.

Gerding, F., Martin, T., and Nagler, F. (2020), The value of fiscal capacity in the face of a rare disaster, Working Paper, SSRN 3572839.

Giglio, S., Maggiori, M., Stroebel, J., and Utkus, S., (2020), Inside the Mind of a Stock Market Crash, NBER Working Paper No. 27272.

Gopinath, G. (2020), The Great Lockdown: Worst Economic Downturn Since the Great Depression, IMF Blog, 14 April.

Gourinchas, P.-O. (2020), Flattening the pandemic and recession curves", Econfip Policy Brief 23.

Gregory, V., Menzio, G., and Wiczer, D.G. (2020), Pandemic Recession: L or V-Shaped? NBER Working Paper No. 27105.

Klose, J., and Tillmann, P. (2020), COVID-19 and Financial Markets: A Panel Analysis for European Countries, Working paper.

Krugman, P. (2020), Crashing Economy, Rising Stocks: What's Going On?, *New York Times*, April 30, 2020.

Haddad, V., Moreira, A., and Muir, T. (2020), When Selling Becomes Viral: Disruptions in Debt Markets in the COVID-19 Crisis and the Fed's Response, NBER Working Paper No. 27168.

Hamermesh, D.S. (2020), Lock-downs, Loneliness and Life Satisfaction, NBER Working Paper No. 27018.

Hassan, TA., Hollander, S., van Lent, L., and Tahoun, A. (2020), Firm-level Exposure to Epidemic Diseases: COVID-19, SARS, and H1N1, NBER Working Paper No. 26971.

Jordà, Ò., Singh, SR., and Taylor, A.M. (2020), Longer-Run Economic Consequences of Pandemics. CEPR Discussion Paper No. DP14543.

Kindleberger, C.P. (2005), Manias, Panics, and Crashes: A History of Financial Crises, John Wiley & Sons.

Landier, A., and Thesmar, D. (2020), Earnings Expectations in the COVID Crisis, NBER Working Paper No. 27160.

Covid Economics 28, 12 June 2020: 29-69

Malkiel, B., and Shiller, R. (2020) Does Covid-19 Prove the Stock Market Is Inefficient?, *Pairagraph*, May 4, 2020.

Montenovo, L., Jiang, X., Rojas, F.L., Schmutte, I.M., Simon, K.I., Weinberg, B.A., Wing, C. (2020), Determinants of Disparities in COVID-19 Job Losses, NBER Working Paper No. 27132.

Ozili, P.K., and Arun, T. (2020), Spillover of COVID-19: Impact on the Global Economy, Working Paper, SSRN 3562570

Piccoli, P., Chaudhury, M., Souza, A., and da Silva, W.V. (2017), Stock overreaction to extreme market events, The North American Journal of Economics and Finance, 41, 97-111.

Pindyck, R.S. (2020), COVID-19 and the Welfare Effects of Reducing Contagion, NBER Working Paper No. 27121.

Ramelli, S., and Wagner, A.F. (2020), Feverish stock price reactions to COVID-19, Swiss Finance Institute, Working Paper.

Rojas, F., Jiang, X., Montenovo , L., Simon, K.I., Weinberg, B.A., and Wing, C. (2020), Is the Cure Worse than the Problem Itself? Immediate Labor Market Effects of COVID-19 Case Rates and School Closures in the U.S., NBER Working Paper No. 27127.

Ru, H., Yang, E., and Zou, K. (2020), What do we learn from SARS-CoV-1 to SARS-CoV-2: Evidence from global stock markets, Working Paper, SSRN 3569330.

Takahashi, H., and Yamada, K. (2020), When Japanese Stock Market Meets COVID-19: Impact of Ownership, China and US Exposure, ESG, and Liquidity Channels, Working Paper, SSRN 3577424.

Zingales, L. (2015), Presidential Address: Does Finance Benefit Society?. The Journal of Finance, 70: 1327-1363.

Covid Economics 28, 12 June 2020: 29-69

Table 1 Summary Statistics

This table presents the summary statistics of the key variables used in the empirical analysis. The sample covers 74 countries from Jan. 2, to Apr. 30, 2020. Appendix Table B provides detailed variable definitions.

	Obs	Mean	Std. Dev.	Min	Max
Stock market data					
Daily stock index (raw) return (%)	6,009	-0.24	2.52	-18.54	13.17
Daily stock index adjusted return (%)	6,009	-0.11	1.79	-15.63	13.17
Daily world stock index return (%)	6,009	-0.18	2.68	-14.43	7.98
Vix index (%)	5,844	33.80	19.92	12.10	82.69
gVix (%)	5,605	1.10	11.94	-26.22	46.73
COVID-19					
COVID (%)	6,009	7.06	15.06	-7.52	248.49
COVID Region (%)	6,009	9.38	14.14	0.00	109.86
COVID RoW (%)	6,009	8.94	10.98	0.00	49.48
COVID RoW*GDP (%)	6,009	11.87	16.25	0.00	104.15
COVID RoW*Dist. (%)	6,009	8.23	10.40	0.00	64.02
COVID RoW*Export (%)	5,944	7.88	11.74	0.00	66.16
COVID RoW*Import (%)	5,944	7.24	11.69	0.00	65.32
IDEMV	6,009	21.79	20.27	0.00	68.41
gIDEMV (%)	6,009	2.35	53.17	-197.82	221.70
Google Trend	6,009	0.19	0.25	0.00	1.00
gGoogle Trend (%)	6,009	2.73	131.89	-461.51	461.51
Country characteristics					
GDP_cap ($ PPP)	6,009	28,123	24,933	642.8	116,597
GDP_growth (%)	6,009	3.21	1.94	-2.48	8.17
Popu_65above (% Pop.)	6,009	13.37	6.63	1.09	27.58
Health Exp. (% GDP)	5,852	7.26	2.71	2.27	17.06
Unemployment (% Labor force)	5,854	6.65	4.85	0.11	26.91
Urban Pop. (% Pop.)	6,009	71.76	18.47	23.77	100.00
Public Debt (% GDP)	5,469	58.50	39.53	9.38	198.44
Stock Mkt. (% GDP)	5,930	0.60	0.62	0.01	3.63
Tourism (% Export)	5,940	10.20	9.83	0.81	53.38
SARS	4,643	0.46	0.50	0.00	1.00
Legal origin: uk	6,009	0.32	0.47	0.00	1.00
Legal origin: fr	6,009	0.39	0.49	0.00	1.00
Legal origin: ge	6,009	0.22	0.41	0.00	1.00
Legal origin: sc	6,009	0.07	0.25	0.00	1.00
Policy interventions & Lockdown					
gFED (%)	6,009	0.57	0.82	-0.35	7.10
Δ Interest rate (%)	3,961	-1.09	13.25	-400.00	25.00
YPT Asset purchases	6,009	0.03	0.17	0.00	1.00
YPT Credit guarantees	6,009	0.11	0.32	0.00	1.00
YPT Financial system	6,009	0.05	0.22	0.00	1.00
YPT Fiscal stimulus	6,009	0.16	0.37	0.00	1.00
YPT Macroprudential	6,009	0.13	0.34	0.00	1.00
YPT Swap lines	6,009	0.01	0.12	0.00	1.00
Stringency	5,675	36.30	35.58	0.00	97.14
Apple mobility	4,239	77.38	34.20	8.27	166.50
Google mobility	3,436	82.32	18.76	37.00	118.00

Covid Economics 28, 12 June 2020: 29-69

Covid Economics 28, 12 June 2020: 29-69

Table 2. Stock index returns in response to the COVID-19 pandemic

This table shows how stock markets around the world (74 countries) react to the COVID-19 pandemic. The dependent variable is daily (raw) stock index return of each country from Jan. 2, to Apr. 30, 2020. In columns (2)-(4) the sample is divided in sub-periods: Outbreak is Jan. 20-Feb. 21; Fever is Feb. 24-Mar. 20; Rebound is March 23- Apr. 30. *COVID* is the daily (avg.) ln-growth rate of the number of confirmed COVID-19 cases in each country. *GoogleTrend* is the daily search interest (0-100) related to the coronavirus in each country. *Outbreak*, *Fever*, *Rebound* are indicator variables equal to 1 (0 otherwise) during the Outbreak, the Fever and the Rebound phases, respectively. *gVix* is the daily growth of the Vix index. *gGoogleTrend* is the daily growth of *GoogleTrend*. *gIDEMV* is the daily growth of the infectious disease equity market volatility tracker. *gFED* is the daily growth of the US Fed's total assets. Appendix Table B provides detailed variable definitions. All regressions include country fixed effects. Table 2a is with day fixed effects, while Table 2b is without day fixed effects.

2a.	(1) All sample	(2) Outbreak	(3) Fever	(4) Rebound	(5) All sample	(6) All sample	(7) All sample	(8) All sample	(9) All sample
COVID	-0.687***	-0.169	-0.650**	0.232		-0.298	-0.667***	-0.621***	-0.229
	(0.248)	(0.243)	(0.293)	(1.017)		(0.219)	(0.249)	(0.230)	(0.209)
GoogleTrend	-0.378**	0.0149	-1.435***	0.622**	-0.398**	-0.385*	-0.306	-0.389**	-0.320
	(0.187)	(0.215)	(0.368)	(0.252)	(0.182)	(0.194)	(0.194)	(0.186)	(0.201)
COVID*Outbreak					-0.351				
					(0.237)				
COVID*Fever					-0.851***				
					(0.301)				
COVID*Rebound					0.704				
					(0.983)				
COVID*gVix						-5.399**			-5.225**
						(2.136)			(2.067)
COVID*gGoogleTrend							-0.211		-0.219
							(0.166)		(0.172)
COVID*gIDEMV								-1.000***	-0.902***
								(0.354)	(0.328)
Constant	0.709***	0.117	-2.275***	3.414***	0.708***	-0.262***	0.709***	0.708***	-0.261***
	(0.110)	(0.122)	(0.171)	(0.475)	(0.110)	(0.0922)	(0.110)	(0.110)	(0.0921)
# Obs.	6,009	1,783	1,503	1,879	6,009	5,605	6,009	6,009	5,605
Adj. R^2	0.492	0.185	0.512	0.347	0.492	0.497	0.492	0.493	0.498
# Countries	74	74	74	74	74	74	74	74	74
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period	Jan.-Apr.	Outbreak	Fever	Rebound	Jan.-Apr.	Jan.-Apr.	Jan.-Apr.	Jan.-Apr.	Jan.-Apr.
Return	Raw	Raw	Raw	Raw	Raw	Raw	Raw	Raw	Raw

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

Table 2 (continued). Stock index returns in response to the COVID-19 pandemic

2b.	(1) All sample	(2) Outbreak	(3) Fever	(4) Rebound	(5) All sample	(6) All sample	(7) All sample	(8) All sample	(9) All sample
COVID	-0.905***	-0.166	-0.551*	-0.455		-0.579**	-0.863***	-0.819***	-0.471**
	(0.263)	(0.246)	(0.316)	(1.052)		(0.237)	(0.267)	(0.242)	(0.231)
GoogleTrend	-0.182	0.291	-1.121***	0.583**	-0.234	-0.193	-0.0557	-0.200	-0.0819
	(0.198)	(0.192)	(0.375)	(0.244)	(0.189)	(0.198)	(0.208)	(0.196)	(0.205)
Wld. Return	0.565***	0.660***	0.582***	0.457***	0.554***	0.545***	0.563***	0.563***	0.541***
	(0.0373)	(0.0705)	(0.0451)	(0.0429)	(0.0384)	(0.0378)	(0.0373)	(0.0374)	(0.0377)
Vix	-0.0151***	-0.00261	-0.000329	-0.00170	-0.0146***	-0.0148***	-0.0160***	-0.0153***	-0.0161***
	(0.00352)	(0.0143)	(0.00537)	(0.00587)	(0.00364)	(0.00355)	(0.00350)	(0.00351)	(0.00353)
gIDEMV	-0.0612**	0.0532**	-0.559***	0.990***	-0.0538**	-0.0577**	-0.0621**	0.0127	0.0121
	(0.0261)	(0.0266)	(0.0880)	(0.152)	(0.0256)	(0.0259)	(0.0262)	(0.0276)	(0.0272)
gFED	0.3299***				0.2760***	0.3061***	0.3250***	0.3332***	0.3057***
	(0.0812)				(0.0849)	(0.0800)	(0.0812)	(0.0812)	(0.0806)
COVID*Outbreak					-0.508**				
					(0.246)				
COVID*Fever					-1.043***				
					(0.310)				
COVID*Rebound					1.122				
					(0.888)				
COVID*gVix						-4.451**			-4.193**
						(1.686)			(1.623)
COVID*gGoogleTrend							-0.386**		-0.390**
							(0.171)		(0.172)
COVID*gIDEMV								-1.586***	-1.522***
								(0.410)	(0.402)
Constant	0.270***	-0.0124	-0.0135	0.113	0.252***	0.267***	0.280***	0.274***	0.282***
	(0.0605)	(0.216)	(0.161)	(0.219)	(0.0637)	(0.0631)	(0.0595)	(0.0608)	(0.0626)
# Obs.	5,844	1,639	1,503	1,858	5,844	5,605	5,844	5,844	5,605
Adj. R^2	0.419	0.178	0.419	0.293	0.420	0.422	0.420	0.421	0.425
# Countries	74	74	74	74	74	74	74	74	74
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	No	No	No	No	No	No	No	No	No
Period	Jan.-Apr.	Outbreak	Fever	Rebound	Jan.-Apr.	Jan.-Apr.	Jan.-Apr.	Jan.-Apr.	Jan.-Apr.
Return	Raw	Raw	Raw	Raw	Raw	Raw	Raw	Raw	Raw

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

Table 3. Country characteristics and stock index returns in response to the COVID-19 pandemic

This table shows how country characteristics shape the stock markets response to the COVID-19 pandemic around the world (74 countries). The dependent variable is daily (raw) stock index return of each country from Jan. 2, to Apr. 30, 2020. *COVID* is the daily (avg.) ln-growth rate of the number of confirmed COVID-19 cases in each country. *GoogleTrend* is the daily search interest (0-100) related to the coronavirus in each country. Country characteristics (prior to 2020) include (*COVID*Eco.*): GDP per capita; GDP growth; the percentage of population aged above 65 among the total population; a set of indicators equal to 1 (0 otherwise) if a country's legal origin is French (fr), German (ge), or Scandinavian (sc), while the omitted group is the English common law; Health expenditure (% of GDP); Unemployment (% of total labor force); Urban population (% of total population); an indicator equal to 1 (0 otherwise) is the country has experienced the SARS pandemic; General government debt (% of GDP); Stock market capitalization (% of GDP); International tourism receipts (% of total exports). Appendix Table B provides detailed variable definitions. All regressions include country fixed effects and day fixed effects.

	(1) All Sample	(2) All Sample	(3) Health Exp.	(4) Unemployment	(5) Urban Pop.	(7) Public Debt	(8) Stock Mkt.	(9) Tourism	(6) SARS
COVID	-0.687***	-0.478	0.0997	-0.229	-1.395	-0.387	-0.704**	-1.099***	-0.842***
	(0.248)	(0.862)	(0.519)	(0.399)	(1.031)	(0.552)	(0.326)	(0.382)	(0.285)
GoogleTrend	-0.378**	-0.366*	-0.345*	-0.389**	-0.386**	-0.417**	-0.405**	-0.386**	-0.563**
	(0.187)	(0.191)	(0.193)	(0.186)	(0.190)	(0.197)	(0.187)	(0.190)	(0.227)
COVID*GDP_cap		1.07e-05							
		(7.99e-06)							
COVID*GDP_growth		0.0196							
		(0.137)							
COVID*Popu_65above		-0.0558							
		(0.0422)							
COVID*fr		0.117							
		(0.519)							
COVID*ge		0.373							
		(0.632)							
COVID*sc		-0.523							
		(0.641)							
COVID*Eco.			-0.1050	-0.0934	0.0095	-0.0036	0.0454	0.0384	-0.0011
			(0.0574)	(0.0657)	(0.0135)	(0.0091)	(0.2510)	(0.0395)	(0.0031)
Constant	0.709***	0.711***	0.700***	0.739***	0.709***	0.738***	0.710***	0.718***	0.813***
	(0.110)	(0.110)	(0.113)	(0.111)	(0.110)	(0.119)	(0.112)	(0.111)	(0.125)
# Obs.	6,009	6,009	5,852	5,854	6,009	5,469	5,930	5,940	4,643
Adj. R^2	0.492	0.493	0.493	0.510	0.492	0.499	0.494	0.492	0.559
# Countries	74	74	72	72	74	67	73	73	57
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period	Jan.-Apr.	Jan.-Apr.	Jan.-Apr.	Jan.-Apr.	Jan.-Apr.	Jan.-Apr.	Jan.-Apr.	Jan.-Apr.	Jan.-Apr.
Return	Raw	Raw	Raw	Raw	Raw	Raw	Raw	Raw	Raw

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

Table 4. Global networks and stock index returns in response to the COVID-19 pandemic

This table shows how global networks shape the stock markets response to the COVID-19 pandemic around the world (74 countries). The dependent variable is daily (raw) stock index return of each country from Jan. 2, to Apr. 30, 2020. *COVID* is the daily (avg.) ln-growth rate of the number of confirmed COVID-19 cases in each country. *GoogleTrend* is the daily search interest 0-100) related to the coronavirus in each country. *COVID RoW* is the daily (avg.) ln-growth rate of the number of confirmed COVID-19 cases in the rest of the world, for each country. *COVID Region* is the daily (avg.) ln-growth rate of the number of confirmed COVID-19 cases in the Region (Africa, Asia, Europe, Latin America, North America, Oceania) for each country. *COVID RoW*Dist.* is, for each country *i*, *COVID RoW* weighted by the bilateral distance with country *j*. *COVID RoW*GDP* is, for each country *i*, *COVID RoW* weighted by the GDP per capita of country *j*. *COVID RoW*Export* is, for each country *i*, *COVID RoW* weighted by the exports to country *j*. *COVID RoW*Import* is, for each country *i*, *COVID RoW* weighted by the imports from country *j*. Appendix Table B provides detailed variable definitions. All regressions include country fixed effects and day fixed effects.

	(1) All Sample	(2) All Sample	(3) All Sample	(4) Distance	(5) Value	(6) Export	(7) Import	(8) All Sample
COVID	-0.687***	-0.685***	-0.612**	-0.680**	-0.671***	-0.701***	-0.712***	-0.565**
	(0.248)	(0.248)	(0.247)	(0.257)	(0.247)	(0.254)	(0.254)	(0.251)
GoogleTrend	-0.378**	-0.377**	-0.367*	-0.377**	-0.378**	-0.386**	-0.392**	-0.381**
	(0.187)	(0.187)	(0.187)	(0.183)	(0.186)	(0.183)	(0.183)	(0.183)
COVID RoW		-2.305						0.228
		(1.992)						(1.957)
COVID Region			-0.573***					-0.612***
			(0.201)					(0.202)
COVID RoW*Dist.				-0.0288				-0.252
				(0.413)				(0.425)
COVID RoW*GDP					-8.927***			-9.059***
					(3.279)			(3.323)
COVID RoW*Export						0.607		-0.809
						(1.414)		(1.626)
COVID RoW*Import							1.141	2.460
							(1.417)	(1.534)
Constant	0.709***	0.709***	0.708***	0.709***	0.709***	0.708***	0.707***	0.705***
	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)	(0.111)	(0.110)
# Obs.	6,009	6,009	6,009	6,009	6,009	6,009	6,009	6,009
Adj. R^2	0.492	0.492	0.492	0.492	0.493	0.492	0.492	0.494
# Country	74	74	74	74	74	74	74	74
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period	Jan.-Apr.	Jan.-Apr.	Jan.-Apr.	Jan.-Apr.	Jan.-Apr.	Jan.-Apr.	Jan.-Apr.	Jan.-Apr.
Return	Raw	Raw	Raw	Raw	Raw	Raw	Raw	Raw

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

Table 5. Policy interventions and stock index returns in response to the COVID-19 pandemic

This table shows how stock markets around the world (74 countries) react to the COVID-19 pandemic and to the policy interventions. The dependent variable is daily (raw) stock index return of each country from Jan. 2, to Apr. 30, 2020. *COVID* is the daily (avg.) ln-growth rate of the number of confirmed COVID-19 cases in each country. *GoogleTrend* is the daily search interest 0-100) related to the coronavirus in each country. YPT is a set of daily indicator variables, for each country, from the Yale Policy Tracker: *YPT Asset purchases*, *YPT Credit guarantees*, *YPT Financial system*, *YPT Fiscal stimulus*, *YPT Macroprudential*, *YPT Swap lines*. *Δ Interest rate* is the daily change in the key interest rate of central banks. Appendix Table B provides detailed variable definitions. All regressions include country fixed effects and day fixed effects.

	(1)	(2)	(3)	(4)
COVID	-0.687***	-0.620**	-0.653***	-0.599**
	(0.248)	(0.241)	(0.237)	(0.236)
GoogleTrend	-0.378**	-0.383*	-0.325*	-0.369*
	(0.187)	(0.223)	(0.181)	(0.217)
Δ Interest rate		-0.279		-0.309*
		(0.170)		(0.154)
YPT Asset purchases			-0.762*	-0.239
			(0.439)	(0.514)
YPT Credit guarantees			0.705***	0.614***
			(0.108)	(0.142)
YPT Financial system			-0.297	-0.172
			(0.192)	(0.244)
YPT Fiscal stimulus			-0.106	-0.128
			(0.0899)	(0.123)
YPT Macroprudential			0.0815	-0.213
			(0.144)	(0.195)
YPT Swap lines			-0.177	-0.164
			(0.520)	(0.660)
Constant	0.709***	-0.292***	0.713***	-0.293***
	(0.110)	(0.105)	(0.110)	(0.106)
# Obs.	6,009	3,961	6,009	3,961
Adj. R^2	0.492	0.592	0.499	0.596
# Countries	74	53	74	53
Country FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Period	Jan.-Apr.	Jan.-Apr.	Jan.-Apr.	Jan.-Apr.
Return	Raw	Raw	Raw	Raw

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

Covid Economics 28, 12 June 2020: 29-69

CEPR PRESS

Covid Economics 28, 12 June 2020: 29-69

Table 6. Lockdown and stock index returns in response to the COVID-19 pandemic

This table shows how stock markets around the world (74 countries) react to the COVID-19 pandemic and the subsequent lockdown. The dependent variable is daily (raw) stock index return of each country from Jan. 2, to Apr. 30, 2020. *COVID* is the daily (avg.) ln-growth rate of the number of confirmed COVID-19 cases in each country. *GoogleTrend* is the daily search interest 0-100) related to the coronavirus in each country. *Stringency* is the daily Stringency index, for each country, from Oxford COVID-19 Government Response Tracker. *Apple mobility* is, for each country, the daily relative volume of directions requests from Apple Maps, compared to a baseline (Jan. 13, 2020). *Google mobility* is, for each country, the daily relative number of visits and length of stay at different places from Google Map, compared to a baseline (Jan. 3-Feb 6., 2020). Appendix Table B provides detailed variable definitions. All regressions include country fixed effects and day fixed effects.

	(1)	(2) Oxford	(3) Apple	(4) Google
COVID	-0.687***	-0.710***	-0.839***	-0.700**
	(0.248)	(0.253)	(0.238)	(0.307)
GoogleTrend	-0.378**	-0.512**	-0.415*	-0.478**
	(0.187)	(0.201)	(0.227)	(0.225)
Stringency		0.00535**		
		(0.00229)		
Apple mobility			-0.00722***	
			(0.00263)	
Google mobility				-0.0133***
				(0.00496)
Constant	0.709***	0.727***	0.852***	1.568***
	(0.110)	(0.113)	(0.263)	(0.528)
# Obs.	6,009	5,675	4,239	3,436
Adj. R^2	0.492	0.502	0.580	0.517
# Countries	74	70	57	68
Country FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Period	Jan.-Apr.	Jan.-Apr.	Jan.-Apr.	Jan.-Apr.
Return	Raw	Raw	Raw	Raw

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

Covid Economics 28, 12 June 2020: 29-69

Table 7. Stock index returns in response to the COVID-19 pandemic: Simultaneous analyses

This table shows how stock markets around the world (74 countries) react to the COVID-19 pandemic. The dependent variable is daily (raw or adjusted) stock index return of each country from Jan. 2, to Apr. 30, 2020. *COVID* is the daily (avg.) ln-growth rate of the number of confirmed COVID-19 cases in each country. *GoogleTrend* is the daily search interest 0-100) related to the coronavirus in each country. *gVix* is the daily growth of the Vix index. *gGoogleTrend* is the daily growth of *GoogleTrend*. *gIDEMV* is the daily growth of the infectious disease equity market volatility tracker. *gFED* is the daily growth of the US Fed's total assets. *Health exp*. is (priori 2020) Health expenditure (% of GDP). *COVID RoW* is the daily (avg.) ln-growth rate of the number of confirmed COVID-19 cases in the rest of the world, for each country. *COVID Region* is the daily (avg.) ln-growth rate of the number of confirmed COVID-19 cases in the Region (Africa, Asia, Europe, Latin America, North America, Oceania) for each country. *COVID RoW*GDP* is, for each country *i*, *COVID RoW* weighted by the GDP per capita of country *j*. *YPT Credit guarantees* is a daily indicator, for each country, from the Yale Policy Tracker. *ΔInterest rate* is the daily change in the key interest rate of central banks. *Stringency* is the daily Stringency index, for each country, from Oxford COVID-19 Government Response Tracker. *Apple mobility* is, for each country, the daily relative volume of directions requests from Apple Maps, compared to a baseline (Jan. 13, 2020). In columns (1-3), we test Equation (1) with country and day fixed effects. In columns (4-6), we test Equation (1) with country and day fixed effects, but with adjusted returns. In columns (7-9), we test Equation (2) with country fixed effects but without day fixed effects. Apple mobility is, for each country, the daily relative volume of directions requests from Apple Maps, compared to a baseline (Jan. 13, 2020). Appendix Table B provides detailed variable definitions.

	Benchmark			Adj. Return			Without Day FE		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
COVID	-0.687***	0.742	0.916*	-0.468**	-0.254	-0.160	-0.471**	0.919	1.143
	(0.248)	(0.522)	(0.521)	(0.181)	(0.469)	(0.462)	(0.231)	(0.669)	(0.703)
GoogleTrend	-0.378**	-0.392	-0.353	-0.0781	-0.231	-0.171	-0.0819	-0.536*	-0.713**
	(0.187)	(0.258)	(0.284)	(0.166)	(0.223)	(0.257)	(0.205)	(0.273)	(0.289)
Wld. Return							0.541***	0.632***	0.650***
							(0.0377)	(0.0441)	(0.0453)
Vix							-0.0161***	-0.0237***	-0.0229***
							(0.00353)	(0.00484)	(0.00546)
gIDEMV							0.0121	0.0745**	0.129***
							(0.0272)	(0.0323)	(0.0352)
gFED							30.57***	42.89***	43.85***
							(8.057)	(8.169)	(8.462)

Table 7 (continued). Stock index returns in response to the COVID-19 pandemic: Simultaneous analyses

	Benchmark			Adj. Return			Without Day FE		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
COVID*gVix		-6.736***	-5.790***		-2.962*	-2.247	-4.193**	-3.768**	-2.491*
		(2.274)	(2.120)		(1.501)	(1.449)	(1.623)	(1.592)	(1.433)
COVID*gGoogleTrend		-0.262*	-0.454**		-0.231*	-0.402**	-0.390**	-0.371**	-0.382*
		(0.139)	(0.184)		(0.125)	(0.163)	(0.172)	(0.165)	(0.199)
COVID*gIDEMV		-0.892**	-0.838**		-0.452	-0.378	-1.522***	-1.744***	-1.759***
		(0.417)	(0.380)		(0.321)	(0.263)	(0.402)	(0.508)	(0.513)
COVID Region		-0.472*	-0.330		-0.184	-0.140		-0.474**	-0.334
		(0.254)	(0.243)		(0.184)	(0.184)		(0.204)	(0.216)
COVID RoW*GDP		-2.617	1.778		2.955	7.480		-0.0108	-0.0364
		(12.76)	(11.81)		(10.83)	(8.751)		(0.0723)	(0.0766)
YPT Credit guarantees		0.546***	0.576***		0.368**	0.441***		0.360***	0.343***
		(0.138)	(0.148)		(0.142)	(0.157)		(0.118)	(0.121)
Δ Interest rate		-0.510*	-0.556*		-0.759***	-0.864***		-0.613**	-0.618*
		(0.265)	(0.306)		(0.251)	(0.275)		(0.246)	(0.310)
Stringency		0.00237			0.00287			0.00510***	
		(0.00295)			(0.00325)			(0.00124)	
Apple mobility			-0.00525			-0.00255			-0.00726**
			(0.00325)			(0.00323)			(0.00302)
Constant	0.709***	-0.312***	0.597*	0.257***	0.0866	0.347	0.282***	0.337***	1.130***
	(0.110)	(0.111)	(0.330)	(0.0969)	(0.105)	(0.339)	(0.0626)	(0.0796)	(0.347)
# Obs.	6,009	3,518	3,156	6,009	3,518	3,156	5,605	3,518	3,014
Adj. R^2	0.492	0.621	0.622	0.206	0.262	0.262	0.425	0.545	0.553
# Countries	74	50	49	74	50	49	74	50	47
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
Period	Jan.-Apr.	Jan.-Apr.	Jan.-Apr.	Jan.-Apr.	Jan.-Apr.	Jan.-Apr.	Jan.-Apr.	Jan.-Apr.	Jan.-Apr.
Return	Raw	Raw	Raw	Adj.	Adj.	Adj.	Raw	Raw	Raw

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

CEPR PRESS

Covid Economics **Issue 28, 12 June 2020**

Women's work, housework and childcare, before and during COVID-19[1]

Daniela Del Boca,[2] Noemi Oggero,[3] Paola Profeta[4] and Maria Cristina Rossi[5]

Date submitted: 5 June 2020; Date accepted: 9 June 2020

Covid Economics 28, 12 June 2020: 70-90

Evidence from past economic crises indicates that recessions often affect men's and women's employment differently, with a greater impact on male-dominated sectors. The current COVID-19 crisis presents novel characteristics that have affected economic, health and social phenomena over wide swaths of the economy. Social distancing measures to combat the spread of the virus, such as working from home and school closures, have placed an additional tremendous burden on families. Using new survey data collected in April 2020 from a representative sample of Italian women, we analyse jointly the effect of COVID-19 on the working arrangements, housework and childcare of couples where both partners work. Our results show that most of the additional workload associated to COVID-19 falls on women while childcare activities are more equally shared within the couple than housework activities. According to our empirical estimates, changes to the amount of housework done by women during the emergency do not seem to depend on their partners' working arrangements. With the exception of those continuing to work at their usual place of work, all of the women surveyed spend more time on housework than before. In contrast, the amount of time men devote to housework does depend on their partners' working arrangements: men whose

1 This research was supported by funding from Programma europeo REC – Rights, Equality and Citizenship (Grant Agreement number: 820763) and coordinated by the Dipartimento per le Pari Opportunità della Presidenza del Consiglio dei Ministri and Collegio Carlo Alberto.
2 Professor, University of Turin and Collegio Carlo Alberto.
3 Post-doctoral researcher, University of Turin and CeRP, Collegio Carlo Alberto.
4 Professor, Bocconi University.
5 Professor, University of Turin and Collegio Carlo Alberto.

partners continue to work at their usual workplace spend more time on housework than before. The link between time devoted to childcare and working arrangements is more symmetric, with both women and men spending less time with their children if they continue to work away from home. For home schooling, too, parents who continue to go to their usual workplace after the lockdown are less likely to spend greater amounts of time with their children than before. Finally, analysis of work-life balance satisfaction shows that working women with children aged 0-5 are those who say they find balancing work and family more difficult during COVID-19. The work-life balance is especially difficult to achieve for those with partners who continue to work outside the home during the emergency.

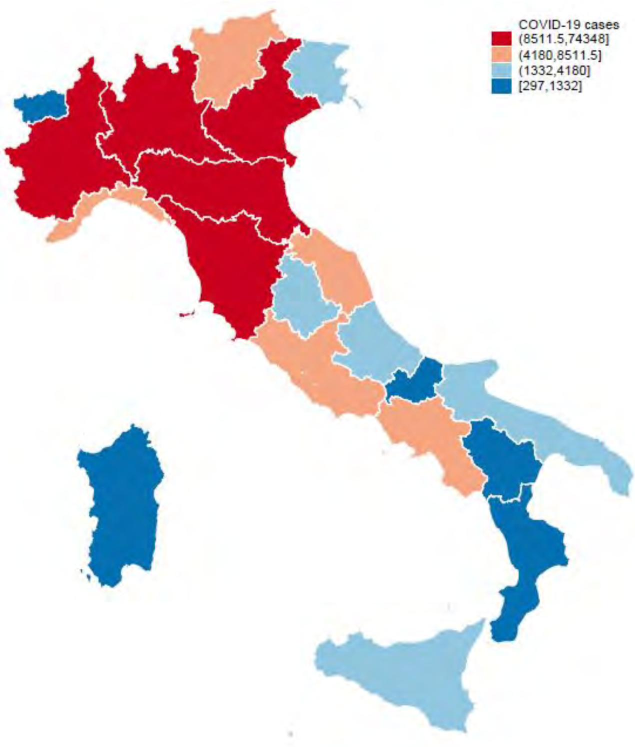
Covid Economics 28, 12 June 2020: 70-90

Covid Economics 28, 12 June 2020: 70-90

1. Introduction

The COVID-19 pandemic has affected the lives of hundreds of thousands of people around the world. Italy has experienced the worst outbreak in Europe, especially in the north (see Figure 1). Italy was the first European country to report people infected with the novel Coronavirus and one of the countries with the highest number of cases (Figure 2). At the beginning of March 2020, the Italian government imposed drastic measures to contain the growing epidemic: a lockdown on activities and public services, regulations prohibiting all movement by individuals unless for justified for work, health or other urgent necessities, school closures (as of February 25th), and required social distancing of at least one meter between individuals.[6] While these measures have largely stemmed the spread of the virus, they have also had a huge impact on male and female labour market participation (see Barbieri, Basso and Scicchitano, 2020; Casarico and Lattanzio, 2020; Centra, Filippi and Quaranta, 2020) and in inequality (Galasso, 2020). We expect them to have substantially affected housework and childcare, too.

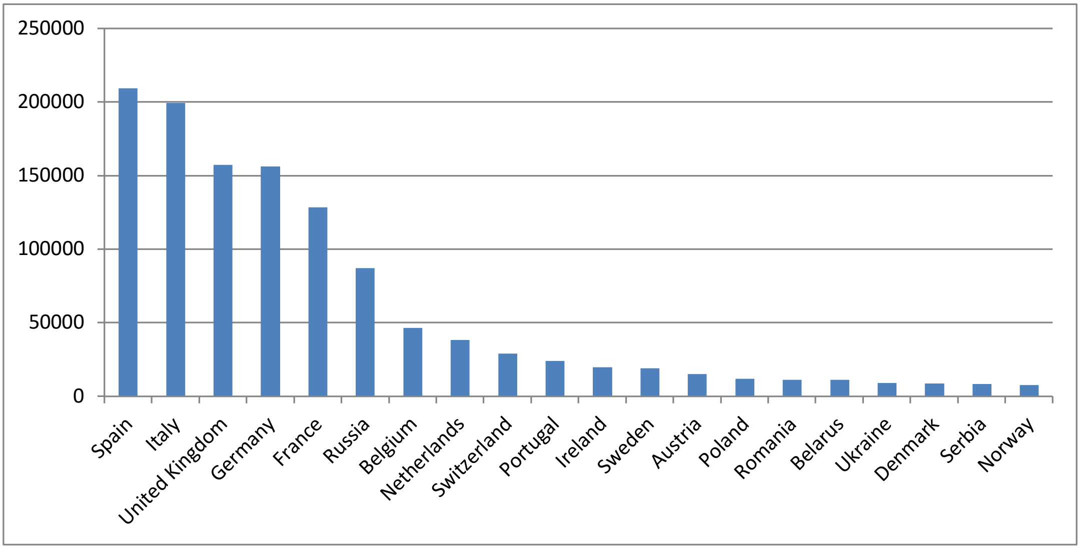
Figure 1. Number of COVID-19 cases by Italian region, as of 28 April 2020.



Note: Data retrieved from the Italian Ministry of Health.

[6] For further details see: http://www.protezionecivile.gov.it/documents/20182/1227694/Summary+of+measures+taken+against+the+spread+of+C-19/c16459ad-4e52-4e90-90f3-c6a2b30c17eb

Figure 2. Number of COVID-19 cases by country, as of 28 April 2020.



Note: The graph includes the 20 most-affected European countries. Data retrieved from the European Centre for Disease Prevention and Control.

Evidence from past economic crises suggests that recessions often affect men's and women's employment differently, with a greater negative effect on men (Rubery and Rafferty, 2013; Hoynes, Miller and Schaller, 2012). As a consequence of the 2008 financial crisis, for instance, job losses were much greater in male-dominated sectors of the economy (notably construction and manufacturing), while women's working hours actually increased. As reported in very recent studies (Hupkau and Petrongolo, 2020, Alon et al., 2020), the current recession is instead likely to have a similar impact on male and female employment, since the social measures taken have affected sectors where both genders are employed (ILO, 2020).

In fact, the current COVID-19 crisis is not just an economic crisis, but a health and social one, too. The labour market is just one dimension of human work. COVID-19 is also expected to have major consequences on family work, due to increased housework and childcare resulting from the closing of schools and nurseries. Many women are already struggling to make it to work at all, given the need for at least one parent to stay home and mind the children (Queisser, Adema and Clarke, 2020). Preliminary evidence from Spain (Farré and Gonzalez, 2020) and from the UK (Sevilla and Smith, 2020) show that there has been a shift towards a more equal distribution of household and childcare between men and women, but most of the extra work caused by the crisis has fallen on women.

We focus on Italy and investigate jointly the effect of COVID-19 on work, housework and childcare arrangements of working women and their male partners.

Covid Economics 28, 12 June 2020: 70-90

The Italian context is particularly interesting, not only because of the particularly strict lockdown measures taken to contain the crisis, but also from a gender standpoint. Italy is characterized by both traditionally high gender gaps in the labour market and conservative gender roles, which put most of the burden of housework and childcare on women.[7] Before the pandemic, a large proportion of grandparents (about 40% according to SHARE data) provided daily childcare. The mandatory implementation of social distancing has substantially reduced the availability of grandparental care, thus increasing the burden on families already caused by school and child-care facility closures. Higher fatality rates among the elderly may also have affected a large number of families living together or close by.[8] In this context, we argue that the impact of COVID-19 on family work is related to the time that couples have to spend at home due to the emergency restrictions. Our goal is to understand how and to what extent family roles have changed since COVID-19 forced domestic partners to reorganize their time at home due to the lockdown. Is the increased time spent at home leading to a reallocation of couples' roles in household chores and family care?

To answer this question, we use data on a representative sample of Italian working women.[9] The data were collected before and during the emergency, allowing us to compare the number of hours spent at work and on housework and childcare before the emergency (April and July 2019) and the hours spent during the first three months of the emergency (April 2020). We hypothesize different impacts on the division of labour between housework and childcare within the household depending on the working arrangements of women and their partners at the time of the outbreak of COVID-19.

Our empirical analysis shows that the new working arrangements have the potential to further increase women's workload, resulting from both job and household responsibilities. Since we consider women and their partners, differently from analysis conducted in other contexts (Sevilla and Smith, 2020), our data allow us to consider the allocation of housework and childcare within the couple. Our results indicate that men and women have reacted differently to the changing circumstances, with women increasing the amount of time they spend on both the housework and childcare. The only areas where men have started spending more time are in childcare and home schooling; they have not contributed more time to doing the housework .This result is similar to findings reported in other countries, such as the UK (Sevilla and Smith, 2020).

Our results raise concerns about the effect of COVID-19 on women's labour market participation. Current work arrangements may make it even harder for women to participate than for men. More importantly, higher rates of male participation in domestic responsibilities, and particularly in housework, is associated to higher rates of female participation in the labour market as well as to higher fertility rates (Fanelli and Profeta, 2019). Thus, the consequences of COVID-19 on female labour market outcomes risk being

[7] Comparative data show that when summing work in the labor market and work at home, Italian women not only work more than Italian men, but also more than men and women in most European countries (ISTAT, 2019).
[8] https://www.wsj.com/articles/family-is-italys-great-strength-coronavirus-made-it-deadly-11585058566
[9] The survey was administered by Episteme, a professional survey company. https://www.carloalberto.org/research/competitive-projects/clear-closing-the-gender-pension-gap-by-increasing-womens-awareness

amplified by the unequal intrahousehold allocation of extra work (housework and childcare) created by the emergency.

The paper is organized as follows: the next section describes the data and report some relevant statistics, section 3 presents our main analysis and results, section 4 discusses relevant policy implications and section 5 concludes.

2. Data and descriptive statistics

As stated in the Introduction, in order to analyse the impact of COVID-19 measures on households and women, we use a representative sample of 800 Italian women interviewed in April and July 2019 with the purpose of understanding inequalities in women's work, savings and pensions. In April 2020, we repeated the interviews, adding specific questions related to the emergency.

We designed the questionnaire to gather information on changes in the respondents' employment status, hours of work, childcare, income and satisfaction regarding their work and family during the emergency. We also included a set of *ad-hoc* questions regarding the time spent on housework and childcare before and after the COVID-19 outbreak. Women were also asked similar questions about their partners.

Thanks to the level of detail of the questions asked, we were able to identify whether the women and their partners were allowed to continue working at their jobs after the lockdown. Since the interviews were conducted in late April 2020, we are able to observe the effects during the first phase of the emergency. Data from Italy's so-called Phase 2, which started on May 4th, does not confound our estimates. We are poised to capture further changes and possible adjustments in women's labour supply and behaviour during the next wave of infections, provisionally forecast for January 2021.

Our survey was designed to gather data on four main areas that may have been affected by the health emergency: work, housework, childcare and home schooling. Changes in terms of work will be dependent on the respondent's field of occupation, but changes in housework are likely to depend on the partner's field, too.

Table 1 describes the sample used in our empirical analysis: coupled women with both partners working before the emergency (520 observations). The average age in our sample is 44 and almost half (47%) of respondents have a university degree. Fifty-four percent of the female workforce in Italy live in the northern regions, a percentage consistent with data from the Italian National Institute of Statistics. More than two-thirds (67%) of working women have children. If we focus on the sub-sample of women living with a partner and at least one child (350 observations), we see that the average number of children is 1.66. We also have information on the age range of the offspring, which is important for determining the time spent on childcare and home schooling.

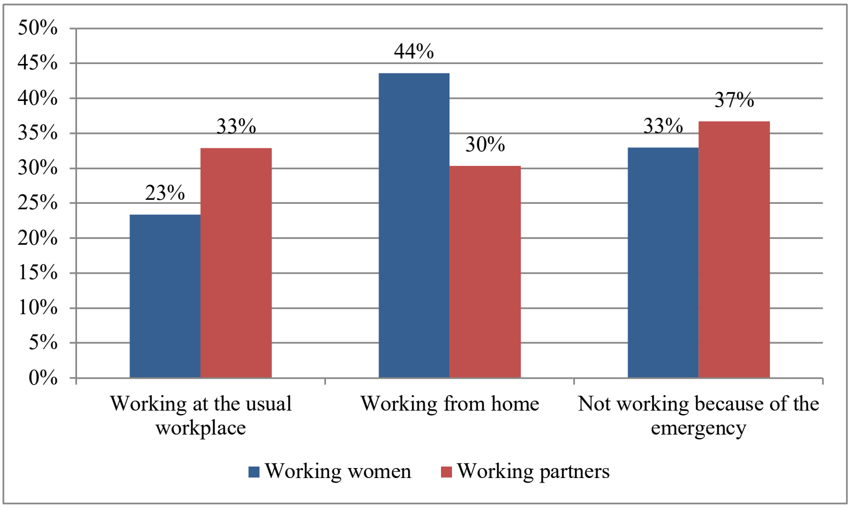
Covid Economics 28, 12 June 2020: 70-90

Table 1. Descriptive statistics. Women

	Mean	*Std. Dev.*	*Min*	*Max*	*N*
Age	43.88	9.21	26	64	520
Having a degree	0.47	0.50	0	1	520
North	0.54	0.50	0	1	520
Centre	0.20	0.40	0	1	520
Having children	0.67	0.47	0	1	520
Number of children	1.66	0.74	1	7	350
Number of children age 0-5	0.36	0.59	0	3	350
Number of children age 6-10	0.37	0.53	0	2	350
Number of children age 11-14	0.25	0.47	0	2	350
Number of children age $\geqslant$15	0.68	0.89	0	5	350

The descriptive statistics give us some preliminary insights. Starting from the job market data in Figure 3, we can see the working arrangements of working women and their partners during the COVID-19 emergency. The first column shows that women are less likely to have kept working in their usual workplace than men: just 23% of women as opposed to 33% of their partners. The second column shows that 44% of working women have kept their jobs by working from home (vs. 30% of men). Women are therefore much more likely to work from home. This increases the likelihood of increasing the overall workload of women, resulting from both their occupation and domestic work. The last column shows that about the same number of women and men have stopped working because of the emergency (33% and 36%).

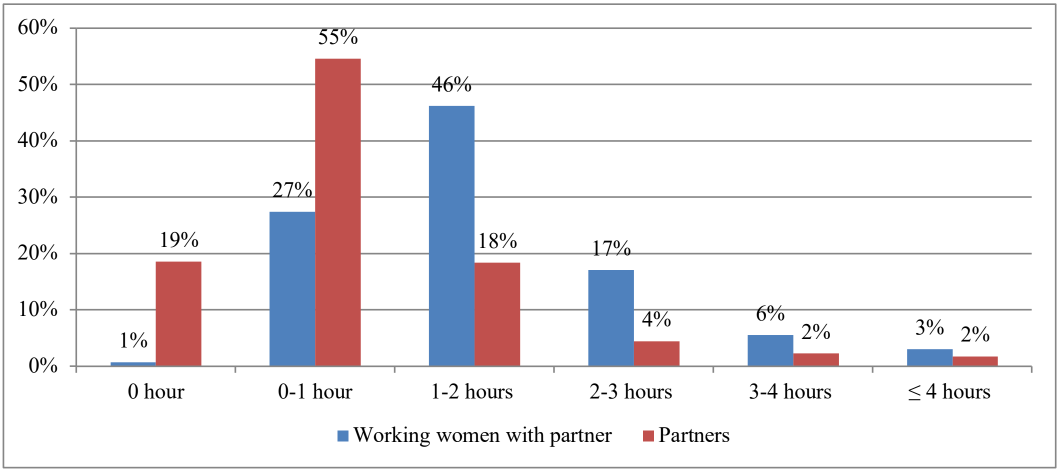
Figure 3. Percentage of working women and their partner by working arrangement during the COVID-19 emergency.



Covid Economics 28, 12 June 2020: 70-90

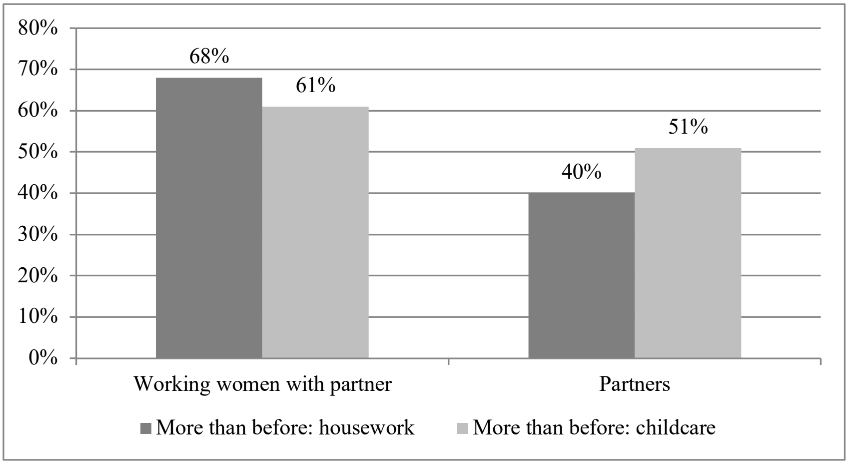
Moving to housework, Figure 4 illustrates the amount of housework spent by women and their partners before the emergency. It appears that women spent significantly more time on housework than their partners: almost three quarters (74%) of men devoted less than one hour a day to housework (as opposed to 28% of women).

Figure 4. Percentage of working women and their partners by hours of housework per day before the COVID-19 emergency.



The COVID-19 measures adopted over the last two months have massively increased the amount of housework and childcare that must be done. How is this extra burden distributed within the couple? Figure 5 shows the increase in housework and childcare done by working women and their partners during the COVID-19 emergency. While both men and women are spending more time on housework and childcare, the distribution is unequal: with 68% of women spending more time and only 40% of men. The percentages for childcare are 61% and 51%, respectively. Hence, while most of the burden has fallen on women, childcare is more equally shared than housework.

Figure 5. Percentage of working women and their partners by proportion of housework and childcare: comparison before/after the COVID-19 outbreak.



While these figures provide an initial assessment of how COVID-19 affected the workload of working women and their partners, they also make clear that, in order to assess whether and how COVID-19 changed the intra-family equilibrium of work and family work, we need to jointly investigate the changes in work arrangements, housework and childcare of women and their partners. We therefore set out to analyse how the division of labour within the household relates to the working arrangements of each of the partners after the lockdown. We show the percentages of men and women doing more housework and more childcare according to these possible combinations in Tables 2 and 3 respectively.

Table 2. Percentage of men and women doing more housework during the COVID-19 emergency by working arrangement.

	Partners working at the usual workplace	Partners working from home	Partners not working because of the emergency
Women working at the usual workplace	Women 49% Partners 28%	Women 40% Partners 55%	Women 61% Partners 58%
Women working from home	Women 78% Partners 28%	Women 65% Partners 40%	Women 64% Partners 58%
Women not working because of the emergency	Women 82% Partners 22%	Women 81% Partners 24%	Women 74% Partners 47%

Note: The sample is made up of coupled women where both partners were working before the emergency (N=520).

Covid Economics 28, 12 June 2020: 70-90

Table 3. Percentage of men and women spending more hours on childcare during the COVID-19 emergency by working arrangement.

	Partners working at the usual workplace	Partners working from home	Partners not working because of the emergency
Women working at the usual workplace	Women 45% Partners 40%	Women 45% Partners 36%	Women 31% Partners 54%
Women working from home	Women 54% Partners 37%	Women 77% Partners 60%	Women 60% Partners 60%
Women not working because of the emergency	Women 70% Partners 38%	Women 68% Partners 63%	Women 71% Partners 59%

Note: The sample is made up of coupled women where both partners were working before the emergency (N=350).

Tables 2 and 3 show that both men and women are spending more time on domestic work. This is in line with results from Angelici and Profeta (2020), who report that in normal times, "smart working" [10] (allowing flexibility in the working hours and location for certain number of hours each week) leads to increased participation of males in domestic work. Interestingly, this increase is seen more in childcare than housework in almost all cases. However, the distribution of the extra work within the couple appears to be highly unbalanced. The extra work is a burden mainly borne by women.

There are some exceptions. Increased participation by men overtakes that of women only when women continue to go to their usual place of work and their partner does not work. However, even under these circumstances, this is true only for childcare (where 54% of partners spend more time on childcare vs. only 31% of women), and not for housework (58% of partners spend more time on childcare and 61% of women). When the woman telecommutes and the partner does not work, 60% of both men and women spend more time on childcare. Yet this balance disappears when we consider the amount of time spent on housework: 64% of women and 58% of men increase the amount of housework they do. Another case in which the increased participation of men in housework overtakes that of women is when women continue at their regular place of work and their partners telecommute. In symmetric situations, the distribution of extra work still penalizes women. For example, when both partners work at home, 65% of women increase their housework versus 40% of men. The corresponding percentages for childcare are 77% for women and 60% for men.

[10] "Smart-working" is a new organization of work which includes flexibility of location (working from home, but also from another place different from the usual workplace) and flexibility of time (a personalized work schedule). Differently from teleworking, there is no strict control of the supervisor on time and place of work. During the COVID-19 emergency, some form of flexibility was used: many workers worked from home and, in some cases, with some flexibility of time. We do not have detailed information on the specific type of flexibility. Hence, we refer to this arrangement as "working from home", or "telecommuting".

Covid Economics 28, 12 June 2020: 70-90

3. The Empirical Analysis

In this section, we estimate the determinants of changes in housework, childcare and home schooling during the COVID-19 emergency.

In order to answer our research question about the possible changes to the share of time spent on housework and childcare by the two partners, we estimate a set of multivariate regressions where we use as the dependent variable a dummy taking the value of one if the spouse/partner has spent more time, compared to the pre-COVID situation, on the following activities: household chores, time devoted to childcare, time devoted to home schooling.[11]

In Tables 4, 5 and 6 we show for both the working woman and her partner the determinants of more time devoted to housework, childcare, and home schooling respectively, conditioning on individual and family characteristics. Our sample consists of all coupled women, where both partners were working before the emergency.[12] In all tables, the first column shows the regression results referring to women, while the second column refers to their partners.

In Table 4, we investigate the factors leading to more housework for working women and their working partners. The results consistently show a constant imbalance in the amount of time spent by men and women. Women spend more time on domestic work no matter where their workplace is, with one exception. The only case in which women are less likely to do more housework during the emergency is when they continue to work at their usual workplace. However, there is no difference in the increased amount of housework between women who keep working from home and those who are not working because of the emergency. Thus, women working remotely have to bear the workload of both their job and domestic responsibilities.

Conversely, when looking at their partners in the second column of Table 4, we notice that both men working at their usual workplace and those working from home are less likely to increase the number of hours spent on household chores than men not working because of the emergency. Moreover, while women's housework is not affected by their partners' working arrangement during the emergency, the opposite holds for men. In fact, men are more likely to spend additional time on chores when their partners are working. Finally, we notice that the partners of older women are less likely to increase the amount of housework they do.

[11] In particular, the dummy is equal to one if the respondent answers "More than before" to the questions "Compared to the pre-emergency period, how did the time you/your partner devoted to chores/childcare/home schooling change?"
[12] We hence exclude households where the woman is not living with a partner and households where the partner is not working.

Table 4. Multivariate regression model of doing more housework during the COVID-19 emergency.

	(1) Women doing more housework	(2) Partners doing more housework
Age	0.001	-0.007***
	(0.002)	(0.002)
Having a University degree	0.014	0.045
	(0.042)	(0.044)
Having children	0.059	0.043
	(0.044)	(0.045)
Woman working at the usual workplace	-0.283***	0.130**
	(0.057)	(0.059)
Woman working from home	-0.073	0.104**
	(0.049)	(0.051)
Partner working at the usual workplace	0.062	-0.284***
	(0.050)	(0.052)
Partner working from home	-0.004	-0.175***
	(0.054)	(0.056)
North	0.042	0.041
	(0.048)	(0.050)
Centre	0.112*	-0.007
	(0.060)	(0.062)
Constant	0.612***	0.688***
	(0.114)	(0.119)
Observations	520	520
R-squared	0.056	0.078

Note: Coefficient estimates from OLS regressions. The sample is made up of coupled women where both partners were working before the emergency. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Interestingly, this asymmetry is apparent only when housework is considered. Turning to childcare, the results on the additional time devoted to children are symmetric when either the woman or her partner works outside the home, as shown in Table 5. Indeed, the only case in which both women and men are less likely to spend more time on childcare is when they work at their usual workplace. The partner's working arrangement affects neither the mother's nor the father's childcare. One predictor of the time spent on taking care of the children is educational attainment: couples in which the mother holds a university degree are more likely to devote time to their children, even after controlling for other factors such as their working arrangements. Another predictor of higher child-related workload is the age of the children: children younger than 10 years old require more time from both working mothers and fathers.

Covid Economics 28, 12 June 2020: 70-90

Table 5. Multivariate regression model of spending more hours in childcare during the COVID-19 emergency.

	(1) Women spending more hours in childcare	(2) Partners spending more hours in childcare
Age	-0.003	0.005
	(0.004)	(0.004)
Having a degree	0.113**	0.158***
	(0.052)	(0.053)
Number of children age 0-5	0.081	0.161***
	(0.057)	(0.058)
Number of children age 6-10	0.168***	0.090
	(0.054)	(0.055)
Number of children age 11-14	0.092	0.050
	(0.058)	(0.060)
Number of children age ⩾15	0.016	-0.105***
	(0.038)	(0.039)
Woman working at the usual workplace	-0.270***	0.018
	(0.069)	(0.070)
Woman working from home	-0.066	0.018
	(0.061)	(0.063)
Partner working at the usual workplace	-0.000	-0.215***
	(0.060)	(0.061)
Partner working from home	0.065	-0.075
	(0.067)	(0.069)
North	0.003	-0.015
	(0.058)	(0.059)
Centre	0.082	-0.026
	(0.073)	(0.074)
Constant	0.638***	0.275
	(0.186)	(0.191)
Observations	350	350
R-squared	0.147	0.160

Note: Coefficient estimates from OLS regressions. The sample is made up of coupled women where both partners were working before the emergency. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

The shutting down of schools, at any level, is likely to increase the amount of household work for parents. Many parents are squeezing in jobs or work-related tasks while also having to take on the responsibility for home schooling their children. Recent empirical evidence has shown that school closures and cancellations of exams are likely to have detrimental effects on children's education as well as being a burden on their parents (Moroni, Nicoletti and Tominey, 2020). According to Sevilla and Smith (2020), the difference between the share of childcare done by women and the share done by men for the additional post-COVID19 hours of childcare is smaller than that for the allocation of pre-COVID19, and the allocation has become more equal in households where men telecommute or where they have lost their jobs.

We look more closely at the question of childcare by analysing the time devoted to children's home schooling. In Table 6, we again see that mothers holding a University degree and their partners spend more time on their children's education. Hence, education translates into additional effort devoted to the care of children, including the amount of time spent on their children's homework. This has the potential to sharpen educational differences among children due to family background. It is worth noting that individuals with higher educations are more likely to devote more time to their children (childcare and home schooling) while they do not significantly change their time devoted to household chores.

The age of children matters in determining the amount of effort devoted to them: one additional child in primary school age more than doubles the probability of devoting more time to home schooling than children in lower secondary school. The number of children below primary school age, instead, does not affect the probability of spending more time on home schooling. This evidence also holds for older children in upper secondary school.

For home schooling, too, parents who continue to work at their usual workplace despite the emergency are less likely to spend more time with their children, while partners' working arrangements have no influence on the number of hours an individual spends with her/his children. Unsurprisingly, primary school aged children are more demanding: both partners spend more time helping primary school children with their homework. However, the increase in time devoted to children is always greater for women than for men. Again, our estimates show larger increases in time spent by women on childcare. Women spend more time on their primary-school age children, while their partners do not. For children over 15, the probability of devoting extra time is actually lower for male partners (Tables 5 and 6).

Table 6. Multivariate regression model of spending more hours in home schooling during the COVID-19 emergency.

	(1) Women doing more home schooling	(2) Partners doing more home schooling
Age	0.004	0.002
	(0.004)	(0.004)
Having a degree	0.090*	0.136**
	(0.053)	(0.053)
Number of children age 0-5	0.092	0.068
	(0.058)	(0.058)
Number of children age 6-10	0.296***	0.161***
	(0.055)	(0.055)
Number of children age 11-14	0.122**	0.034
	(0.060)	(0.059)
Number of children age ⩾15	-0.031	-0.071*
	(0.039)	(0.039)
Woman working at the usual workplace	-0.123*	0.047
	(0.070)	(0.070)
Woman working from home	-0.098	0.024
	(0.063)	(0.062)
Partner working at the usual workplace	-0.011	-0.191***
	(0.061)	(0.061)
Partner working from home	0.062	-0.106
	(0.069)	(0.069)
North	-0.038	0.024
	(0.059)	(0.059)
Centre	-0.021	0.022
	(0.074)	(0.074)
Constant	0.206	0.250
	(0.191)	(0.190)
Observations	350	350
R-squared	0.160	0.122

Note: Coefficient estimates from OLS regressions. The sample is made up of coupled women where both partners were working before the emergency. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

We also investigated the factors that are making women's work-life balance more difficult to achieve during the emergency. In particular, we use as a dependent variable a dummy taking the value of one if the respondent reported that work and life balance was more difficult for them.[13] Unsurprisingly, in the first column of Table 7, we can observe that those still working are those most likely to report an excessive workload from their job. Interestingly, the second column of Table 7 shows that working women with children age 0-5 are those most likely to report excessive domestic responsibilities. The work-life balance is especially difficult to achieve when the partner continues working outside of the home during the

[13] The dummy variable takes the value of one if the respondent's answer is "to some extent" or "very much" to the questions "To what extent does an excessive amount of work/housework make it more difficult to balance work and family?"

emergency. Also, older working women find the domestic work harder than their younger counterparts, even after controlling for the age of the children.

Table 7. Multivariate regression model of reporting that "an excessive amount of work/housework made it more difficult to balance work and family" during the COVID-19 emergency.

	(1) Work	(2) Housework
Age	-0.002	0.009**
	(0.004)	(0.004)
Having a degree	0.069	0.045
	(0.055)	(0.056)
Number of children age 0-5	0.055	0.176***
	(0.059)	(0.060)
Number of children age 6-10	0.068	0.088
	(0.057)	(0.058)
Number of children age 11-14	-0.029	0.060
	(0.061)	(0.062)
Number of children age ⩾15	-0.049	-0.079*
	(0.040)	(0.041)
Woman working at the usual workplace	0.284***	0.020
	(0.072)	(0.073)
Woman working from home	0.180***	0.043
	(0.064)	(0.065)
Partner working at the usual workplace	-0.109*	0.112*
	(0.063)	(0.064)
Partner working from home	-0.093	0.104
	(0.071)	(0.072)
North	-0.006	-0.011
	(0.060)	(0.061)
Centre	0.008	-0.016
	(0.076)	(0.077)
Constant	0.374*	-0.100
	(0.195)	(0.198)
Observations	350	350
R-squared	0.082	0.087

Note: Coefficient estimates from OLS regressions. The sample is made up of coupled women where both partners were working before the emergency. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4. Policy implications

Are policy measures to contain COVID-19 gender neutral? Our results help understand important policy implications on the gender balance in the household.

The decision about work arrangements of different types of jobs has affected men and women differently, not only in terms of health exposure to the virus, but also because they have a significant impact on the amount of housework and childcare and its allocation within the couple. This in turn has potential substantial consequences on gender equality, as they challenge female participation to the labor force.

Our results also suggest that specific policy interventions introduced to face the emergency of COVID-19 may have important, perhaps neglected, indirect effects. The Italian government has introduced, among other measures, two policy interventions towards families and their work-life balance: an additional time period of parental leave and a babysitter voucher. Starting from the extra parental leave, according to the most recent data from the Italian National Social Security (INPS), 76% of the requests come from women, of which 58% are in the age between 35 and 44, i.e., when women are likely to experience the highest pressure from work and family duties. The numbers are very similar across Italian regions. While it is true that leaves are a necessary and desirable relief for many families facing the sudden shock of COVID-19 and the related containment measures, this gender difference raises some concerns. In fact, if women are the main (or only) beneficiaries of leaves, this policy will translate into a higher workload at home for women, not shared within the couple, and may ultimately compromise their return to work. How to target leaves to men or make the leave equally attractive for men and women workers and for firms when dealing with male and female employees is a difficult, though necessary policy change.

The baby-sitter voucher, which will be extended to childcare centers as soon as they re-open, also represents a key policy for families with young children. Italian families resort little to care external to the family, because of its high cost and because of cultural stereotypes against the use of formal childcare for children aged 0-3. However, the literature (e.g., Del Boca, Monfardini, and See, 2018) suggests that formal childcare has positive effects on children's future learning and social skills and it is positively related to maternal employment. Hence, subsidizing childcare is expected to bring positive consequences on gender balance.

Critical determinants of both the prevalent use of leaves by women and the scarce use of formal childcare are the well-established gender stereotypes and cultural bias, which, as our analysis suggests, resist also the COVID-19 pandemic and the related changes of work arrangements. Thus, our results also suggest that these policies cannot be effective without a neutral and scientific information on their beneficial effects, for example on the benefit of attending formal childcare for children.

Additional gender effects may arise from policy related to the educational system, mainly schools. Clearly, the decision about opening schools or not depends on health risks. However, our data show that the closure of schools critically increases childcare for parents in such a way which disproportionately affects women and which is likely unsustainable after the first months of emergency. The extent to which countries value gender equality and how much effort they are exerting in plans to re-open schools as soon as possible, seem, not surprisingly, going hand to hand.

Finally, working from home may also have important consequences on gender gaps. On one side, an appropriate flexibility is desirable for better work-life balance of both men and women. We have also highlighted the advantages of working from home, which may generate a better sharing of family work within the couple. On the other side, however, if this becomes a female-dominated option, with men mostly working at the workplace and women working from home, our results suggest a critical increase of unbalanced family work with most of the work borne by women. Thus, an appropriate regulatory framework for this measure is required, to ensure a symmetric use by men and women. Similarly, rules should be established to the right of disconnecting, which risks otherwise to disproportionately affect women.

5. Conclusions

While very recent studies have investigated the consequences of the COVID-19 outbreak on either female employment or housework or childcare separately, this is the first study that investigates them jointly. Our results show that changes in these activities are interrelated and also depend on partners' working arrangements during the emergency. Moreover, this is the first study which focuses on couples rather than on men and women separately, and thus appropriately addresses the allocation of duties within the family.

We show that the current crisis further increased the workload of women, resulting from both their occupation and the housework. In contrast with men, there is no difference in the increase of housework between women who telecommute and those who do not work because of the emergency. Compared to their partners, working women bear the brunt of the increased time needed for household chores and childcare. Men are more likely to be spending more time with the children, hence in more gratifying family work rather than chores. This result has important implications on female contributions to the economy, since greater male participation in housework would encourage women's participation in the labour market.

We also shed light on a specific and crucial component of childcare: home schooling. The closure of schools has imposed a massive burden on parents, and especially on working parents. However, not all parents look after their children in the same way. While other studies have mentioned that men who telecommute are more likely to deal with childcare, and more educated people are more likely to telecommute, our unique data set allowed us to disentangle the effect of working from home from that of parents' education on childcare. In particular, we show that mothers holding a degree and their partners spend much more time on their children's education, even after controlling for their work arrangements. This has the potential to exacerbate educational differences among children due to their family background, as early education has a significant impact on child development. Thus, the long interruption due to the lockdown is likely to affect children's outcomes later in life. We will analyse this outcome in future studies.

Finally, we identify the groups that are most vulnerable and most aware of the difficult work-family balance. We show that working women with young children, especially those aged 0-5, are those particularly affected, by bearing the excess burden to a higher extent. For women, the work-life balance is especially difficult to achieve when their partners keep working outside of the home during the emergency.

These results may have long-term implications, and implications that are potentially negative for women,

Covid Economics 28, 12 June 2020: 70-90

especially if both the labour market crisis and school closures persist. There are also, however, some positive implications, if it means that couples are taking the opportunity of the crisis to share the burden of childcare more equally.

Covid Economics 28, 12 June 2020: 70-90

References

Alon, T.M., M. Doepke, J. Olmstead-Rumsey, and M. Tertilt (2020). "The impact of COVID-19 on gender equality." *Covid Economics*, 2020 (4), 62-85.

Angelici, M., and P. Profeta (2020). "Smart-working: work flexibility without constraints." Working Paper No. 137 Dondena Research Centre, Bocconi University.

Barbieri, T., G. Basso, and S. Scicchitano (2020). "Italian workers at risk during the Covid-19 epidemic." INAPP Working Paper No. 46.

Casarico, A., and S. Lattanzio (2020). "Nella "fase 2" a casa giovani e donne." Lavoce.info. https://www.lavoce.info/archives/66106/nella-fase-2-a-casa-giovani-e-donne/

Centra, M., M., Filippi, and R. Quaranta (2020). "Covid-19: misure di contenimento dell'epidemia e impatto sull'occupazione." INAPP Policy Brief No. 17.

Del Boca, D., C. Monfardini, and S. G. See (2018). "Government Education Expenditures, Pre-Primary Education and School Performance: A Cross-Country Analysis." IZA Discussion Paper No. 11375, Institute of Labor Economics (IZA).

Fanelli, E., and P. Profeta (2019). "Fathers' involvement in the family, fertility and maternal employment: Evidence from Central and Eastern Europe." Working Paper No. 131 Dondena Research Centre, Bocconi University.

Farré, L., and L. González (2020). "¿Quién Se Encarga de Las Tareas Domésticas Durante El Confinamiento? Covid-19, Mercado de Trabajo Y Uso Del Tiempo En El Hogar." Nada Es Gratis.April 23, 2020. https://nadaesgratis.es/admin/quien-se-encarga-de-las-tareas-domesticas

Galasso, V. (2020). "Labour market inequalities." CEPR VoxEu.org, May.

Hoynes, H., D. Miller, and J. Schaller (2012). "Who Suffers During Recessions?" *Journal of Economic Perspectives* 26(3): 27-48.

Hupkau C., and B. Petrongolo (2020) "COVID-19 and the gender gaps: Latest evidence and lessons from the UK." CEPR VoxEu.org, April.

ILO (2020). ILO Monitor: COVID-19 and the world of work. Second edition.

ISTAT (2019). I tempi della vita quotidiana. Lavoro, conciliazione, parità di genere e benessere soggettivo.

OECD (2020). Women at the core of the fight against COVID-19 crisis.

Moroni G., C. Nicoletti, and E. Tominey (2020). “Children’s socio-emotional skills and the home environment during the COVID-19 crisis.” CEPR VoxEu.org, April.

Queisser, M., W. Adema, and C. Clarke (2020). ”COVID-19, employment and women in OECD countries.” CEPR VoxEu.org, April.

Jessen J., and S. Waights (2020). “COVID-19 day care centre closures and parental time use.” CEPR VoxEu.org, April.

Rubery, J., and A. Rafferty (2013). “Women and recession revisited.” *Work, Employment and Society* 27(3), 414-432.

Sevilla A., and S. Smith (2020). “Baby steps: The Gender Division of childcare after COVID19.” CEPR Discussion Paper No. 14804.

Covid Economics 28, 12 June 2020: 70-90

Covid Economics Issue 28, 12 June 2020

The mental health effects of the first two months of lockdown and social distancing during the Covid-19 pandemic in the UK[1]

James Banks[2] and Xiaowei Xu[3]

Date submitted: 8 June 2020; Date accepted: 10 June 2020

Using longitudinal microdata for the UK over the period 2009-2020 we control for pre-existing previous trends in mental health in order to isolate and quantify the effects of the Covid-19 pandemic. Mental health in the UK worsened by 8.1% on average as a result of the pandemic and by much more for young adults and for women which are groups that already had lower levels of mental health before Covid-19. Hence inequalities in mental health have been increased by the pandemic. Even larger effects are observed for measures of mental health that capture the number of problems reported or the fraction of the population reporting any frequent or severe problems, which more than doubled.

1 We are grateful to the ESRC-funded Centre for the Microeconomic Analysis of Public Policy (ES/M010147/1) for funding this research. Essex/UKDA for data and access. The Understanding Society COVID-19 study is funded by the Economic and Social Research Council and the Health Foundation. Fieldwork for the survey is carried out by Ipsos MORI and Kantar. Understanding Society is an initiative funded by the Economic and Social Research Council and various Government Departments, with scientific leadership by the Institute for Social and Economic Research, University of Essex. The data are distributed by the UK Data Service. We are grateful to Richard Blundell, Rachel Griffith, Paul Johnson, Robert Joyce for their helpful comments on this paper. Responsibility for the analysis and interpretation of the data, and any errors, is the authors' alone.
2 Professor of Economics, University of Manchester and Senior Research Fellow, Institute for Fiscal Studies.
3 Senior Research Economist, Institute for Fiscal Studies.

Covid Economics 28, 12 June 2020: 91-118

CEPR PRESS
Covid Economics 28, 12 June 2020: 91-118

1. Introduction

From the outset it has been clear that the potential mental health effect of the Covid-19 pandemic, and the lockdown and social distancing that was imposed in response to it, was going to be one of the most important aspects of the crisis. Mental health and subjective wellbeing outcomes are important in their own right, and they are also risk factors for future physical health and longevity (see Kivimäki et al 2017) so will be an indication of the future indirect health consequences of the pandemic. In addition, mental health and wellbeing will influence and drive a number of other individual choices, behaviours and hence outcomes.

The impacts of Covid-19 on mental health has been identified as an important area of research going forward (Holmes et al. 2020), and a number of papers have pointed out that mental health considerations should be an important element of decisions regarding at what speed and in what way to lift the lockdown and social distancing restrictions that have been imposed (e.g. Layard et al. 2020).

Early indicators from cross-sectional studies or bespoke online Covid-specific surveys have already shown lower levels of subjective wellbeing and higher anxiety in the UK population than those observed in the last quarter of 2019 (ONS, 2020) and that these reduced levels are being sustained through the weeks of the lockdown and social distancing albeit with some small and gradual improvement in recent weeks (Fancourt et al. 2020). And similar findings have emerged for other countries using a variety of different data sources and methodologies such as internet surveys (Yamamura and Tsutsui (2020) for Japan), helpline data (Brülhard and Lalive (2020) for Switzerland and Armbruster et al (2020) for Germany) or narrative methods based on Google trends search data for UK, Italy and Sweden (Tubadji et al (2020).

In the absence of geographical variation in the lockdown and social distancing response to the pandemic within the UK over our sample period we cannot use spatial variation to identify effects of interest as in Yamamura and Tsutsui (2020), Armbruster et al (2020) or Tubadji et al (2020). Going beyond description of trends, these studies are able to establish large effects of the pandemic on mental health in Japan, Germany, UK and Italy, with the Japanese study also investigating gender differences and showing that effects are greater for women than for men. In contrast, in our study we exploit newly available data on a pre-existing national longitudinal sample and construct a model of prior trajectories of mental health in order to identify a counterfactual level of mental health in the absence of the pandemic. With this in hand we show that the UK effects are in line with that from the other countries referred to above – the effects of the pandemic and lockdown in the UK are substantial and are greater for women. In addition, however, we use our models to show that the effects are also much greater for the young, and hence particularly for young women. Our use of detailed individual-level survey data also allows us to show that only a relatively small part of the disproportionate effect on women and young people can be explained by differential economic and health impacts of the pandemic on these groups. Finally, we show that effects for all groups are greater when we consider measures designed to capture the number of mental health problems or the proportion of the population reporting any problems 'much more than usual' as opposed to a more generic indicator of the average level of mental health.

We document and analyse the individual level effects of the pandemic on mental health using longitudinal data from the Understanding Society study (University of Essex, 2020a, 2020b) in order to look at the distribution of individual's mental health outcomes in the context of their pre-pandemic trajectories.[4] Since the latest publicly available pre-pandemic data for the Understanding Society sample is already somewhat dated[5] and since there are important pre-existing trends in mental health by age, year and month of interview, it is important that we do not attribute all changes between waves to the pandemic itself. Thus, in our analysis we create a simple individual-specific counterfactual prediction of the likely level of mental health in April 2020 in the absence of the pandemic, based on the trajectories previously observed for that respondent and changes in (observed) personal circumstances between the latest pre-pandemic wave and February 2020. We then then compare the actual April 2020 observations to that prediction. We also discuss how this changes the results in comparison to looking at the raw differences between the most recent Understanding Society wave and the April 2020 observation.

The main outcome measure we use in this analysis is the GHQ-12 measure of mental health, distress and wellbeing (see Cox et al, 1987) which is a commonly used indicator although somewhat more broad and non-specific than would be ideal if one wanted to study specific mechanisms underlying changes in individual mental health conditions such as

[4] Understanding Society has been collecting information annually on a sample of almost 100,000 individuals since 2010 (see University of Essex (2019) for details) and introduced a monthly internet component in May 2020 for a subset of almost 20,000 respondents to cover the duration of the pandemic (see University of Essex (2020)). The COVID-19 data used here are those for the first COVID wave, collected in April 2020.
[5] The most recent pre-Covid observation currently publicly available on Understanding Society respondents relates to some time between May 2017 and May 2019, depending on when the respondent was interviewed, with only very few cases being collected after January 2019.

Covid Economics 28, 12 June 2020: 91-118

depression, anxiety or stress. The main advantage of the GHQ-12, however, is that since it is a relatively brief 12-item scale it has been collected in all waves of Understanding Society to date and was also included in the COVID-19 module.[6]

In keeping with the other 'real-time' evidence on mental health that has already emerged in the UK, the Understanding Society Covid-19 data indicate a sizeable deterioration in mental health, and this is true regardless of whether or not (and if so how) we control for recent per-crisis trends. The average GHQ-12 score (indicating poor mental health) rose by 10.8% between wave 9 and the Covid module, and the 'effect' of the crisis was a deterioration of 8.1% when taking into account pre-crisis trends. This average deterioration (of one point on the 36-point GHQ scale) is large, being of a magnitude roughly equivalent to the mean difference in GHQ scores between the top decile and the bottom decile of the income distribution in 2017/8, nearly double the rise in average GHQ scores in total over the last four waves of the pre-pandemic data. We also show that this overall deterioration was driven by more reported problems, and a higher fraction of problems being reported 'much more than usual' (which we refer to as 'severe' for the purposes of this paper), as opposed to just mild deteriorations in existing problems for all. The number of problems reported rose by one – an increase of 50% – and the fraction of the sample reporting at least one severe problem doubled from 10.2% to 23.7%. Our individual level analysis shows that these average effects arose from much greater than average changes for women and for young adults, with some groups (particularly older men) being relatively unaffected.[7]

The size of these age and gender effects depend on how we control for pre-crisis trends but they are relatively unaffected when we add more idiosyncratic factors to our model in order to control for the individual-level exposure to the effects of the pandemic. Other things equal, key workers had less of a deterioration, and those who were laid off, had young children, or who had Covid symptoms on the day of the interview had a greater deterioration. There was no evidence of statistically significant differential effects of other factors such as the respondent's pre-existing health vulnerabilities, employment or furlough status, marital status, ethnicity or region of residence. This is despite the fact that, with a sample size of

---

[6] In addition, with the exception of wave 1 of Understanding Society when it was collected as part of the face to face interview, it has always been collected as part of a self-administered module so we might expect minimal mode effects in measurement as a result of the COVID-19 questionnaire being administered online.
[7] The raw gender effects in terms of changes between wave 9 and the Covid module are also documented in Etheridge and Spantig (2020), who argue social factors (friends and loneliness) and, to some extent, changes in family and caring responsibilities, can account for these differences.

Covid Economics 28, 12 June 2020: 91-118

CEPR PRESS

nearly 12,000 observations we would have a good degree of statistical power to pick up potential effects.

Our results also show clearly that, in addition to impacting on mental health on average, the Covid pandemic has widened mental health inequalities, with the groups that had the poorest mental health pre-crisis also having had the largest deterioration. Qualitatively, this conclusion is obtained regardless of whether one uses past data in its raw form or attempts to control for pre-crisis trends, and indeed this is also unsurprising given what is already known about the deterioration in mental health for specific groups from the pre-existing cross-sectional analysis. In our framework though, we are able to quantify the increase in prevalence, and the increase in between-group inequalities, taking into account individual heterogeneity and with some control for the trends that would have happened anyway.

In addition to showing that some groups were more affected than others, and that the magnitude of these (relative) effects depends on how one controls for pre-crisis trends, we also provide some concluding analysis of the individual elements of the GHQ-12 questionnaire to show that some dimensions of mental health were affected more than others, and by more for some groups than others. We show that whilst measures relating to general happiness deteriorated for all age groups, trends in other dimensions are particularly negative and/or specific to young adults.

2. Data and methodology

We use panel data from the UK Household Longitudinal Study (UKHLS), also known as Understanding Society. The study began in 2009 and included 36,000 individuals in the latest wave (wave 9). Interview waves span three overlapping years, with the vast majority of interviews taking place in the first two years, so that wave 1 runs from 2009 to 2011, wave 2 from 2010 to 2013 and so on. Adults aged 16 or older in each household are re-interviewed approximately one year apart, including individuals who move addresses or leave their original households to form new households. The sample is weighted to be nationally representative.

In April 2020, participants of the UKHLS were asked to complete a short online survey on the impact of the Covid-19 pandemic and this survey included the GHQ-12 instrument as well as information on demographics economic conditions in February 2020 (just before the start of the pandemic) and in April 2020. Full details of sample design,

Covid Economics 28, 12 June 2020: 91-118

response rates and response patterns are given in Institute for Social and Economic Research (2020). There were 17,452 full responses to the survey, and response rates for individuals previously interviewed at wave 9 were 46.0%.[8] After dropping cases without wave 9 information which we need for our pre-crisis analysis and other cases with zero weight (N=4,506) and dropping cases with missing responses to the GHQ-12 scale (N=966), we are left with a resulting analysis sample of 11,980 individuals. We use this data to study the impact of Covid-19 on mental health, and how it relates to demographic characteristics and other factors like the health and economic impact of the pandemic. We consider three measures of mental health based on the GHQ-12: the overall GHQ score (the Likert scale), the number of components with a score of 3 or above (the Caseness scale) and a binary indicator of whether any of the components has a score of 4. The last two measures can be interpreted as the number of problems reported, and whether any frequent/severe problems are reported, respectively. See Appendix B for further details on the GHQ-12.

Estimating the impact of Covid-19 requires an estimate of counterfactual mental health in the absence of Covid-19. Identification of a full and robust individual-specific counterfactual will be a challenge even in the longer run when more extensive data become available. Nevertheless, we should still attempt to create the best pre-crisis measure possible since if one is to investigate the effects of the pandemic by looking at individual-level changes before and during (or after) the crisis then this implicitly attributes all observed changes to the crisis, which will be differentially problematic for different groups.

The latest data on each respondent's mental health is from wave 9, which was carried out between January 2017 to May 2019, with 96% of interviews taking place between 2017 and 2018. There are a number of reasons we would expect individuals' mental health at the onset of Covid-19 to differ from their wave 9 values. First, wellbeing is U-shaped over the lifecycle, with mental health problems peaking in middle age and particularly steep differences changes in mental health within young adults and those approaching and moving into retirement. This is shown in Figure 1 which pools data across all waves of the UKHLS.

Second, there are pre-existing trends in mental health that vary by age and gender. Figure 2 shows that between wave 6 (January 2014-May 2016) and wave 9 (January 2017-May 2019), mental health problems as measured by the overall GHQ score and the number of

[8] In all our analysis we use the Covid-19 module cross-sectional weights to adjust for unequal selection probabilities and differential non-response since even though our predictions are formed from longitudinal data our key analysis is of the Covid module cross-sectional data. These weights model response probabilities conditional on past response to wave 9 and assign zero weight to individuals that had not responded to wave 9, hence we are implicitly providing estimates that are representative of the UK household population in 2017/18.

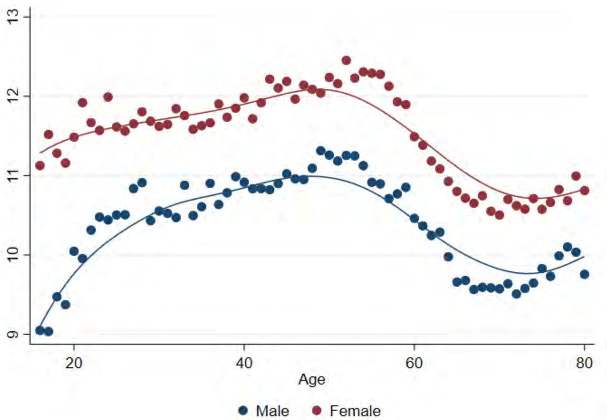
CEPR PRESS

problems increased across most age groups, especially among the young. Meanwhile, the share of individuals with any severe problems declined over recent years, with older individuals seeing a steeper decline.

Third, there are seasonal trends in mental health. GHQ scores fall (mental health improves) in the spring and summer months, as shown in Figure 3 which means that a sample interviewed entirely in April will not be comparable to a sample interviewed across a previous year.

Finally, individuals may have had idiosyncratic changes in circumstances over the two to three years that elapsed between their wave 9 interview and the month immediately preceding the Covid-19 pandemic that may have affected their pre-crisis wellbeing levels. Some of these changes will be captured in the Covid-19 module which asks a limited number of questions referring to the respondent's situation in February 2020, for example on employment status, and so it is possible to include controls for these in our analysis.

Figure 1. Age profile in GHQ scores, waves 1-9 (January 2009 to May 2019)



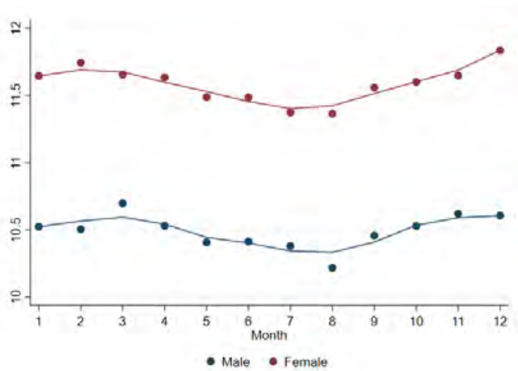
Source: UKHLS Waves 1-9 and April Covid-19 survey
Notes: Excludes individuals over the age of 80.

Covid Economics 28, 12 June 2020: 91-118

Figure 2. Trends in mental health by age and gender, waves 1-9 (January 2009 to May 2019)

Source: UKHLS waves 1-9 and April Covid-19 survey
Note: The waves ran as follows: wave 1 January 2009-March 2011, wave 2 January 2010-March 2012, wave 3 January 2011-July 2013, wave 4 January 2012-June 2013, wave 5 January 2013-June 2015, wave 6 January 2014-May 2016, wave 7 January 2015-May 2017, wave 8 January 2016-May 2018, wave 9 January 2017-May 2019.

Figure 3. Seasonal trends in GHQ scores, waves 1-9 (January 2009 to May 2019)



Source: UKHLS Waves 1-9 and April Covid-19 survey

In the analysis that follows we therefore define the 'effect' of the pandemic as the difference between and individuals April 2020 mental health and a prediction of the likely level of mental health in April 2020 in the absence of the pandemic. We compare this to a measure of the effect that is just the simple difference between the respondent's April 2020 and wave 9 values. We use three sets of prediction models, each estimated using waves 6-9 (covering the period 2015-2019) and including individual fixed effects. The models are estimated separately for six subsamples defined by gender and the individual's broad age group in wave 9 (split into 16-34, 35-64 and 65 and over) to allow time trends to vary by gender and age group, as we see in Figure 2 above. The models are nested and defined as follows: Model (a) simply controls for quadratic age and month effects, Model (b) adds an additional linear year effect, and model (c) includes additional controls for work status in February 2020 (i.e. just before the pandemic), living in a couple, the number of children in the household in three age groups (0-4, 5-15 and 16-18) and the region of residence. Each model is then used to predict the respondent's mental health in April 2020 and this will be an individual specific prediction due to the inclusion of the individual fixed effect.

The estimates for the most sophisticated prediction model (model c) for the GHQ score is given in Table A.1in the Appendix, additional results are available from the authors on request. Figures A.1 to A.3 in the appedix show wave 9 values alongside the three predicted counterfactual values from the models described above. We see that predicted counterfactual GHQ scores and the number of problems are higher than their wave 9 values across most gender and age groups, and particularly for younger individuals, which reflects the upward trend in mental health problems over recent years. This means that a naïve comparison of April 2020 to wave 9 GHQ scores would overstate the impact of the pandemic, particularly for young people for whom the pre-trend has been steepest. On the other hand, a naïve comparison would understate the impact on severe mental health problems for some gender and age groups, which have been on a downward trend.

3. Results

3.1 Changes in overall GHQ

Figure 4 shows the distribution of mental health for the April 2020 sample across our three measures by gender and age group. Group-level averages are given for wave 9, our counterfactual prediction ('April 2020 predicted') and in April 2020 ('Covid'). The predictions are based on a model which includes the full set of covariates, as shown in Appendix Table A1 although Figures A.1 to A.3 show that group-level averages are very similar across the three prediction models. The blue dots show age group averages for men and the red dots for women. Average GHQ scores across all individuals are marked by the grey squares.

Mental health levels have deteriorated during the Covid-19 pandemic, relative to both Wave 9 levels and our counterfactual prediction. Average GHQ scores across all individuals in April 2020 were 1.23 points (10.8 %) higher than in Wave 9 and 0.94 points (8.1%) higher than our counterfactual prediction. It is helpful to have a sense of the distribution of mental health scores before the pandemic to interpret the magnitude of these changes. The distribution and subgroup means of the three mental health measures are given in Table A.2. For context, one point on the GHQ (Likert) scale is roughly equivalent to the average difference between men and women at wave 9, and to the average difference between those in the top quintile of the household income distribution and those in the bottom quintile. The previous four waves of data combined, collected over the period 2015-2019 during which there was concern about the rising prevalence of mental health problems, showed a rise of GHQ average scores of just over half a point (0.54).

The deterioration in mental health was more marked for our indicators of the number of problems or the fraction of people with any severe problems. Individuals reported an average of one more problem, which is roughly twice the average difference between men and women at wave 9, and twice the difference between the top and bottom income quintiles. The share reporting any severe problems more than doubled, from 10.6% in wave 9 and 10.2% in our counterfactual prediction to 23.7% in April 2020.

Covid-19 appears to have widened inequalities in mental health across gender and age groups and exacerbated pre-existing inequalities. Across all three measures, groups that had poor mental health before the pandemic hit generally suffered the largest deterioration in mental health, both in absolute and percentage terms. Young women saw the largest deterioration in mental health as result of Covid-19: average GHQ scores among women aged 16-24 rose by 2.5 points or 18.2% relative to the counterfactual prediction, and the share reporting a severe problem doubled from 17.6% to 35.2%. On the other hand, men aged 65 and over saw relatively little change in their GHQ scores and the number of problems reported, though the share reporting any severe problems increased sharply in percentage terms.

Covid Economics 28, 12 June 2020: 91-118

Figure 4a. GHQ-12 score by gender and age group

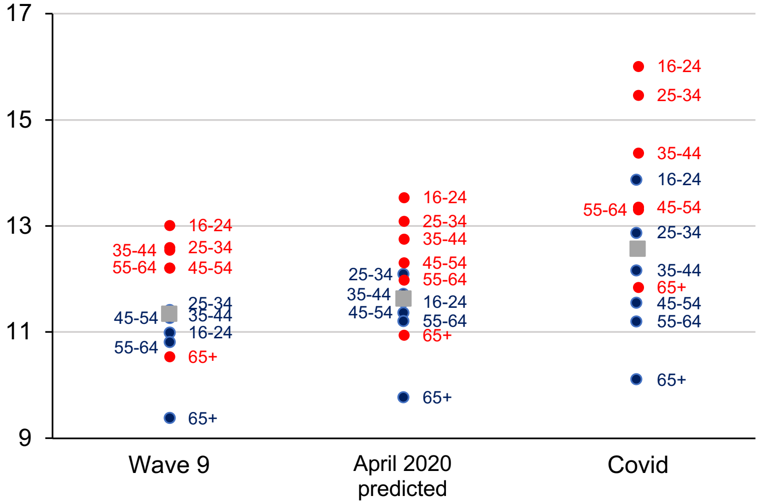
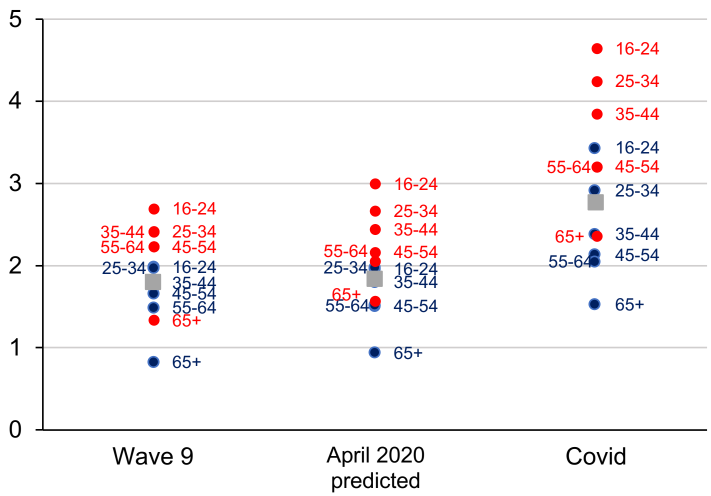
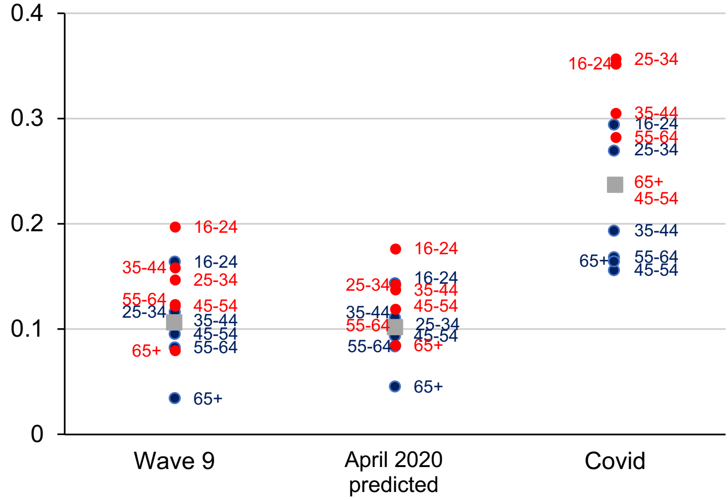


Figure 4b. Number of problems by gender and age group



Source: UKHLS Waves 6-9 and April Covid-19 survey
Notes to Figure 4a-4c: Wave 9 refers to January 2017-May 2019. Predicted values based on prediction using full set of controls (model c), with time effects set to April 2020. Values for male age groups indicated in Blue, values for female age groups in red. Grey squares are unconditional averages.

Figure 4c. Proportion with severe problems by gender and age group



Source: UKHLS Waves 6-9 and April Covid-19 survey
Notes to Figure 4a-4c: Wave 9 refers to January 2017-May 2019. Predicted values based on prediction using full set of controls (model c), with time effects set to April 2020. Values for male age groups indicated in Blue, values for female age groups in red. Grey squares are unconditional averages.

We now turn to examining how the effects of Covid-19 on mental health vary across individuals with different characteristics and different levels of exposure to the pandemic in terms of economic and health impacts. Table 1 and Table 2 show regression results of the change in mental health measures (GHQ score, number of problems and the share with any severe problems), assessed relative to wave 9 and our counterfactual prediction, respectively. Recall that a one-point increase in GHQ scores is roughly equivalent to moving from the top to bottom quintile of the household income distribution at wave 9; an increase in one mental health problem is roughly double the distance between the richest and poorest groups.

In both Table 1 and Table 2 the first column (a) shows the change in GHQ scores regressed on gender and age group alone (relative to men aged 45-54). As with the figures above, we see that the increase in GHQ scores is larger for women and young people. The coefficient on women is larger and the coefficients on younger age groups smaller using the counterfactual prediction than wave 9, which reflects differential pre-trends prior to Covid-19. Using the counterfactual prediction – our preferred specification (Table 2) – the coefficient on women is 0.98. The increase in GHQ scores is 1.7 points higher than among 16-24-year olds than among those aged 45-54, and 0.99 points higher among 25-34-year olds.

Table 1. Determinants of change in GHQ-12 relative to wave 9 (robust p-values in parentheses)

	(1) GHQ score a. Age and gender		(1) GHQ score b. All covariates		(2) Number of problems		(3) Any severe problems	
	Coef.	p-val	Coef.	p-val	Coef.	p-val	Coef.	p-val
Female	0.80	**<0.01**	0.78	**<0.01**	0.53	**<0.01**	0.05	**<0.01**
16-24	2.16	**<0.01**	2.13	**<0.01**	0.98	**<0.01**	0.05	0.15
25-34	1.47	**<0.01**	1.26	**<0.01**	0.56	**<0.01**	0.09	**<0.01**
35-44	0.63	**0.01**	0.35	0.19	0.15	0.35	0.03	0.15
55-64	0.02	0.94	0.28	0.22	0.25	0.06	0.04	**0.03**
65 and over	0.30	0.09	0.75	**0.01**	0.59	**<0.01**	0.06	**0.01**
High risk			-0.14	0.43	-0.12	0.24	0.03	0.06
Very high risk			-1.13	**0.01**	-0.66	**<0.01**	-0.04	0.20
NHS shielding			-0.05	0.89	-0.04	0.86	0.04	0.13
Had Covid-19 symptoms			0.36	0.12	0.30	**0.03**	0.02	0.26
Has Covid-19 symptoms			2.02	**0.03**	0.96	**0.05**	0.11	**0.05**
Self-employed in Feb			0.03	0.92	-0.07	0.63	0.02	0.40
Not working in Feb			0.06	0.81	-0.09	0.53	0.03	0.15
Hours fell Feb-Apr			0.25	0.28	0.16	0.22	0.03	0.11
Furloughed Feb-Apr			-0.20	0.48	-0.05	0.78	0.03	0.17
Laid off Feb-Apr			1.79	**0.03**	1.05	**0.02**	0.01	0.83
Pay fell Feb-Apr			-0.03	0.89	-0.04	0.78	-0.00	0.88
HH earning fell Feb-Apr			0.22	0.29	0.22	0.07	0.02	0.17
Shutdown sector in W9			0.73	**0.01**	0.46	**<0.01**	0.04	0.06
Key worker			-0.20	0.32	-0.13	0.26	0.00	0.90
Caring responsibilities			0.18	0.21	0.16	**0.05**	0.01	0.22
Youngest child 0-4			0.98	**<0.01**	0.47	**<0.01**	0.01	0.71
Youngest child 5-15			0.40	0.11	0.27	0.06	0.01	0.52
Youngest child 16-18			-0.35	0.30	-0.22	0.26	-0.01	0.67
Constant	0.32	**0.05**	-0.24	0.61	0.01	0.98	0.03	0.43
Observations	11,980		11,980		11,980		11,980	
R^2	0.015		0.030		0.030		0.017	
Adjusted R^2	0.014		0.026		0.026		0.013	

Note: Columns 1.b, 2 and 3 also include controls for highest qualification, ethnicity, region, whether in a couple and whether living with others (coefficients not reported)

The second column of each table (b) adds controls for other demographic variables (educational qualifications, ethnicity, region) and individual-level exposure to Covid-19 in terms household composition and caring responsibilities, whether they are medically vulnerable to Covid-19[9] or have suffered symptoms of Covid-19, and the extent to which they have been economically affected by the pandemic. We see that the size of the coefficients on gender and younger age groups are relatively unaffected by the inclusion of these controls, which indicates that they matter in their own right and are not simply proxying for other dimensions of exposure. However, the size of the coefficients on older age groups increases when controls are added, and we start to see more of a U-shaped profile in age, with larger mental health impacts on younger and older individuals relative to those in middle age.

[9] Based on whether they have ever having been diagnosed with a medical condition that places them at 'high risk' or 'very high risk' to the virus, and/or have been asked by the NHS to shield. See Covid-19 derived variables documentation for more details on medical conditions.

Table 2. Determinants of change in GHQ-12 relative to counterfactual prediction (robust p-values in parentheses)

	(1) GHQ score a. Age and gender		(1) GHQ score b. All covariates		(2) Number of problems		(3) Any severe problems	
	Coef.	p-val	Coef.	p-val	Coef.	p-val	Coef.	p-val
Female	0.98	**<0.01**	1.01	**<0.01**	0.51	**<0.01**	0.06	**<0.01**
16-24	1.70	**<0.01**	1.80	**<0.01**	0.80	**<0.01**	0.07	0.06
25-34	0.99	**<0.01**	0.82	**<0.01**	0.35	**0.04**	0.10	**<0.01**
35-44	0.43	**0.05**	0.17	0.46	0.03	0.81	0.04	**0.04**
55-64	0.05	0.76	0.28	0.17	0.21	0.08	0.05	**<0.01**
65 and over	0.01	0.96	0.55	0.03	0.37	**<0.01**	0.05	**<0.01**
High risk			-0.05	0.78	-0.09	0.31	0.02	0.06
Very high risk			-0.34	0.30	-0.26	0.18	0.01	0.82
NHS shielding			0.01	0.98	-0.07	0.69	0.05	**0.02**
Had Covid-19 symptoms			0.27	0.19	0.21	0.08	0.02	0.32
Has Covid-19 symptoms			2.04	**<0.01**	0.99	**0.02**	0.08	0.10
Self-employed in Feb			0.15	0.53	0.03	0.80	0.01	0.59
Not working in Feb			-0.32	0.17	-0.28	**0.03**	0.01	0.64
Hours fell Feb-Apr but not furloughed or laid off			0.26	0.21	0.16	0.18	0.04	**0.02**
Furloughed Feb-Apr			-0.21	0.42	-0.04	0.79	0.02	0.42
Laid off Feb-Apr			1.89	**0.01**	1.16	**<0.01**	0.01	0.90
Pay fell Feb-Apr			-0.10	0.68	-0.07	0.61	-0.01	0.59
HH earnings fell Feb-Apr			0.28	0.15	0.24	**0.03**	0.03	**0.04**
Shutdown sector in W9			0.57	**0.03**	0.36	**0.01**	0.04	**0.03**
Key worker			-0.36	**0.04**	-0.20	**0.05**	-0.02	0.13
Caring responsibilities			0.12	0.36	0.11	0.13	0.02	0.12
Youngest child 0-4			0.95	**<0.01**	0.49	**<0.01**	0.00	0.87
Youngest child 5-15			0.36	0.12	0.27	**0.04**	0.02	0.36
Youngest child 16-18			-0.43	0.13	-0.20	0.22	-0.02	0.46
Constant	0.12	0.40	0.13	0.76	0.48	**0.04**	0.06	**0.05**
Observations	11,980		11,980		11,980		11,980	
R^2	0.016		0.033		0.033		0.022	
Adjusted R^2	0.016		0.029		0.029		0.018	

Note: Columns 1.b, 2 and 3 also include controls for highest qualification, ethnicity, region, whether in a couple and whether living with others (coefficients not reported)

The positive coefficients on older cohorts disappear when our covariates capturing the economic impacts and the presence of children are dropped (the results of this additional regression are not presented here). So, whilst being older is associated with a larger deterioration in mental health all else equal, the smaller effects on older ages that are apparent in column (1.a) are a consequence of the fact that older people are more insulated from the economic and childcare shocks of the pandemic.

Women and younger people also experienced a larger increase in mental health problems controlling for other factors. Using our preferred specification (the counterfactual prediction model presented in Table 2) women saw an increase of half a mental health problem more than men, all else equal, and the share of women with any severe problems increased by 6 percentage points more than men. Recalling Table A.2, this doubles the wave

Covid Economics 28, 12 June 2020: 91-118

9 gender gap in the number of problems, and more than doubles the percentage point difference in the shares of men and women with severe problems.

Medical vulnerabilities do not significantly affect the impact of Covid-19 on mental health using our preferred specification. But using a naïve comparison to wave 9, being at 'very high risk' of Covid-19 complications (based on pre-existing conditions) appears to *reduce* the impact of the virus on mental health. This is because this group consists of older people, who have had better mental health trends in recent years – which again illustrates the need to account for differential pre-trends in assessing the impact of Covid-19. Having symptoms of the virus at the time of the survey – predictably – has a very large and significant effect on all three measures. The coefficient on the overall GHQ score is 2.04 under our preferred specification, and the increase in the share with severe problems is 8 percentage points. Having had Covid-19 symptoms is also associated with more deterioration in mental health, but to a much smaller degree, and this is only statistically significant when looking at the number of mental health problems (not the other two measures).

Falls in household earnings since February 2020 are associated with a larger deterioration in mental health as result of Covid-19 that is statistically significant in some specifications and measures. Being laid off since February 2020 has a large impact on overall mental health problems (a 1.89 higher GHQ score and 1.16 more problems in our preferred specification), but does not appear to affect the measure of severe mental health problems. Conditional on changes in earnings, being furloughed appears to reduce the negative impact on mental health. Working in a sector that has been shut down during the lockdown – based on the classification in Joyce and Xu (2020) and wave 9 values since information on industries is not available in the April 2020 survey – appears to have a negative effect over and above the direct effect on hours and earnings, perhaps reflecting increased precarity in these roles and uncertainty about future prospects. All else equal, the deterioration in mental health was smaller among key workers, and the effect is statistically significant using our preferred specification and the difference between this group and other workers will be explored in a little more detail in our final analysis.

Those with very young children aged 0-4 saw a significantly larger increase in overall mental health problems (but not severe problems), by around one GHQ point and half a mental health problem under our preferred specification. Those with school-aged children aged 5-15 also saw a larger increase in mental health problems that is statistically significant in some measures and specifications – the coefficient is between a third and half of that on very young children.

Covid Economics 28, 12 June 2020: 91-118

Coefficients are not shown in the tables due to a lack of statistical significance, but there is no evidence of differential effects by whether individuals are single or live alone or by educational qualifications. There are also no significant differences by ethnicity, with the exception of black individuals who saw a smaller deterioration in mental health all else equal. There is no evidence of differential effects across regions of the UK, despite differences in the spread of the virus in April.

We also ran our preferred specification run separately for men and women (results available from authors), mainly in order to assess whether any of the crisis exposure variables have impacted on mental health differentially across genders. The unconditional age profile is steeper for men, which reflects the fact that the impact of Covid-19 on mental health is concentrated in younger men (with only a small effect on older men), whereas women of all ages were negatively affected. Having symptoms of Covid-19 at the time of the survey appeared to have a much larger effect on the mental health of women: the coefficient on GHQ score is nearly four times larger. The negative effect of being laid off and working in a shutdown sector (in wave 9) are mainly driven by women: the effects are not statistically significant for men The differential effect of having very young children aged 0-4 is higher for women – the coefficients on GHQ score and the number of problems is around twice those for men (for whom they are not statistically significant) – which may reflect the uneven distribution of childcare responsibilities under lockdown (Andrew et al. 2020).

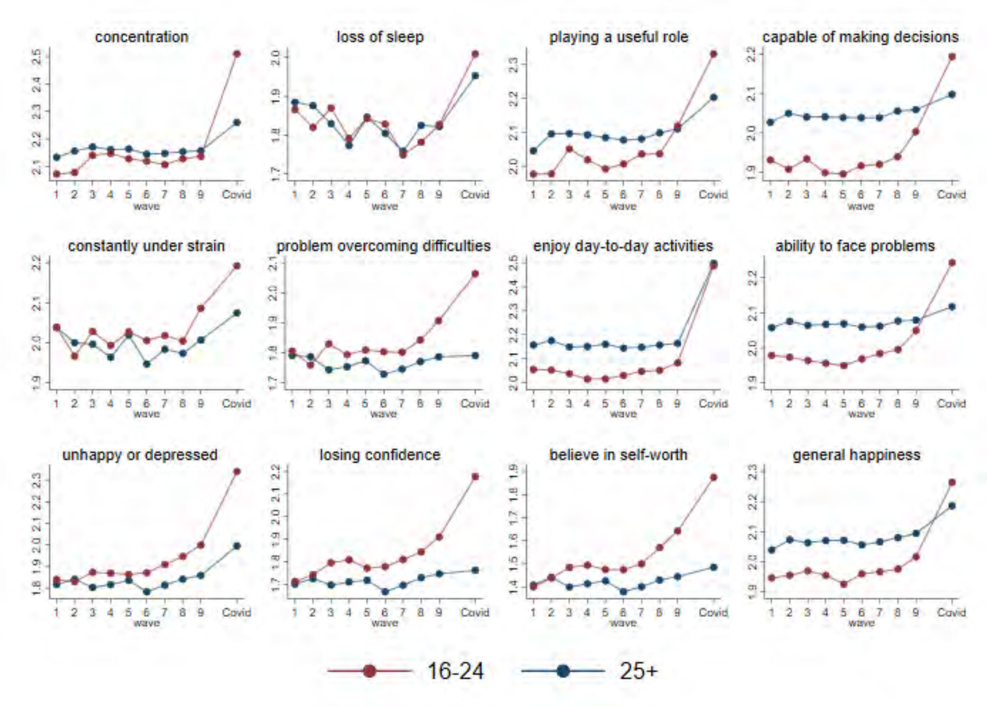
3.2 Changes in individual GHQ components

Given that the GHQ-12 mental health scores are calculated from responses in twelve separate dimensions as described in Appendix A, it is possible to consider each of these dimensions separately in order to build an understanding of which types of dimensions are underlying the striking deterioration in mental health scores identified above. Such analysis can only be indicative, since the single questions in each dimension do not capture the dimension with enough precision or granularity to build a definitive picture on what is happening within that dimension. For example, the question on depression in the GHQ-12 questionnaire – 'Have you recently been feeling unhappy or depressed?' – is not sufficiently detailed to study the effects on depression in its own right. In addition, negative and positive language issues in the wording of individual questions mean that the GHQ-12 scale should be primarily thought of as a unidimensional measure of general mental health rather than a set of subscales representing distinct constructs (Gnambs and Staufenbiel, 2018).

Covid Economics 28, 12 June 2020: 91-118

Nevertheless, to conclude our empirical analysis we provide some preliminary descriptive findings along these lines to get some broad idea of the underlying changes in dimensions and to suggest future directions for analysis when more granular data on the various dimensions do become available. Reflecting the more limited goals of this exercise, rather than re-run the detailed multivariate analysis previously carried out for our overall mental health outcomes, we simply chart the main underlying trends.

Figure 5. GHQ-12 component scores, waves 1-9 (January 2009 to May 2019) and April 2020 by age group



Source: UKHLS waves 1-9 and April Covid-19 survey
Note: All items are scored negatively, so higher numbers indicate worse outcomes in each domain. The waves ran as follows: wave 1 January 2009-March 2011, wave 2 January 2010-March 2012, wave 3 January 2011-July 2013, wave 4 January 2012-June 2013, wave 5 January 2013-June 2015, wave 6 January 2014-May 2016, wave 7 January 2015-May 2017, wave 8 January 2016-May 2018, wave 9 January 2017-May 2019.

Figure 5 shows trends in each individual component of the GHQ-12 scale over the course of the Understanding Society study from wave 1 (January 2009-March 2011) up until the Covid module in April 2020, with trends plotted separately for young adults versus those 25 and over. The charts are labelled to reflect the question content (see Appendix A), but coded on a scale of 1 to 4 so that in each case higher values reflect poorer mental health.

There was a marked deterioration in measures relating to happiness – enjoying day-to-day activities, general happiness, feeling unhappy or depressed – that is seen across both age groups, though to somewhat different extents. But in many dimensions where young adults saw large declines in mental health – such as feeling capable of making decisions, having problems overcoming difficulties, and the ability to face problems – we do not see any particular deviation from the pre-Covid trend for older adults.

For dimensions of particular interest, we can also break down trends by the six age-gender groups that we have been working with previously in our analysis. We consider four key dimensions: enjoyment of day to day activities, sleep, depression, and the perception of playing a useful role. Figure 6 indicates that changes in enjoyment of day to day activities were strikingly similar for all age-gender groups, perhaps unsurprisingly since the lockdown and social distancing has affected all our lives and the way that we live them. There is more variability, however, in the evolution of specific dimensions that might be thought more fundamentally important for current or future health such as sleep, depression and even perhaps sense of purpose, which is where we see many of the changes that underlie the age and sex differences in the overall GHQ score. Increases in feelings of unhappiness or depression have been greater for the young (Figure 7), and reductions in sleep have been apparent for women but not for men, although somewhat similar across age groups within each gender, with the exception of a small rise in difficult sleeping for younger males, as shown in Figure 8. The gender difference in loss of sleep through worry is likely to be particularly important when coupled with recent evidence that has emerged on time-use differences between women and men (see Andrew et al (2020)). Similarly, when it comes to looking at whether people feel they are playing a useful role, it is also the youngest group (both male and female) and the older groups of women where we see the largest deterioration relative to pre-Covid trends.

Covid Economics 28, 12 June 2020: 91-118

Figure 6. (Lack of) enjoyment of day-to-day activities, waves 1-9 (January 2009 to May 2019) and April 2020 by gender and age group

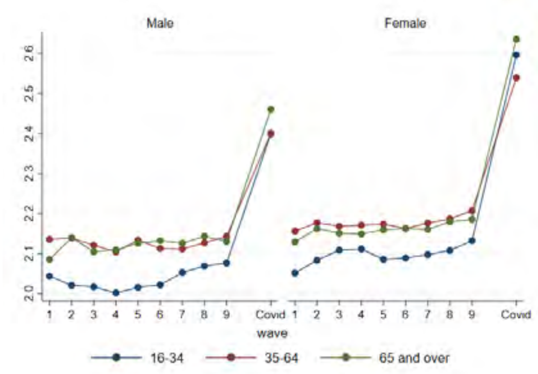
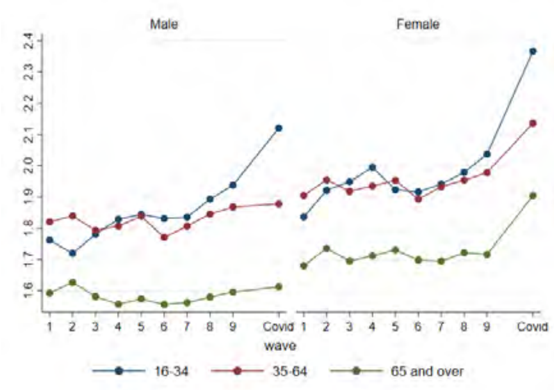


Figure 7. Unhappy or depressed, waves 1-9 (January 2009 to May 2019) and April 2020 by gender and age group



Source: UKHLS waves 1-9 and April Covid-19 survey
Note to Figures 6-9: The waves ran as follows: wave 1 January 2009-March 2011, wave 2 January 2010-March 2012, wave 3 January 2011-July 2013, wave 4 January 2012-June 2013, wave 5 January 2013-June 2015, wave 6 January 2014-May 2016, wave 7 January 2015-May 2017, wave 8 January 2016-May 2018, wave 9 January 2017-May 2019. Higher values reflect poorer mental health.

Covid Economics 28, 12 June 2020: 91-118

Figure 8. Loss of sleep, waves 1-9 (January 2009 to May 2019) and April 2020 by gender and age group

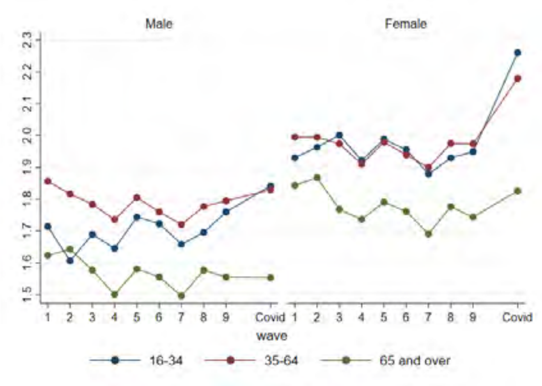
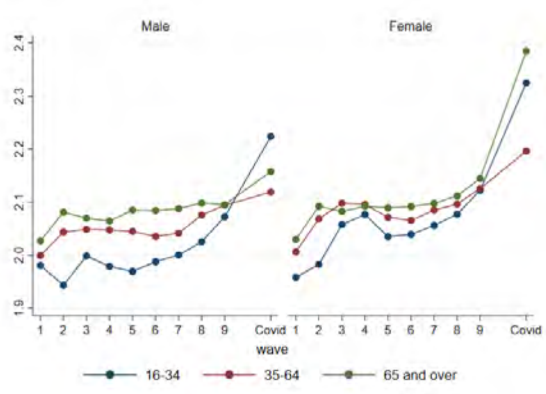


Figure 9. (Not) playing a useful role, waves 1-9 (January 2009 to May 2019) and April 2020 by gender and age group



Source: UKHLS waves 1-9 and April Covid-19 survey
Note to Figures 6-9: The waves ran as follows: wave 1 January 2009-March 2011, wave 2 January 2010-March 2012, wave 3 January 2011-July 2013, wave 4 January 2012-June 2013, wave 5 January 2013-June 2015, wave 6 January 2014-May 2016, wave 7 January 2015-May 2017, wave 8 January 2016-May 2018, wave 9 January 2017-May 2019. Higher values reflect poorer mental health.

4. Conclusions

The mental health effects of the Covid-19 pandemic have been large, as initially speculated and as previous cross-sectional real-time analysis has shown. Our contribution in this paper has been to set these changes in the context of the distribution of individuals' previous longitudinal trajectories of mental health, to form a prediction of what mental health would have been in April 2020 in the absence of the pandemic, and to use this framework to quantify the size of the effects of the crisis on mental health as measured by the GHQ-12. We show that the effects are large and that they differ both in size and in nature according to which population sub-groups are being looked at, with young people and women experiencing the largest declines in mental health.

Differing patterns and magnitudes are also seen when we look at the number of reported problems or the severity of mental health problems as opposed to just average scores, and our analysis reveals that the deterioration in average scores is driven by more problems, and more 'severe' problems, as opposed to just a general mild worsening of pre-existing problems for everyone. Indeed, the increase in the prevalence of reporting at least one severe problem, and the increase in between-group inequality in this prevalence, is striking. More generally, as well as worsening mental health on average, the Covid pandemic in the UK can clearly be seen to have increased mental health inequalities.

Our data relate to April 2020 when the UK was in the depths of the full lockdown and Covid deaths were still rising rapidly. Future waves of data on the same respondents, to be collected monthly over the next year, will provide an invaluable resource for documenting month to month variation and tracking the permanence or otherwise of these mental health effects in the context of the longer run mental health trajectories that have been observed for these same individuals over the previous ten years. Thus, researchers will be able to look at the permanence or otherwise of the mental health effects, and at the extent and speed at which different groups are able to bounce back as the distancing restrictions unwind and as government policies aiming to protect groups from the harmful effects of the crisis.

Whilst the pre-existing longitudinal data and the large representative sample from the Understanding Society study are undoubted advantages of the analysis we have been able to carry out here compared to previous work on Covid and mental health, our analysis has nevertheless been limited by only being able to use the somewhat crude GHQ-12 measure of mental health, due to the general-purpose nature of the Understanding Society survey questionnaire. But our results on the magnitude of GHQ changes and on the differences in trends in some of the components driving those changes do suggest that it will be imperative that researchers assess the complex and multifaceted mental health consequences of the pandemic in more detail as more and better data become available. Specifically, soon to be available Covid-specific data modules from UK studies such as the Centre for Longitudinal Studies (CLS) cohort studies and the English Longitudinal Study of Ageing (ELSA), or European studies such as the Survey of Health Ageing and Retirement in Europe (SHARE), will provide more granular and detailed measures of specific dimensions of mental health

Covid Economics 28, 12 June 2020: 91-118

dimensions both in terms of respondents' outcomes and in terms of their past trajectories and these data will facilitate more detailed analysis of outcomes such as depression, anxiety and sleep, and the specific mechanisms that might underlie changes. As this paper has shown, it is important to understand these effects within the contexts of the individuals' longer run trajectories and so research using these and other pre-existing nationally representative longitudinal studies, as well as further research using the Understanding Society Covid modules, should be considered a priority for the next few months as researchers and policymakers alike seek to understand the distribution and permanence of the mental health effects of the crisis in more detail.

Covid Economics 28, 12 June 2020: 91-118

References

Andrew, A., S. Cattan, M. Costa Dias, C. Farquharson, L. Kraftman, S. Ktutikov, A. Phimister and A. Sevilla, 2020, How are mothers and fathers balancing work and family under lockdown?, London: IFS, https://www.ifs.org.uk/publications/14860

Armbruster, S. and V. Klotzbücher, 2020, Lost in lockdown? Covid-19, social distancing, and mental health in Germany, Covid Economics, Issue 22, 117-154, 26 May 2020, CEPR

Brülhart, M. and R. Lalive, 2020, 'Daily suffering Helpline calls during the Covid-19 crisis', Covid Economics, Issue 19, 143-158, 18 May 2020, CEPR

Cox, B.D, M. Blaxter, A.J.L. Buckle, 1987, The Health and Lifestyle Survey, Health Promotion Research Trust, London

Etheridge, B. and Spantig, 'The gender gap in mental well-being during the Covid-19 outbreak: Evidence from the UK', University of Essex, ISER Working paper 2020-08, 08 June 2020

Fancourt, D., Bu, F., Mak, H-W, and Steptoe, A., 2020, Covid 19 Social Study: Results release 11, UCL mimeo, 3 June 2020, https://www.covidsocialstudy.org/results, accessed 4 June 2020

Gnambs, T., and T. Staufenbiel, 2018, The structure of the Genral Health Questionnaire (GHQ-12): two meta -analytic factor analyses, Health Psychology Review, 12 (2), 179-194

Holmes, E. A., O'Connor, R., Perry, V. H., Tracey, I., Wessely, I., Arseneault, L., Ballard, C., Christensen, H., Silver, R. C., Everall, I., Ford, T., John, A., Kabir, T., King, K., Madan, I., Michie, S., Przybylski, A. K., Shafran, R., Sweeney, A., Worthman, C. M., Yardley, L., Cowan, K., Cope, C., Hotopf, M., Bullmore, E. (2020), Multidisciplinary research priorities for the COVID-19 pandemic: a call for action for mental health science, Lancet Psychiatry, 7, 547–60

Institute for Social and Economic Research (2019) Understanding Society: The UK Household Longitudinal Study, Waves 1-9 User Guide, Colchester: University of Essex.

Institute for Social and Economic Research (2020) Understanding Society COVID-19 User Guide. Version 1.0, May 2020. Colchester: University of Essex.

Janke, K., Lee, K., Propper, C., Shields, K., & Shields, M. A. (2020). Macroeconomic Conditions and Health in Britain: Aggregation, Dynamics and Local Area Heterogeneity. CEPR Discussion Paper No. DP14507.

Joyce, R. and Xu, X. (2020). Sector shutdowns during the coronavirus crisis: which workers are most exposed? London: IFS, https://www.ifs.org.uk/publications/14791

Kivimäki, M., G. Batty, A. Steptoe and I. Kawachi, 2017, The Routledge International Handbook of Pschosocial Epidemiology. Abingdon: Routledge, Routledge Handbooks Online, https://doi.org/:10.4324/9781315673097, accessed 4 June 2020

Layard, R., D. Fancourt, A. Clark, N. Hey, J-E De Neve, G. O'Donnell and C.Krekel, 2020, 'When to release the lockdown? A wellbeing framework for analysing costs and benefits', IZA Discussion Paper No 13186, April 2020, http://ftp.iza.org/dp13186.pdf

ONS, 2020, 'Personal and economic well-being in Great Britain: May 2020', London: Office for National Statistics, accessed 4 June 2020. https://www.ons.gov.uk/peoplepopulationandcommunity/wellbeing/bulletins/personalandeconomicwellbeingintheuk/may2020,

Tubadji, A., F. Boy and D. Webber, 2020, Narrative economics, public policy and mental health, Covid Economics, Issue 20, 109-131, 20 May 2020, CEPR Press

University of Essex, Institute for Social and Economic Research. (2020a). *Understanding Society: Waves 1-9, 2009-2018 and Harmonised BHPS: Waves 1-18, 1991-2009*. [data collection]. *12th Edition*. UK Data Service. SN: 6614, http://doi.org/10.5255/UKDA-SN-6614-13

University of Essex, Institute for Social and Economic Research. (2020b). *Understanding Society: COVID-19 Study, 2020*. [data collection]. UK Data Service. SN: 8644, http://doi.org/10.5255/UKDA-SN-8644-1, dataset downloaded 29 May 2020.

Yamamura, E. and Y. Tsutsui, 2020, Impact of the state of emergency declaration for Covid-19 on preventative behaviours and mental conditions in Japan: Difference in difference analysis using panel data, Covid Economics, Issue 23, 303-324, 28 May 2020, CEPR

Covid Economics 28, 12 June 2020: 91-118

Appendix A: Additional tables and figures

Table A.1. Prediction model for GHQ score: run separately by gender and age in Wave 9

Coefficients (p-values)	(1) Men 16-34	(2) Men 35-64	(3) Men 65+	(4) Women 16-34	(5) Women 35-64	(6) Women 65+
Age	0.03	0.01	-0.03	-0.02	0.03	-0.07
	(0.220)	(0.408)	(0.126)	(0.463)	(0.023)	(0.001)
Age^2	0.00	-0.00	0.00	0.00	-0.00	0.00
	(0.915)	(0.098)	(0.076)	(0.698)	(0.003)	(0.006)
Interview month: Feb	-0.01	0.01	0.02	0.00	-0.00	0.00
	(0.624)	(0.150)	(0.184)	(0.787)	(0.824)	(0.848)
March	-0.01	0.02	0.03	0.01	-0.00	-0.01
	(0.502)	(0.055)	(0.027)	(0.458)	(0.691)	(0.635)
April	-0.02	0.02	0.01	0.02	-0.00	0.01
	(0.381)	(0.144)	(0.621)	(0.374)	(0.685)	(0.417)
May	-0.03	0.01	0.01	0.03	-0.01	0.02
	(0.253)	(0.283)	(0.530)	(0.153)	(0.606)	(0.380)
June	-0.01	0.01	-0.00	0.01	-0.01	0.01
	(0.674)	(0.363)	(0.946)	(0.686)	(0.247)	(0.729)
July	-0.02	0.00	0.01	0.02	-0.01	-0.00
	(0.427)	(0.881)	(0.747)	(0.465)	(0.611)	(0.826)
August	-0.06	-0.00	0.02	-0.01	-0.00	0.00
	(0.024)	(0.932)	(0.280)	(0.673)	(0.898)	(0.977)
September	-0.01	0.01	0.01	-0.00	0.00	-0.01
	(0.608)	(0.542)	(0.610)	(0.937)	(0.771)	(0.652)
October	-0.04	0.01	0.02	0.02	-0.01	-0.01
	(0.191)	(0.614)	(0.186)	(0.393)	(0.555)	(0.718)
November	-0.03	0.01	0.00	0.03	-0.01	0.00
	(0.229)	(0.439)	(0.915)	(0.133)	(0.668)	(0.916)
December	-0.05	0.01	-0.00	0.00	-0.00	0.01
	(0.086)	(0.236)	(0.958)	(0.878)	(0.884)	(0.541)
Year of interview	-0.03	0.00	0.00	0.01	-0.00	0.02
	(0.067)	(0.700)	(0.947)	(0.688)	(0.579)	(0.095)
Self-employed	0.02	-0.02	-0.03	0.03	0.01	0.01
	(0.447)	(0.075)	(0.093)	(0.233)	(0.574)	(0.619)
Not working for pay	0.07	0.04	-0.01	0.03	0.03	0.00
	(0.000)	(0.000)	(0.431)	(0.007)	(0.000)	(0.920)
Single	0.03	0.04	0.01	-0.03	0.03	-0.01
	(0.171)	(0.002)	(0.481)	(0.100)	(0.006)	(0.534)
1 child aged 0-4	-0.00	0.00	-0.06	-0.00	0.01	-0.01
	(0.971)	(0.832)	(0.274)	(0.786)	(0.244)	(0.884)
2+ children aged 0-4	0.01	-0.01	0.16	0.00	0.02	-0.12
	(0.822)	(0.470)	(0.071)	(0.970)	(0.274)	(0.187)
1 child aged 5-15	0.02	-0.01	0.02	0.01	-0.02	-0.05
	(0.405)	(0.293)	(0.651)	(0.630)	(0.062)	(0.404)
2+ children aged 5-15	-0.03	-0.02	-0.02	0.00	-0.03	0.02
	(0.392)	(0.264)	(0.792)	(0.913)	(0.030)	(0.827)
1 child aged 16-18	0.02	-0.01	-0.01	-0.01	-0.01	0.07
	(0.378)	(0.306)	(0.830)	(0.576)	(0.137)	(0.334)
2+ children aged 16-18	0.08	-0.05	-0.09	0.01	0.02	0.04
	(0.306)	(0.024)	(0.253)	(0.854)	(0.295)	(0.837)
North West	0.28	-0.07	0.07	0.06	-0.11	-0.18
	(0.043)	(0.443)	(0.779)	(0.625)	(0.414)	(0.205)
Yorkshire+ Humber	0.17	-0.11	0.15	0.01	0.04	-0.02
	(0.190)	(0.207)	(0.371)	(0.937)	(0.774)	(0.907)
East Midlands	0.19	0.02	-0.05	0.05	0.04	-0.06
	(0.172)	(0.824)	(0.804)	(0.675)	(0.777)	(0.736)
West Midlands	0.11	0.23	-0.20	0.12	0.08	-0.09

Covid Economics 28, 12 June 2020: 91-118

	(0.442)	(0.019)	(0.265)	(0.315)	(0.525)	(0.626)
East of England	0.14	0.01	0.08	0.04	0.01	0.02
	(0.278)	(0.877)	(0.651)	(0.749)	(0.957)	(0.885)
London	0.18	-0.01	-0.17	0.02	-0.02	-0.18
	(0.171)	(0.895)	(0.361)	(0.893)	(0.850)	(0.282)
South East	0.21	-0.02	-0.04	0.11	-0.08	-0.23
	(0.105)	(0.833)	(0.810)	(0.350)	(0.499)	(0.162)
South West	0.07	-0.14	-0.09	-0.03	0.02	-0.22
	(0.614)	(0.148)	(0.597)	(0.793)	(0.849)	(0.134)
Wales	0.06	0.07	-0.06	0.12	-0.03	0.01
	(0.666)	(0.535)	(0.759)	(0.386)	(0.822)	(0.967)
Scotland	0.18	-0.07	0.07	0.31	-0.18	-0.20
	(0.224)	(0.504)	(0.828)	(0.094)	(0.217)	(0.425)
Northern Ireland	0.10	-0.13	-0.50	-0.17	-0.03	0.15
	(0.585)	(0.658)	(0.053)	(0.380)	(0.902)	(0.578)
Constant	67.81	-6.95	-0.22	-13.02	8.98	-38.75
	(0.067)	(0.691)	(0.992)	(0.694)	(0.591)	(0.113)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,281	26,846	13,508	11,520	34,262	15,729

Covid Economics 28, 12 June 2020: 91-118

Table A.2. Distribution of GHQ-12 in Understanding Society Wave 9 (January 2017-May 2019)

	(1) GHQ score	(2) Number of problems	(3) Any severe problems
All			
Mean	11.40	1.83	0.11
	(5.60)	(3.12)	(0.32)
p10	6	0	0
p25	7	0	0
p50	10	0	0
p75	13	2	0
p90	19	7	1
Sex			
Male	10.82	1.52	0.09
	(5.26)	(2.86)	(0.29)
Female	11.92	2.10	0.13
	(5.84)	(3.31)	(0.33)
Age			
16-24	11.83	2.14	0.16
	(5.92)	(3.08)	(0.36)
25-34	11.98	2.14	0.14
	(5.94)	(3.26)	(0.34)
35-44	11.84	2.02	0.12
	(5.77)	(3.28)	(0.33)
45-54	12.06	2.10	0.12
	(5.92)	(3.41)	(0.33)
55-64	11.45	1.81	0.10
	(5.68)	(3.21)	(0.30)
65 and over	10.21	1.27	0.08
	(4.65)	(2.55)	(0.27)
Household income quintile			
1 (Lowest)	11.92	2.06	0.14
	(5.88)	(3.29)	(0.34)
2	11.35	1.84	0.11
	(5.55)	(3.13)	(0.31)
3	11.35	1.74	0.10
	(5.18)	(2.94)	(0.30)
4	11.03	1.59	0.08
	(5.12)	(2.91)	(0.28)
5 (Highest)	10.80	1.51	0.07
	(4.77)	(2.71)	(0.26)

Note: Numbers in parentheses are standard deviations

Covid Economics 28, 12 June 2020: 91-118

Covid Economics 28, 12 June 2020: 91-118

Figure A.1. Mean Wave 9 and predicted mental health, GHQ-12 score

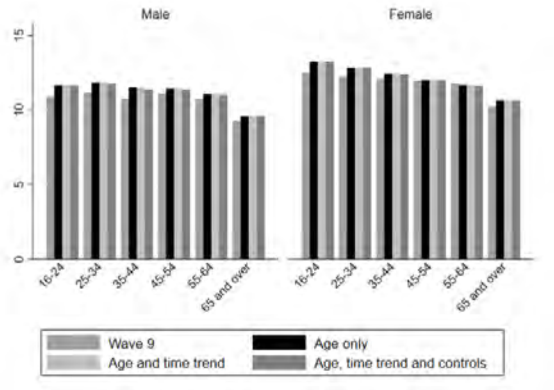


Figure A.2. Mean Wave 9 and predicted mental health, number of problems

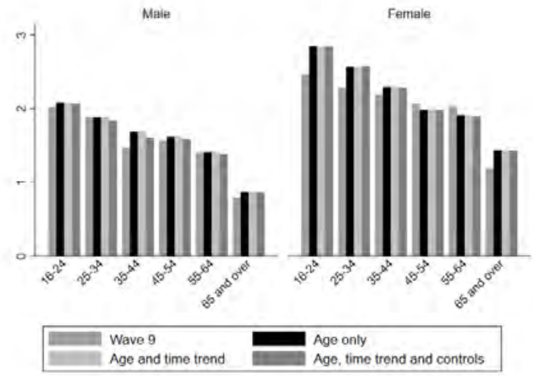
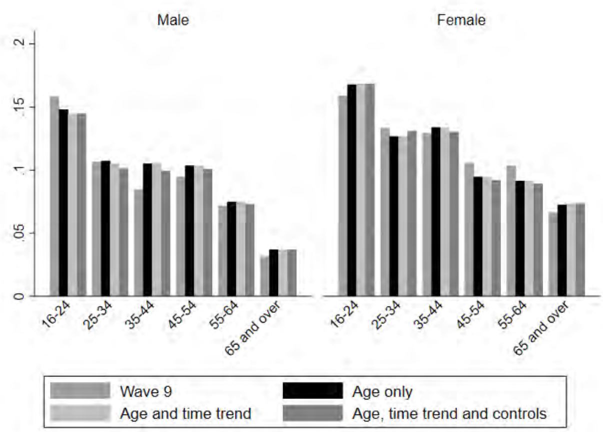


Figure A.3. Mean Wave 9 and predicted mental health, any severe problems



Note to figures. Full prediction model for GHQ-12 score presented in Appendix A table A1. Results for other prediction models available from authors on request

CEPR PRESS

Appendix B: Coding the GHQ-12 measure in Understanding Society

With the exception of wave 1, when it was administered in the face to face interview, the GHQ-12 scale has been collected in the self-completion element of Understanding Society in every wave. Following standard conventions (see Cox et al 1987), the overall value of the GHQ-12 (Likert) measure is computed by assigning values 0 to 3 for each of the four possible response categories to each item, and hence arriving at a value between 0 (least distressed) and 36 (most distressed). The alternative (caseness) way of scoring is to assign a value of 1 to each item where response categories are indicated in italics below, and summing these values, thus resulting in a scale between 0 (least distressed) and 12 (most distressed) that captures the number of dimensions in which individuals are reporting a problem and a greater than usual level of distress. As an additional indicator for our study, and in order to capture a more extreme measure of frequent or severe distress, we compute a simple binary indicator of whether individuals report at least one of the problems 'much more than usual'. Thus our 'severe' indicator takes the value 1 if an individual answers any of the twelve items with a response indicated in bold italics below, and 0 otherwise. The precise question wording on which these derivations are made is the following:

> "The next questions are about how you have been feeling recently…
>
> Have you recently been able to concentrate on whatever you're doing?
> {Better than usual, Same as usual, *Less than usual*, ***Much less than usual***}
>
> Have you recently lost much sleep over worry?
> {Not at all, No more than usual, *Rather more than usual*, ***Much more than usual***}
>
> Have you recently felt that you were playing a useful part in things?
> {More so than usual, Same as usual, *Less so than usual*, ***Much less than usual***}
>
> Have you recently felt capable of making decisions?
> {More so than usual, Same as usual, *Less so than usual*, ***Much less capable***}
>
> Have you recently felt constantly under strain?
> {Not at all, No more than usual, *Rather more than usual*, ***Much more than usual***}
>
> Have you felt you couldn't overcome your difficulties?
> {Not at all, No more than usual, *Rather more than usual*, ***Much more than usual***}
>
> Have you recently been able to enjoy your normal day-to-day activities?
> {More so than usual, Same as usual, *Less so than usual*, ***Much less than usual***}
>
> Have you recently been able to face up to problems?
> {More so than usual, Same as usual, *Less so than usual*, ***Much less able***}
>
> Have you recently been feeling unhappy or depressed?
> {Not at all, No more than usual, *Rather more than usual*, ***Much more than usual***}
>
> Have you recently been losing confidence in yourself?
> {Not at all, No more than usual, *Rather more than usual*, ***Much more than usual***}
>
> Have you recently been thinking of yourself as a worthless person?
> {Not at all, No more than usual, *Rather more than usual*, ***Much more than usual***}
>
> Have you recently been feeling happy, all things considered?
> {More so than usual, About the same as usual, *Less so than usual*, ***Much less than usual***}

Covid Economics 28, 12 June 2020: 91-118

What and how did people buy during the Great Lockdown? Evidence from electronic payments[1]

Bruno P. Carvalho,[2] Susana Peralta[3] and João Pereira dos Santos[4]

Date submitted: 1 June 2020; Date accepted: 3 June 2020

Covid Economics 28, 12 June 2020: 119-158

This paper uses novel and comprehensive data on electronic payments from SIBS, the main provider of point of sale terminals and on-line payments in Portugal, to study the impact of the Great Lockdown on purchases. The data aggregates all individual transactions into monthly observations, by municipality and sector, between 2018 and 2020. We employ a difference-in-differences event study that relies on the assumption that the monthly evolution of purchases in the first four months of 2020 would be parallel to that of the two previous years. We identify a massive causal impact on overall purchases, from a baseline year-on-year monthly growth rate of 10% to a decrease of 45%. The sign and magnitude of the impact varies considerably across sectors. Purchases of essential goods such as supermarkets and groceries increase mildly, contrasting with severe contractions in sectors that were closed by government order or depend heavily on tourism, including the leisure industry and restaurants. We find suggestive evidence of initial stockpiling of goods, postponing of essential expenditures, and rapid recovery of purchases in tech and

1 The authors are grateful to Sónia Cabral and José Tavares for helpful discussions. Outstanding data assistance by Filipe Afonso is recognized. João Pereira dos Santos gratefully acknowledges financial support by FCT – Fundação para a Ciência e Tecnologia – PD/BD/128121/2016. This work was funded by Fundação para a Ciência e a Tecnologia (UID/ECO/00124/2013, UID/ECO/00124/2019 and Social Sciences DataLab, LISBOA-01-0145-FEDER-022209), POR Lisboa (LISBOA-01-0145-FEDER-007722, LISBOA-01-0145-FEDER-022209) and POR Norte (LISBOA-01-0145-FEDER-022209) and the research project PTDC/EGE-ECO/31213/2017. All errors are our own.

2 Post-Doc at ECARES, Université Libre de Bruxelles.
3 Associate Professor at Nova School of Business and Economics, Universidade Nova de Lisboa.
4 Ph.D. Candidate at Nova School of Business and Economics, Universidade Nova de Lisboa.

entertainment, possibly to adapt to the confinement. Transactions with foreign-owned cards cause an even greater negative contraction. We disentangle the total effect into the intensive margin of the average transaction and the extensive margin of the number of transactions. Buyers adjust their shopping strategies in rational ways to minimize public health risks: they go less often to supermarkets and buy more each time, and visit local groceries more.

Covid Economics 28, 12 June 2020: 119-158

1 Introduction

"The world has changed dramatically in the three months" since January: these are the opening words of The World Economic Outlook released by the IMF in April 2020. While experts had warned about the likelihood of a pandemic given the increasing frequency of outbreaks in this century (Sands, 2017), the truth is that SARS-CoV-2 caught the world largely unprepared. Pandemics are responsible for devastating losses of human life – over the last century, they have been responsible for more deaths than armed conflicts (Adda, 2016).[1] Individuals and governments react to these extreme health risks by restricting social interaction and economic exchanges (Rasul, 2020), leading to severe economic downturns. Evaluating the tremendous speed and magnitude of the economic effects of the Covid-19 is important. On the one hand, sound evidence is a necessary tool to design appropriate policy responses. On the other hand, raising awareness about the disruptive shocks that pandemics and other natural phenomena, such as catastrophic events due to climate change, are bound to cause, is important to invest in preparedness to accommodate this ever more frequent events (Sands, 2017).

In this paper, we shed light on the very short-run economic effects of the Covid-19 pandemics in the Portuguese economy. We take advantage of a novel dataset that comprises all monthly electronic payments, both on-site and on-line. The data comes from SIBS, the main provider of point of sale payment terminals and on-line payments in Portugal, publicly available on the company's website.[2] The available data aggregates all individual transactions into monthly observations, for each of the 308 municipalities and 39 sectors of activity.

We use this data to explore purchasing behavior of individuals in the first two months of the pandemic. We identify the causal impact of the pandemic shock by implementing a difference-in-differences event study. Our identification strategy relies on the assumption that, in the absence of the pandemic, monthly evolution in the first four months of 2020 would follow the monthly evolution of the same four months in the two previous years.

[1] Jordà et al. (2020) study rates of return on assets since the 14th century, and compare the economic effects of major pandemics and major armed conflicts. They find that macroeconomic effects of the pandemics persist for about 40 years, with real rates of return substantially depressed. In contrast, wars have no such effect. For more information on the socioeconomic impacts of the Spanish flu (1918-1920) see, *inter alia*, Barro et al. (2020); Almond (2006); Correia et al. (2020); Karlsson et al. (2014). For more information on other more recent epidemics see Wong (2008) for SARS, Christensen et al. (2020); Campante et al. (2020) for Ebola, and Bandiera et al. (2019) for Zika.

[2] https://www.sibsanalytics.com/

Covid Economics 28, 12 June 2020: 119-158

Covid Economics 28, 12 June 2020: 119-158

Our data covers *all* electronic transactions in Portugal between January and April of 2018, 2019, and 2020 that use the SIBS network. SIBS is the largest player in electronic payments in Portugal; the five biggest Portuguese banks own 85% of the company.[3] In addition, it runs the interbank compensation system through a contract with the central bank. Its strong incumbent position in the market has led the Competition Authority to question potential barriers to entry in the market (ADC, 2018). The main strength of our paper is the comprehensiveness of our data. As we discuss below, most recent papers using individual transaction data rely on a single bank whose costumers are a selected sample of the population.

Portuguese consumers are among the Europeans who use more electronic payments. The latest available household survey data by the European Central Bank (Esselink and Hernández, 2017) shows that cash amounted to 81% of the number of payments in Portugal in 2014, but it accounted for 52% of the value of transactions, which was by then the eighth lowest value in the EU. The ECB Statistical Data Warehouse, that includes cash transactions made by people below 18 and businesses, points to a lower share of 34% in 2015. If anything, this figure has decreased, given the increasing importance of electronic payments and the introduction of e-money in smartphones through the new MB Way system in 2016, that reached 1.4 million users in 2019. Moreover, the government issued a decree-law on March 26 to encourage electronic payments, understood to be safer from a public health perspective.[4] The decree abolishes commissions paid by the retailers to the point of sale providers, and prohibits retailers from setting minimum amounts to accept card payments. Moreover, the Bank of Portugal raised the maximum amount for contactless payments without pin code to 50 euros, up from the limit of 30 before the pandemic.

Our main results are the following. We identify a massive causal impact of the lockdown on overall purchases, i.e., from a baseline growth rate of 10% to a decrease of 45%. We show that purchases of essential goods (supermarkets, groceries and pharmacies) increase mildly, contrasting with severe contractions in sectors that were closed by government order (such as retail shops and restaurants) or depend heavily on tourism. We find clear evidence that the lockdown forced people to postpone or forego essential expenditures related to their health and

[3] Banco Comercial Português, Caixa Geral de Depósitos, Santander Totta, Banco Português de Investimento, Novo Banco.

[4] *Decreto-Lei* n.º 10-H/2020)

relationship with the state. Gas stations display a small contraction compared to transportation, showing that people tended to rely on private cars. Purchases of Tech and Entertainment decrease in March but recover in April, possibly reflecting the adaptation to home working and schooling. Our evidence suggests that buyers adjust their shopping strategies in rational ways to minimize public health risks: they go less often to supermarkets and buy more each time, and visit local groceries more. We do not find evidence of heterogeneous effects across municipal characteristics such as income, the labour market, and demography, except for purchases in supermarkets in poorer, more remote and older communities. Lastly, we show that supermarkets and groceries in municipalities whose economies depend more on foreign tourists face a decrease in purchases with foreign cards.

We contribute to a growing literature on the economic impacts of Covid-19. Portugal offers an interesting laboratory for this question for a number of reasons. First, the virus arrived to Portugal relatively late, which allowed the residents to acquire information about the risks and start implementing voluntary social distancing before the government imposed a lockdown. According to the Google mobility data analysed by Midoes (2020), in Portugal people started to refrain from going out to the restaurant eight days before the government closed all restaurants (together with Denmark, it is the country with the earliest self-imposed mobility restrictions). Second, the same learning from the distressing events in Italy and Spain also led the government to act very early; schools were closed before the first (know) death caused by the disease. The management of the crisis in Portugal attracted substantial interest from international media in the early days of the confinement. In the first weeks of April 2020, Spanish El País called the Portuguese the "Southern Swedes", praising the discipline and rationality of the technical decisions taken in a context of political unity to fight the pandemic. They added that Portugal tackled the issue "better than other countries with more resources".[5] A few days before, The New York Times mentioned a Spanish epidemiologist claiming that "Portugal so far deserved admiration"[6] and Germany's Der Spiegel described the situation as "the Portuguese miracle".[7] Finally, Portugal's health system was ill-prepared for the pandemics, with the lowest number of critical beds per 100 thousand inhabitants in Europe, according to Rhodes et al. (2012). As

[5]https://elpais.com/sociedad/2020-04-11/portugal-los-suecos-del-sur.html
[6]https://www.nytimes.com/2020/04/07/world/europe/spain-coronavirus.html
[7]https://www.spiegel.de/international/europe/portugal-how-lisbon-has-managed-the-corona-crisis-a-b6e3c7ba-a172-4c11-a043-79849ff69def

Covid Economics 28, 12 June 2020: 119-158

such, Portugal is a paramount example of the trade-off between (ex-ante) preparedness and (ex-post) severe measures.[8]

Other papers have used individual transaction data to investigate the early effects of the pandemics. Chen et al. (2020) implement a difference-in-differences using daily transaction data in 214 cities in China. They find that daily offline consumption – via bank card and mobile QR code transactions – fell by 32%, or 18.57 million RMB per city. Furthermore, Carvalho et al. (2020), using high-frequency/high-resolution transaction data from both credit cards and point-of-sales terminals from the second-largest bank in Spain, examine the dynamics of expenditure in Spain during the Covid-19 pandemic and find a modest reduction in expenditure prior to the lockdown, but then immediate, very large, drops in expenditures thereafter. Similar findings are reported by Andersen et al. (2020a) exploiting transaction-level customer data from the largest bank in Denmark. The 25% drop following the shutdown is larger for individuals more exposed to the economic risks and health risks introduced by the Covid-19 pandemic. Andersen et al. (2020b) contrasts Denmark and Sweden with data from a large Scandinavian bank, two neighbouring countries with different confinement strategies, and show that differences were modest. Baker et al. (2020a) explore how household consumption react in the US and conclude that the sharp initial increase in retail, credit card spending and food items was followed by a decrease in overall spending. The authors also explore heterogeneity across state confinement policies, partisan affiliation, demographics, and income.[9]

Other pieces of early evidence about the impacts of Covid-19 rely on survey data. Statistics Portugal and Banco de Portugal conducted a survey on a reprsentative sample of firms between April 20$^{\text{th}}$ and 24$^{\text{th}}$. The survey shows that 80% of the firms were facing reduced turnout, with 39% reporting losing more than half of the pre-pandemic sales, and 59% had layed-off workers. Adams-Prassl et al. (2020) conducted a large representative survey of UK workers on 25$^{\text{th}}$ March 2020, two days into the government-imposed lockdown. They find significant idiosyncratic economic disruption. Their findings suggest that inequality is likely to increase across the income distribution, between young and old, and between those on insecure and

[8] This is the latest available data; if anything, the situation has been made worse with the austerity cuts of the last 10 years.

[9] Baker et al. (2020b) analyze households' spending responses to the receipt of fiscal stimulus payments, with spending increasing by $0.25-$0.35 per dollar during the first 10 days. Households with lower incomes and greater income drops display stronger responses.

Covid Economics 28, 12 June 2020: 119-158

secure contracts.[10] Moreover, Bartik et al. (2020) conduct a survey on small businesses in the early days of the outbreak in the US and show that entrepreneurs have varying beliefs about the likely duration of the disruption and quickly reacted by downsizing the business through mass layoffs and closures.

The remainder of the paper is organized as follows. In Section 2 we describe the Institutional Background and the Data used in this paper while in Section 3 we give more detail on the empirical strategy used to identify causal parameters. In Section 4 we highlight the aggregate results on the effects of the pandemics on purchases and in Section 5 we zoom in on interesting heterogeneous impacts. In Section 6 we focus our attention on how people changed their consumption patterns in the early months of the Great Lockdown. Finally, Section 7 concludes.

2 Background and Data

In this section, we provide some information about the timing and evolution of the Covid-19 shock in Portugal, as well as the main measures taken to contain the virus and mitigate its economic impact. We then carefully describe the data used in the paper.

2.1 Institutional Background

The first official case of Covid-19 in Portugal was reported on March 2, in the north of the country. On March 13, the Portuguese Prime Minister addressed the nation and warned that fighting Covid-19 pandemic would be a "fight for our own survival". Schools were closed and restrictions were imposed on the border with Spain. Five days later, the President declared the State of Emergency, "based on the confirmation of a public calamity situation". The National State of Emergency covers the entire national territory and lasts for 15 days. The first period started the next day and was renewed for two consecutive equal periods, "based on the continuation of the public calamity situation".

The Great Lockdown caused an unprecendented crisis in the country. The IMF released the economic forecast in April, according to which GDP will contract 8% and the unemployment

[10] Alstadsæter et al. (2020) uses register data to study the impact of the shock on inequality in layoffs in Norway. They report that the shock hit a financially vulnerable population (especially younger couples with kids) and financially weaker small firms.

Covid Economics 28, 12 June 2020: 119-158

Covid Economics 28, 12 June 2020: 119-158

rate will rise to 13.9%. This gloomy prospect was reinforced three weeks later by the European Commission's estimates (GDP contraction of 6.8% and unemployment rate 9.7%). The official figures available at the time we are writing this paper are aligned with these forecasts, which show that the year-on-year GDP decrease in the first quarter amounts to 2.4%. In April, almost 400 thousand individuals registered to receive unemployment benefits, a 22% increase *vis-à-vis* April 2019. This negative impact on GDP, compounded with the spending effort that the government is making to support workers and firms, is expected to increase the public deficit to 6.5% in 2020, implying that the country will reach a soaring public debt level of 131.6% in 2020. Portugal's economic prospects are just slightly above those for the European Union average, with a forecasted GDP contraction of 7.4% and an observed year-on-year contraction of 3.2% in the first quarter.

The economic strain has reached families very quickly. *Sondagens ICS/ISCTE*, a poll center run by two Social Sciences' research units in Lisbon reported, in the beginning of May, that 81% of the families feel "very worried" or "worried" about their financial situation, with a higher incidence among the least educated and lower income individuals. Evidence about the asymmetry of the burden in the society is also available from a survey by the National School of Public Health in Lisbon (*Escola Nacional de Saúde Pública*), which states that 1 in 4 families with income levels below 650 euros lost all their monthly income.

Although in terms of number of cases and deaths Portugal is not one of the countries more severely hit by the pandemic, figures are still sizeable. On April 30, and according to official statistics from the Public Health Authority (*DGS Direção-Geral da Saúde*), the number of confirmed cases was 25351, from a total of 251269 suspect tested cases. Tests per capita were in the upper end of the EU spectrum. The number of recoveries was 1647 while deaths amounted to 1007.

Even so, confinement has been particularly severe in the country. The Google Mobility Report for Portugal shows how visits and length of stay at different places changed compared to a baseline for that day of the week (the median value during the 5- week period Jan 3–Feb 6, 2020). As shown in Appendix Figure B.1, with the exception of time spent in the residency, mobility decreased substantially in all other categories.

Covid Economics 28, 12 June 2020: 119-158

Given the striking evidence about mobility and the strict lockdown measures imposed by the government, the transaction data is bound to reveal a severe downturn and sharp behavioral changes.

2.2 Data

To analyse how Covid-19 impacted purchasing habits in Portugal we rely on data from SIBS (the Portuguese abbreviation for *Sociedade Interbancária de Serviços*), which manages the integrated banking network in Portugal, comprising Automated Teller Machines (ATM) and Point-of-sales (POS) terminals.[11] SIBS Analytics provides aggregate data on all payments with bank cards in Portugal, performed with national and foreign bank-issued cards.[12] This information comprises the value (in euros) and number of payments in 39 sectors, grouped into 5 aggregates, i.e. Specialised Retail Trade, Non-specialised Retail Trade, Wholesale Trade, Services and Production and Industry.[13] Geographically, the smallest unit of aggregation available is the municipality.[14] SIBS Analytics also provides information about cash withdrawals for each geographical unit, which are then apportioned to activity sectors using statistical models. As our main goal is to assess the differing impacts per activity sector, we exclude data on cash withdrawals, to avoid that our analysis is influenced by any confounding effects stemming from differences in cash vs. electronic payments patterns in the Covid-19 period.[15]

Our sample includes aggregate monthly purchases for all the 39 sectors and the 308 Portuguese municipalities, between the months of January and April, for 2018, 2019 and 2020. For each pair year/month, this amounts to between 10532 and 10640 observations, of a total 116419 for the full sample. Summary statistics for the value and number of transactions (both with Portuguese and foreign cards), for the average municipality are provided in Table 1, where we report figures in thousands. As shown in the first row, the average purchase value with Portuguese cards for the full sample amounts to 369.8 thousand euros (column 1), while for

[11] For more information regarding the geographic dispersion as well as the importance of ATMs in Portugal see Santos et al. (2019).

[12] `https://www.sibsanalytics.com/en/`.

[13] The full breakdown of the aggregates and individual sectors, as well as some information on what type of purchases are included in each sector is provided in Appendix Table A.1.

[14] Portugal is divided in 308 municipalities, 278 in mainland Portugal and 30 in the Autonomous Regions of Madeira and Azores. Municipalities in Portugal have an average population of 33,366 inhabitants, according to Statistics Portugal.

[15] Electronic payment operations includes purchases, bill payments, mobile top-ups, payments to government, public transport ticket loading, and others.

Covid Economics 28, 12 June 2020: 119-158

foreign cards this value amounts to 24.8 thousand euros (column 6). The breakdown of these figures across the 5 aggregates is shown in the following rows of Table 1, which shows that the aggregates with higher average purchases using Portuguese cards are, first, Non-Specialized Retail (1125.3 thousand euros) and, second, Services (with 345.1 thousand euros). For foreign cards the picture is similar, with an average municipal purchase of 44.2 and 34.6 thousand euros, respectively. The aggregate with higher number of transactions is Non-Specialized Retail, with 39.6 and 1.3 thousand average municipal purchases, respectively for Portuguese and Foreign cards (columns 4 and 8 of Table 1).

In order to analyze how the purchasing behavior of Portuguese households was affected by the Covid-19 pandemic, we start by assessing how patterns for the overall sample and the five aggregates changed. Then, we focus on fifteen disaggregated sectors that we deem most relevant. We dropped the aggregates that are more likely to involve business-to-business (b2b) payments, i.e., Production and Minery and Wholesale. We kept all the Retail (Specialized and Non-specialized), with the exceptions of Other categories, whose content is unspecified, and the two sectors with the lowest values of purchases, Toys and Childcare Products and Sports and Leisure Gear. In order to keep as much information as possible we combine some sectors when they include similar goods and services. Decor and Home Equipment and Building and DIY materials are combined into Decoration and DIY; Clothing, Footwear and Accessories and Fragrances and Beauty Products are aggregated into Fashion an Beauty; Traditional Trade and Grocery Stores are also together in Traditional and Grocery Stores. This leaves us with a total of the eight retail sectors for which we also provide summary statistics in Table 1. Within the retail sectors, Supermarkets are by far the sector with higher average purchases, with a value of 2806.8 thousand euros with Portuguese cards and 99.8, for Foreign cards (columns 2 and 6 of Table 1).

The choice of which service sectors to include was less straightforward. We ignore the Other category, because it is not well defined, and the Real Estate, Construction and Architecture sector, because it is bound to be polluted by B2B payments. For the sake of brevity, we kept only one sector amongst the three that most directly involve private and public players, i.e., we dropped Education and Training and Social Services, and kept Healthcare Services, given its prominence in the pandemic. We also kept Public Administration which is the only fully

Covid Economics 28, 12 June 2020: 119-158

public sector available in the data. We dropped two sectors with negligible volumes, namely IT Services and Press, Media and Advertising. And lastly, we combine Hotels and other lodgings and Leisure and Travel into Leisure and Tourism. Given these choices, we are left with 7 services, which adding to the 8 retails sectors amounts to a total of 15 sectors in Table 1. The service sectors with the highest average municipal purchase value with Portuguese cards are Public Administration and Restaurants and Catering, with 1257.4 and 896.8 thousand euros (column 2), respectively. For foreign cards, in turn, Restaurants and Catering and Leisure and Tourism are the sectors with higher municipal purchases, with averages of 142.7 and 131.9 thousand euros, respectively.

Table 1: Average Value and Number of transactions (in thousands).

	Obs.	Portuguese Cards				Foreign Cards			
		Value		Number		Value		Number	
		Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Overall Sample	116419	369.8	1806.1	9.5	64.4	24.8	365.8	0.4	7.6
Aggregates:									
Specialized Retail	35787	298.7	932.8	7.5	24.4	17.2	205.5	0.3	2.3
Non-Specialized Retail	10347	1125.3	3818.3	39.6	150	44.2	232.5	1.3	8.6
Wholesale	15886	225.2	725	3.8	12.9	6.9	52.5	0.1	0.8
Services	48012	345.1	1946.6	7.3	67	34.6	529	0.5	10.9
Production and Industry	6387	89.7	288.8	2.2	11.4	7.2	47.1	0.2	2
Sectors:									
Tech. and Entertainment	3470	286.4	806.4	3.9	11.8	13.7	81.6	0.2	1.2
Home Decoration and DIY	6222	238.9	666.9	3.8	10.9	13.7	54.4	0.2	1
Fashion and Beauty	5437	352.3	1526.5	8.4	32.4	47.1	498.9	0.6	5.3
Vehicles and Accessories	3065	329.9	883	1.6	3	6.9	27.7	0	0.1
Pharmacies and Drugstores	3623	334.4	907.9	13.1	35.4	5.5	33.4	0.2	1.2
Gas Stations	3596	657.4	1217.6	20.8	42.1	19.7	46.2	0.5	1.2
Supermarkets	3556	2806.8	5967.4	103.4	241.4	99.8	314.4	3.2	14.1
Traditional and Grocery Stores	7052	169.7	433.4	7.2	18.8	5.5	32.3	0.2	1.2
Leisure and Tourism	6476	140.5	623.2	1.4	5.4	131.9	1132.7	0.9	6.9
Insurance and Financial Services	3668	155.1	328.8	1	2	0.4	3.4	0	0
Restaurants and Catering	3658	896.8	3769.2	48	230.5	142.7	1130.3	4.1	36.9
Healthcare Services	3458	370.9	1869.5	5.5	23.9	10.3	66.1	0.1	0.3
Transportation and Car Rentals	3364	86.3	503.3	2.9	24.2	21.7	156.7	0.8	9.1
Telecom and Utilities	3660	602	1371.7	16	33.6	1.5	13	0	0.3
Public Administration	3660	1257.4	4690.2	7.7	21.6	7.1	60.5	0.3	3.1

Notes: Sample arithmetic mean and standard deviation of Value and Number of transactions in thousands, for each group and sector.

Besides the transactions data, we also collected a number of socioeconomic variables at the municipal level. We use these variables to split the sample and inspect possible heterogeneity across municipalities.[16] We use one income indicator, the median net-at-source income[17], and

[16] Descriptive statistics for all these variables is available in Appendix Table A.2.

[17] That is, the gross taxable income deducted of witholding taxes (*IRS - Imposto sobre o Rendimento das Pessoas Singulares*).

Covid Economics 28, 12 June 2020: 119-158

one inequality indicator, the 90th to 10th percentile ratio of this variable. Both variables are obtained from Statistics Portugal. Furthermore, the unemployment rate, measured as the number of people registered in employment offices divided by the working age population, and the share of workers with permanent contracts in the private sector are used as labor market indicators. The first variable is obtained from IEFP (*Instituto de Emprego e Formação Profissional*) while the other comes from PORDATA, based on data from *Quadros de Pessoal*, a linked employer-employee dataset covering the universe of workers in firms with at least one paid employee. To reflect the differences in demographic characteristics of Portuguese municipalities, we use population density and the share of citizens with more than 65 years old, both obtained from Statistics Portugal. Lastly, to proxy the relevance of Tourism in the municipal economic activity, we consider the number of overnight stays in each municipality per 100 inhabitants, obtained from PORDATA.

The bulk of our analysis is performed considering only the information about transactions with Portuguese cards (columns 1-4 of Table 1), to have more parsimonious estimates of the effect of the pandemic. In Section 5.2, however, we contrast purchases by Foreign owned bank cards with those made by Portuguese.

3 Empirical Methodology

In order to obtain the causal impact of the great lockdown on electronic purchases, we define March and April as the treated months (recall that the first case in Portugal was diagnosed in March 2$^{\text{nd}}$). The comparison months are January and February and treatment assignment occurs in 2020. Our identifying assumption is that the year-on-year change between March/April 2020 and March/April 2019 would be parallel to the the year-on-year change between January/February 2020 and January/February 2019, in absence of the pandemic.

We estimate the following event study equation:

$$\ln(y)_{ismt} = \eta + \alpha_i \mathbb{1}_i + \gamma_s \mathbb{1}_s + \lambda_m \mathbb{1}_m + \delta\, \mathbb{1}_{Y2020} + \beta_m \times \mathbb{1}_{Y2020} \times \mathbb{1}_m + \varepsilon_{ismt}, \tag{1}$$

where $\ln(y)_{imst}$ is the outcome for municipality i, month $m \in \{1, 2, 3, 4\}$, sector s and year

$t \in \{2018, 2019, 2020\}$; α_i is a municipality fixed effect, λ_m is a month fixed effect, and γ_s is a sector fixed effect.

The indicator variables are $\mathbb{1}_i$, $i \in \{1, \ldots, 308\}$ for the municipality, $\mathbb{1}_s$ for sector, $\mathbb{1}_m$, $m \in \{1, 3, 4\}$ for month, and $\mathbb{1}_{Y2020}$ is an indicator for the year 2020. February 2020, the month before the crisis unfolded, is the omitted month. Our coefficients of interest are, β_{ms}, $m \in \{1, 3, 4\}$. Standard errors are clustered at the NUTS III and time period level (month, year) (Bertrand et al., 2004).[18]

When we estimate (1) for a single sector, we omit the corresponding fixed effect.

We consider three possible outcome variables: the natural logarithm of the value of purchases, the natural logarithm of the number of purchases, and the natural logarithm of the average value of purchases.

This specification deserves a number of comments. First, note that, since we estimate one equation for each sector, we obtain sector specific estimates of the coefficients. Second, one may use (1) to write

$$\hat{\beta}_{ms} = \left(\widehat{\ln(y)}_{im,2020} - \widehat{\ln(y)}_{im,2019}\right) - \left(\widehat{\ln(y)}_{i2,2020} - \widehat{\ln(y)}_{i2,2019}\right)$$

Now let

$$g_{m,2020} = \frac{y_{im,2020}}{y_{im,2019}} - 1$$

denote the year-on-year (YoY) growth rate for month m of 2020. Then,

$$\hat{\beta}_{ms} = \ln\left(\widehat{\frac{y_{im,2020}}{y_{im,2019}}}\right) - \ln\left(\widehat{\frac{y_{i2,2020}}{y_{i2,2019}}}\right) = \ln\left(\frac{1 + \hat{g}_{m,2020}}{1 + \hat{g}_{2,2020}}\right)$$

$\hat{\beta}_{ms}$ is therefore a measure of excess (or lack) of year-on-year (YoY) growth between March (or April) and February 2020. Given that we are using month fixed effects to control for seasonality, our identification assumption is that, absent the great lockdown shock, the YoY growth rates

[18] The NUTS classification (Nomenclature of territorial units for statistics) is a hierarchical system for dividing up the economic territory of the EU for the purpose of the collection, development, and harmonisation of European regional statistics. In Portugal there are 25 NUTS III regions. Municipalities are subdivisions of these regions and there is no government layer between the central government and municipalities in mainland Portugal. For more information see Santos and Tavares (2018).

Covid Economics 28, 12 June 2020: 119-158

Covid Economics 28, 12 June 2020: 119-158

would be the same across the four months we are analyzing, January to April. Conversely, $\hat{\beta}_{1s}$ validates our identification strategy if it is not statistically different from zero.

Third, when the growth rates are small, the equality above can be approximated by $\hat{\beta}_{ms} = \frac{\hat{g}_{m,2020}}{\hat{g}_{2,2020}}$. In this case, $\hat{\beta}_{ms}$ is the difference between the YoY growth rates of month $m \in \{1,3,4\}$ of 2020 and the YoY growth rate of February 2020 for sector s and measures the causal impact of the great lockdown on the purchases in this sector.

Forth, as will become clear, given the abrupt nature of the great lockdown shock that we are analyzing, the growth rates are not always sufficiently small that we can apply the above approximation. In that case,

$$\left(\frac{1+\hat{g}_{m,2020}}{1+\hat{g}_{2,2020}}\right) = \exp(\hat{\beta}_{ms}) \tag{2}$$

and it is still the case that $\hat{\beta}_{ms} < 0$ (resp., $\hat{\beta}_{ms} < 0$) means that the causal impact of the great lockdown on purchases in March 2020 (or April 2020) in sector s is negative (resp., positive). In particular, $\exp(\hat{\beta}_{ms})$ is an estimate of the causal (multiplicative) effect of the great lockdown on the gross growth rate of purchases in month m.

Finally, the length of our pre-treatment period (1 month) is conditioned by data availability constraints. At the time we are writing this paper, monthly data on payment card purchases is only available from January 2018 onwards. Thus, for the period between May and December, our sample spans 2 years, while from January until April it spans 3 years. To ensure that the comparison group is the same across months, we restrict the pre-treatment period to January. If, instead, we increase the pre-treatment group until September of the previous year, our results remain as we show in the Robustness section.

On Section 5.1, we explore whether the effects are stronger in some municipalities, depending on the average income, inequality, labor market characteristics, or demography. Heterogeneous effects are explored using the difference-in-differences specification below, for each sector s and subsample of municipalities in each of the quartiles $q = 1,2,3,4$ of the municipal variable.

$$\ln(y)_{ismt} = \eta + \alpha_i \mathbb{1}_i + \gamma_s \mathbb{1}_s + \lambda_m \mathbb{1}_m + \delta\, \mathbb{1}_{Y2020} + \theta\, \mathbb{1}_{Y2020} \times (\mathbb{1}_{m_3} + \mathbb{1}_{m_4}) + \epsilon_{ismt} \tag{3}$$

We therefore obtain the estimates of four coefficients, one for each quartile of the municipal variable. In this case, θ measures the causal impact of the great lockdown on the YoY growth rate of the treated months of March and April 2020, vis-à-vis the comparison ones of January and February 2020. We will compare β_{sq} across quartiles to conclude about potential heterogeneous effects.

4 What do people buy?

4.1 Aggregate evidence

We begin by estimating (1) for the five aggregate sectors considered by SIBS, namely, specialised retail, non-specialised retail, wholesale, services, and production and industry.

The coefficient estimates for each sector are presented in Figure 1. The estimates for β_{s2} are not statistically different from zero, which validates our identification assumption, as explained in Section 3.

The top-left graph of Figure 1 shows the sharp decline in the overall value of electronic purchases in March and April. Using (2), the YoY gross growth rate of purchases was cut by around 23% in March and more than one half in April. This is consistent with the fact that the State of Emergency was declared in mid March. The observed YoY gross growth rates were 1.09 for January and 1.12 for February, i.e, the average is around 1.1. The causal impact of the great lockdown is to bring the gross growth rate down to 0.55, i.e., from a growth rate of 10% to a decrease of 45% in purchases.

The remaining graphs show the impact of the pandemic in the five groups of sectors used by the SIBS payment system classification. The overall picture is the same in four out of the five groups, with varying magnitudes, which offer some insights into the economics of the great lockdown.

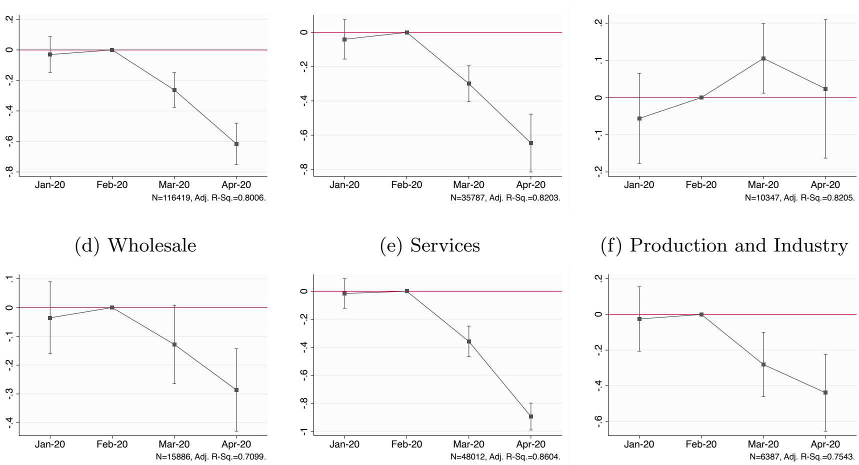
First, Wholesale and Production and Industry are the least affected sectors, an expected result given that these rely relatively more on business-to-business transactions. Indeed, several production sectors functioned more or less partially throughout the lockdown, such as food retail,transport, manufacturing, and health services.

Covid Economics 28, 12 June 2020: 119-158

Second, Specialized Retail and Services experienced the largest drops, with gross growth rates down by 60% and 45% in April. As will become clear when we analyze disaggregated data in Section 4.3, these include the businesses with full close downs, such as restaurants and various street shops.

The Non-Specialized Retail is our closest proxy to essential goods (excluding pharmacies), since it includes supermarkets and grocery stores. Gross growth rates of purchases were 10% higher in March than they would have been in the absence of the great lockdown. This positive impact, however, seems short lived, as in April there are no statistically significant changes compared to what would be expected if there had been no pandemic. The disaggregated analysis in Subsection 4.3 will shed more light on the purchases of essential goods.

Figure 1: Event Study: Aggregates (value of transactions)



(a) Overall Sample (b) Specialised Retail (c) Non-specialised Retail
(d) Wholesale (e) Services (f) Production and Industry

In order to better characterize purchasing behavior during the great lockdown, we move to the 15 disaggregated sectors presented in 2.2. In the next subsection, we study the volume of purchases in each sector.

4.2 Robustness

To assess the validity of our identification strategy we run a set of robustness tests. In all cases, we re-estimate Equation (1) for a different sub-sample or change the fixed effects, and compare

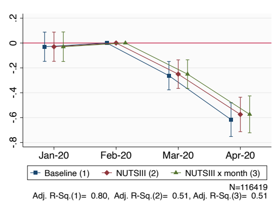
Covid Economics 28, 12 June 2020: 119-158

the results with those from baseline estimates. The goal of these robustness tests is twofold: provide each case, we find evidence supporting the parallel trends assumption and show that our coefficient estimates for the post-treatment period remain stable.

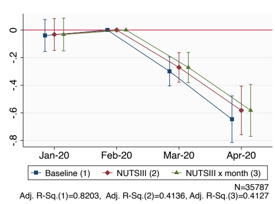
One possible concern regarding our baseline specification is that results may be driven by unobserved regional seasonality, which we can address by replacing month fixed effects by NUTS III x month fixed effects. Results are shown in Figure 2, where we plot the event studies for the five aggregate sectors. In each panel we compare the baseline specification (in blue) with a specification where the municipal dummies are replaced by NUTS III x month fixed effects (in green). For completeness we also show the results for the case where municipal fixed effects are replaced by NUTS III fixed effects (in red).

Figure 2: Value of purchases (Aggregates): Changing Fixed Effects

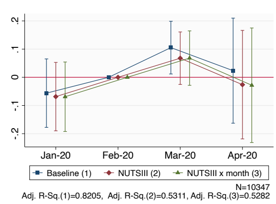
(a) Overall Sample



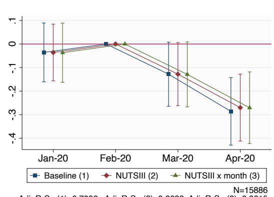
(b) Specialised Retail



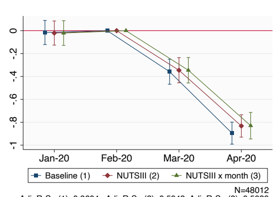
(c) Non-specialised Retail



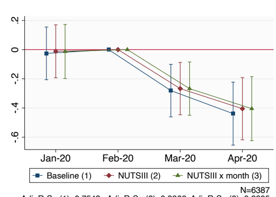
(d) Wholesale



(e) Services



(f) Production and Industry



It is also important to establish that our results are not driven by a particular part of the sample, that could be behaving in an abnormal way. To assess this, we exclude in turn the Metropolitan Areas of Lisbon and Oporto, and the Islands. Excluding the Metropolitan Areas is relevant because of the concentration of tourism activities, and workers rely a lot on commuting through public transportation. As a result, mobility is likely more conditioned due to the lockdown.[19]. In turn, the exclusion of the Azores and Madeira Islands is justified not only because of their remote

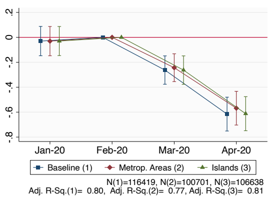
[19]Moreover, as shown in Harris (2020), the structure of public collective transportation was key to explain the spread of the pandemic in New York.

Covid Economics 28, 12 June 2020: 119-158

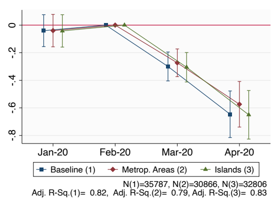
location, but also because these Autonomous Regions have their own regional governments, for which the policy response to the pandemic was in some dimensions different.[20] Results for the usual aggregates are shown in Figure 3.

Figure 3: Value of purchases (Aggregates): Removing Metropolitan Areas and Islands

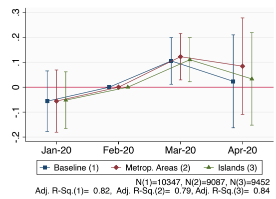
(a) Overall Sample



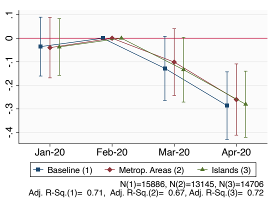
(b) Specialised Retail



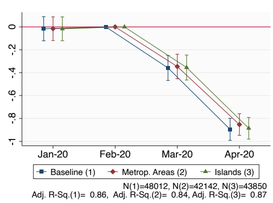
(c) Non-specialised Retail



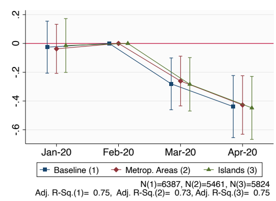
(d) Wholesale



(e) Services



(f) Production and Industry



Comparing the baseline results (in blue) with the the ones obtained for the restricted sample without the Metropolitan areas (in red) and the Islands (in green), our results remain. Notice that these sample restrictions remove between 9 to 14% of the overall sample, shown in Panel (a).

This stability across sub-samples is further established in Section 5.1, where we assess the heterogeneous effect of the Covid-19 shock across three dimensions: differences in municipal income, labour market conditions and demographic characteristics.

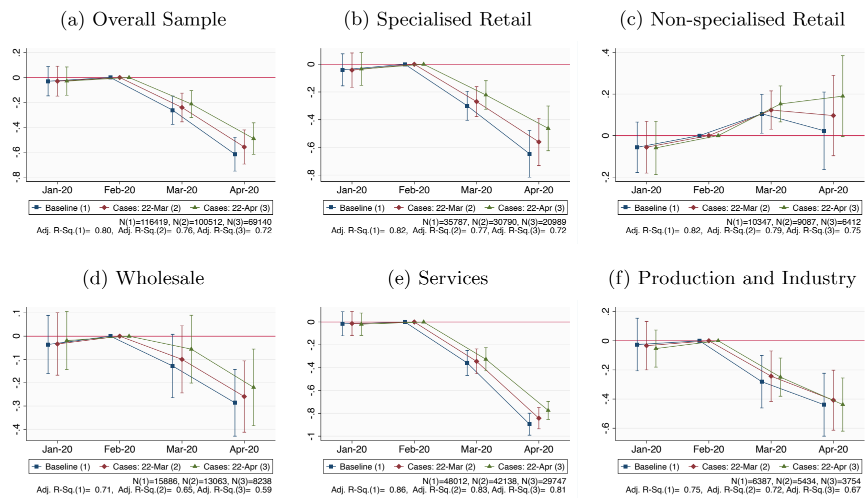
Lastly, it is important to establish that the results are not driven by the areas most hit by the pandemic, in terms of number of cases. This allows us to distinguish whether results are picking up the effect of the spread of the virus, or more broadly the effects of the lockdown policies imposed by the government.

In Figure 4 we compare our baseline estimates (in blue) with those obtained from restricting

[20] In particular, these areas implemented a mandatory confinement period of two weeks for everyone landing in their territory, which from late March onward paid for by the regional governments.

the sample to the municipalities below the median of the municipal number of Covid-19 cases, reported by *DGS* (the Portuguese acronym for the National Directorate for Public Health in Portugal). We start by removing the municipalities with less than 7 cases (in red, in Figure 4), the national median of the municipal number of cases in March 22$^{\text{th}}$, the first day for which *DGS* has made revealed municipal data. At this point, there were 66 municipalities with at least 3 cases.[21] The municipality with the higher number of cases was Lisbon, with 175 at the time. As our sample spans until April, we also run a specification keeping the municipalities below the median of the number of cases exactly on month after, on April 22$^{\text{th}}$ (in green, in Figure 4). At this point, 217 municipalities had at least 3 cases and the municipality with most cases was still Lisbon, with 1266.

Figure 4: Value of purchases (Aggregates): Below Median of Covid-19 Cases



These two robustness checks remove between 13 and 40% of the overall sample, but results remain.

Overall, these robustness tests provide evidence that our findings are consistent, as the magnitude of coefficients remains stable, and that our identification strategy is suitable, as in all cases the parallel trend assumption is not violated for January 2020.

[21] To ensure the publicly available data could not be used to target who was infected, *DGS* only reports the number of cases in a municipality if it is greater or equal than 3.

Covid Economics 28, 12 June 2020: 119-158

Covid Economics 28, 12 June 2020: 119-158

4.3 Which retail sectors and which services have more purchases?

We estimate Equation (1) for each of the 15 sectors in Table 1, with individual sector dummies in the 4 cases where the modified sector combines two original sectors to account for potential heterogeneity. All the remaining 11 sectors are defined according to the SIBS classification system.

The lockdown is bound to change people's purchasing behavior through a number of channels. The first is the physical restriction of the closing down of some sectors. One may argue that shopping could have moved online as a response (which would be still captured by our electronic transaction data); however, it is important to bear in mind that our data includes all points of sale in the country, with many small businesses that do not use the online channel. The second is financial; since the great lockdown caused a sharp and immediate decrease in income of some families, with one in four living on less than 650 euros per month reporting to have lost all their income in the early weeks of the pandemic (according to a non-representative, wide internet-based poll by the National School of Public Health) and 81% of the families reporting to be worried or very worried about their financial situation in a representative poll by the Institute of Social Sciences / University Institute of Lisbon pollster conducted in early May. The third is related to the health risk; even absent restrictions imposed by the government and financial constraints, individuals refrain from going out shopping because they fear contagion. Figure B.1 shows that people refrained from moving more than one week before the officially imposed lockdown. The impact of the pandemic in each sector results from a combination of the three effects above.

The event studies in Figure 5 show that the pandemic had a strong and immediate impact on the purchasing habits of Portuguese buyers. We find strong evidence of shifting purchases towards essential goods in both March and April, as can be seen from the results on Supermarkets and Traditional and Grocery Stores. The effect on Traditional and Grocery Stores is twice as high as that of supermarkets. This suggests that people relied more on proximity shops, avoiding public transportation and higher concentration of people. It may result partially from business decision to move to online payments for public health reasons. Although we have no direct way to disentangle the two effects, the analysis in Section 6 sheds some light on this.

Covid Economics 28, 12 June 2020: 119-158

The results for Pharmacies are suggestive of initial stockpiling of essential health goods such as disinfecting products and personal protection equipment, such as masks. There is a lot of anecdotal evidence of this type of behavior that led the stocks of these goods to sell out across the country, illegal trade and speculation. These episodes led the *Autoridade de Segurança Alimentar e Económica*, the Portuguese authority in charge of monitoring and enforcing hygiene and price laws to intervene in several instances.[22]

Which sectors did buyers turn away from? We observe that Leisure and Tourism (lodging, travelling, museums and live events), closely followed by Restaurants and Catering, are the most hurt sectors. This is expected, since they combine the three channels discussed above. Recall that the purchases considered so far do not include foreign cards. Therefore, this very negative effect is solely due to domestic purchases and it can be seen as a lower bound of the impact of the pandemic on such sectors. The point estimates for Leisure and Tourism imply that the pandemic caused the gross growth rate of purchases in this sector was 35% of the baseline in March, and around 7% in April. Restaurants had a similar impact in March, but a slightly less severe one in April (gross growth rate at 11% of the baseline), reflecting the fact that take-away services were allowed in this sector during the state of emergency. Fashion and Beauty is the third most affected. In Home decoration and DYI, together with Vehicles and Accessories, we observe more modest negative impacts of the great lockdown.

Tech and Entertainment is an interesting case, because it quickly recovers in April after a small drop in March, which can be interpreted as evidence of the investment in digital equipment that individuals and firms had to make in order to cope with teleworking and homeschooling. This is consistent with the fact that Telecom and Utilities did not experience any impact of the great lockdown. This latter includes services like electricity, water supply or internet, which are very inelastic in the great lockdown context in which individuals are asked to stay at home to the extent possible.

Two sectors in Figure 5 are related with mobility, one of the aspects of everyday life most affected by the lockdown. Transportation and Car Rentals (which includes public transportation tickets and taxi) suffered a severe shock, specially in April, with the gross growth rate at just 27% of what it would have been, absent the pandemic. The impact for Gas stations is smaller, probably

[22] https://www.asae.gov.pt/Covid-19-asae/comunicados.aspx

Covid Economics 28, 12 June 2020: 119-158

reflecting the preference for private transportation mode due to public health concerns.

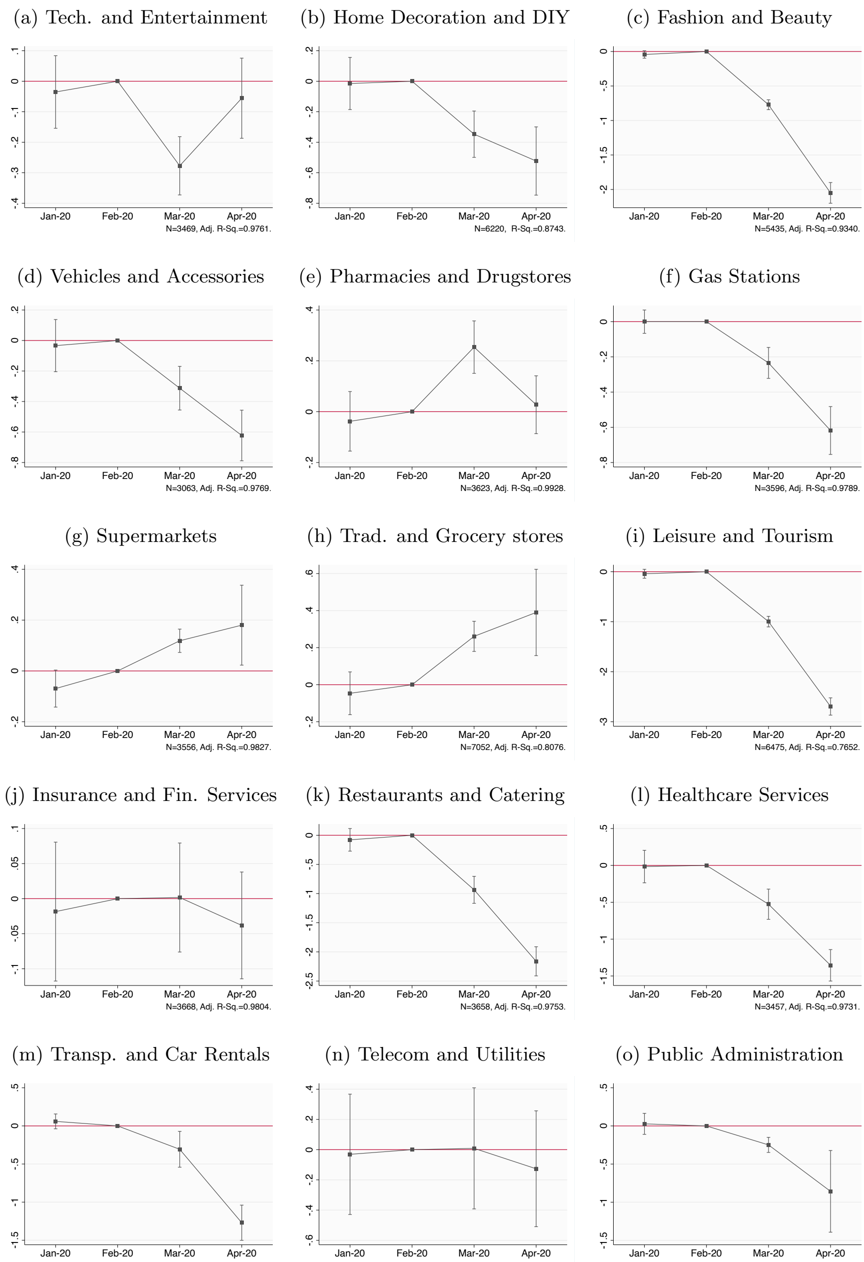
Even the healthcare sector faced a contraction in both March and April. The causal impact of the great lockdown is to bring the gross growth rate to only 25% of what it would have been otherwise. This reflects the fact that as a result of the containment measures and the need to concentrate resources on the response to the pandemic, many other non-covid healthcare services were cancelled or postponed. In addition, some specific practices such as dental ones were fully closed. The Public Administration sector includes administrative offices such as passport and identity cards issuance, courts, or social security. The negative impact is more pronounced in April, given that these offices closed on March 19$^{\text{th}}$. The negative impact on these two sectors is suggestive of the fact that individuals refrained from or postponed essential expenditures due to Covid-19.

It is not surprising that the Great Lockdown does not cause any impact on Insurance and Financial Services, which relies a lot on the online channel.

We conduct robustness tests for the 15 sectors we analyse in this subsection, similar to those presented for the aggregates in Section 4.2. Overall, results shown in Appendix Figures C.1 to C.3 suggest that both the parallel trends assumption and the post-treatment coefficient estimates are consistent across different specifications and sub-samples.

So far, we have dealt with the question of what people buy. In the sections, we use our data to further characterize the reaction to the Great Lockdown.

Figure 5: Event Studies, by sector



Covid Economics 28, 12 June 2020: 119-158

Covid Economics 28, 12 June 2020: 119-158

5 Municipal characteristics and the Covid-19 shock

In this section we concentrate on the 3 sectors that experienced an increase in purchases (Supermarkets, Traditional and Grocery, Pharmacies) and contrast them with the ones that experienced the greatest decreases (excluding public administration), namely, Leisure and Tourism, Restaurants and Catering, and Fashion and Beauty, Health Services, Transportation and Car Rental, and Gas Stations. We start by exploiting possible regional heterogeneity with respect to three dimensions that could mask differences in the coefficients of our baseline estimates. In Section 5.2, we evaluate how estimates vary according to whether the payments cards are issued by Portuguese or foreign banks.

5.1 Heterogeneity

Differences across municipalities could lead to different changes in purchases in reaction to the Covid-19 shock. If this is the case, our baseline estimates could average-out some regional heterogeneity. In this section we exploit this possibility focusing on three dimensions, that is, with respect to municipal income, labor market situation, and demographics. The outcome variable is, once again, the natural logarithm of the value of purchases, as written in (3). We divide the baseline sample in four quartiles measured by several indicators at the municipal level in a pre-treatment period (i.e., the last year available on official statistics). Summary statistics for the variables underlying the construction of these indicators is provided in Appendix Table A.2.

Figure 6: Municipal Heterogeneity: Income related

(a) Quartiles of Income

(b) Quartiles of P90p10

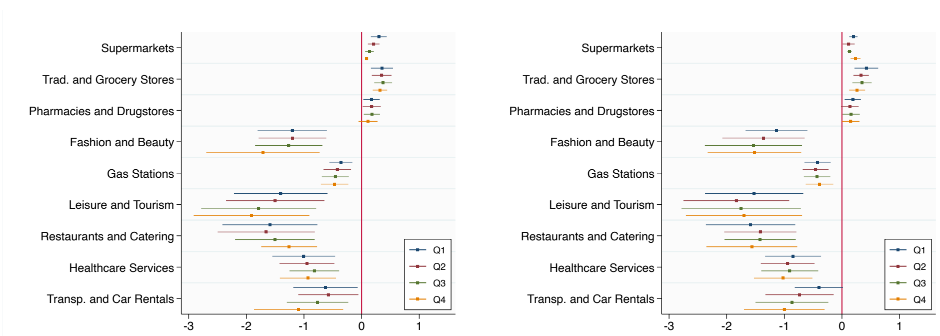


Figure 6 plots the coefficients of (3) for quartiles of median value of net-at-source personal income in 2017 and income inequality measured by the ratio of the 90$^{\text{th}}$ to the 10$^{\text{th}}$ percentiles of the same variable.[23]

Figure 7: Municipal Heterogeneity: Labor market related

(a) Quartiles of unemplyment rate

(b) Quartiles of share of perm. contracts

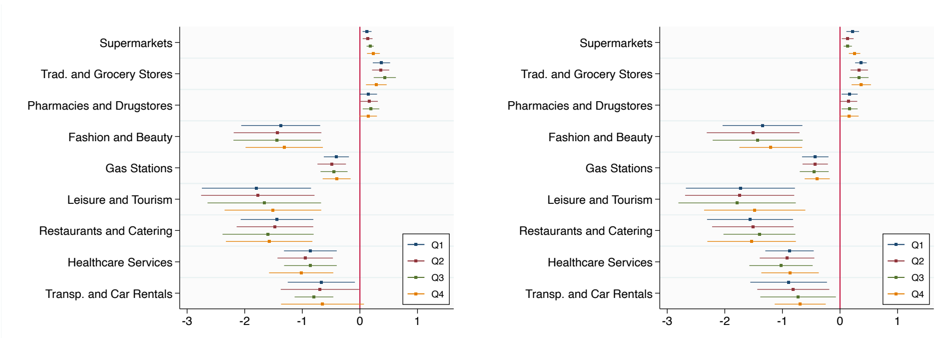


Figure 7 plots the coefficients of (3) for quartiles of the unemployment rate, measured as the number of people registered in unemployment centers divided by the working-age population of the municipality in 2018, and the share of workers with a permanent contract in private sector workforce in 2017. This last indicator proxies employment security. The point estimates for Supermarkets confirm the results in Figure Figure 6, as the point estimate for municipalities with higher unemployment is higher.

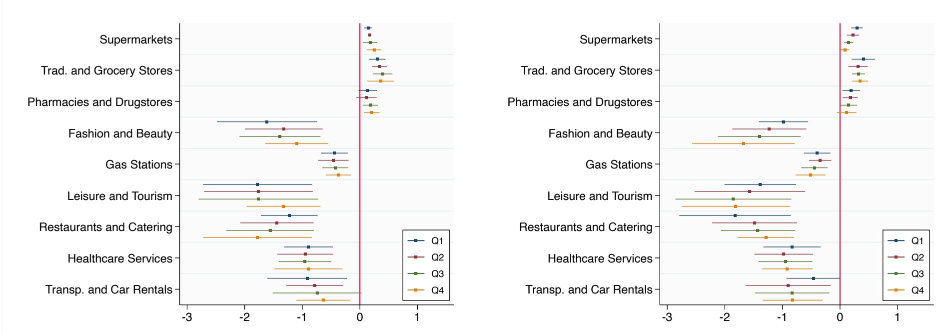
Lastly, Figure 8 plots the coefficients of (3) for quartiles of population density and the share of citizens with more than 65 years old, a population fringe particularly affected by the pandemics.

[23]Net-at-source income is gross income deducted of withholding taxes.

Covid Economics 28, 12 June 2020: 119-158

Figure 8: Municipal Heterogeneity: Demographics related

(a) Quartiles of share of pop. above 65y (b) Quartiles of population density



Overall, the evidence in Figures 6 to 8 suggests very limited heterogeneous effects across municipalities. This can result from the fact that we use aggregated municipal data, as opposed to individual card purchases. On a positive tone, the coefficients are similar in sign and significance to the ones in Figure 5, showing the robustness of our results.

If anything, the only sector for which we find suggestive heterogeneity is Supermarkets, where the increase in purchases caused by the pandemic is stronger in the poorest municipalities, the ones with higher unemployment, with a higher share of elderly and lower population density. This is suggestive that poorer, more rural and older communities rely more on supermarkets and is compatible with the characterization of consumer types provided by SIBS Analytics, which shows that supermarkets concentrate 35% of the purchases made by individuals in the bottom quartile, and 18% of the purchases of individuals in the top quartile.

5.2 Spending with Foreign Cards

We now contrast the evolution of the logarithm of the value of purchases for Portuguese and Foreign owned bank cards. Again, we focus our attention on the subset of sectors that experienced increases in purchases in Figure 9 and the six sectors that were particularly hit in Figure 10. This is particularly relevant for the case of Portugal, as Tourism was responsible for 14.6% of Portuguese GDP in 2018, increasing 7.7% from the previous year (Statistics Portugal). Moreover, tourism accounted for 9% of employment in the country in 2017.

Covid Economics 28, 12 June 2020: 119-158

Covid Economics 28, 12 June 2020: 119-158

Figure 9: Event Studies, by sector: Foreign vs. Portuguese Cards [Up]

(a) Supermarkets (b) Trad. and Grocery stores (c) Pharmacies and Drugstores

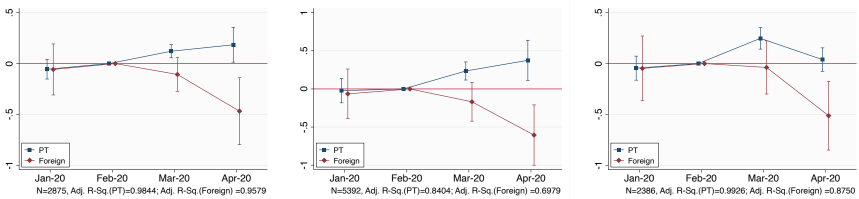
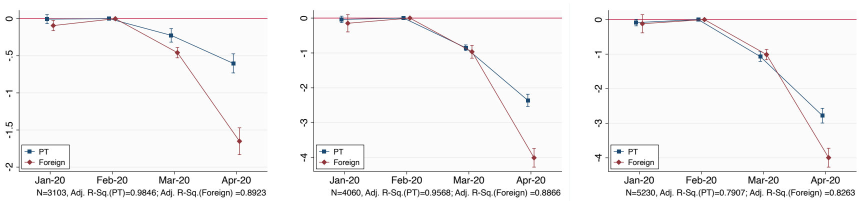
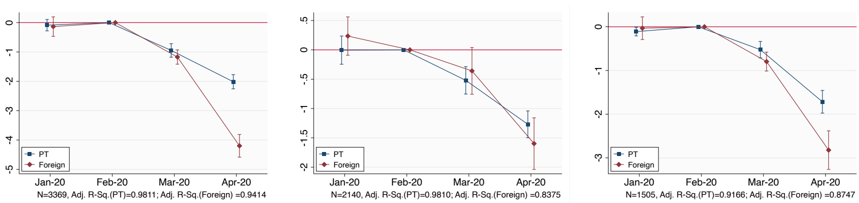


Figure 10: Event Studies, by sector: Foreign vs. Portuguese Cards [Down]

(a) Gas Stations (b) Fashion and Beauty (c) Leisure and Tourism



(d) Restaurants and Catering (e) Healthcare Services (f) Transp. and Car Rentals



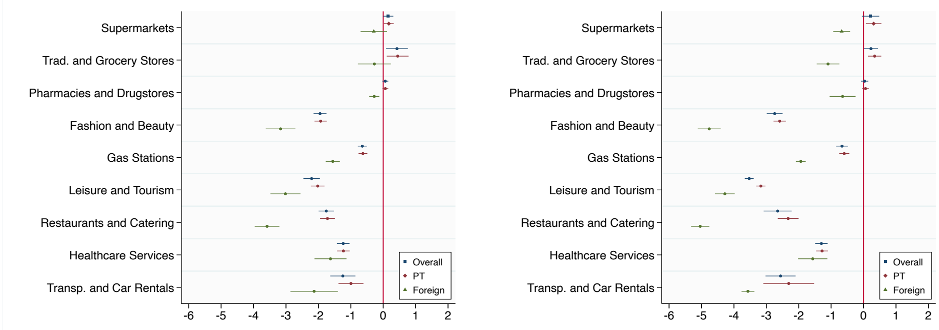
Our findings show that *(i)* purchases from Foreign bank cards dropped significantly even in sectors that witnessed an increase in purchases, and *(ii)* purchases from Foreign bank cards dropped significantly more in the most affected sectors in our sample.

Finally, we inspect heterogeneity between the least and the most touristic areas computing Equation (3), by estimating (3) for municipalities in the first and fourth quartiles of the number of overnight stays per 100 inhabitants. Results are presented in Figure 11. Again, purchases from Foreign bank cards are always significantly more affected than Portuguese ones.

Purchases in Supermarkets and in Traditional Retail and Grocery Stores do not seem to be affected in the least touristic municipalities in panel (a). This is in clear contrast with the sharp reductions, for both sectors, for the most touristic areas in panel (b). This contrasting results show that local economies that depend strongly on the tourism sector bear more risks in face of the pandemic.

Figure 11: Municipal Heterogeneity: Overnight stays

(a) 1^{st} Quartile of overnight stays (b) 4^{th} Quartile of overnight stays



6 How do people buy during the lockdown?

Up to this point, we focused on the impact of the Covid-19 shock on the value of purchases at the municipal level. However, we can take advantage of the rich dataset provided by SIBS Analytics to decompose this effect between the number of purchases (which can be interpreted as the extensive margin) and the average consumption level (which can be interpreted as the intensive margin) of the change in purchases. As in Section 5, we concentrate in the three sectors that experienced a positive impact and the six sectors for which the pandemic caused the greatest decrease. The interpretation as the intensive and extensive margins has to be qualified, since we are analyzing aggregated data. A higher number of transactions may imply that each individual purchases more often or that more individuals purchase.

We estimate Equation (1) for the intensive margin impacts in Figure 12 and Figure 14 and for the extensive margins in Figure 13 and Figure 15.

Covid Economics 28, 12 June 2020: 119-158

Figure 12: Event Studies, by sector: Average Transaction [Up]

(a) Supermarkets (b) Trad. and Grocery stores (c) Pharmacies and Drugstores

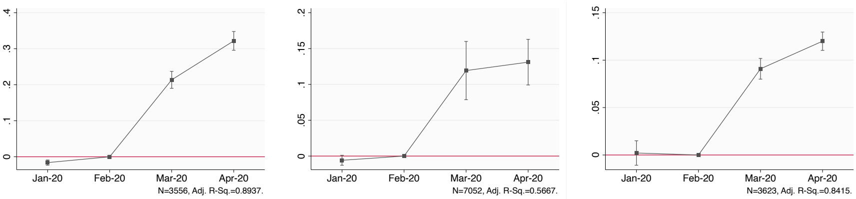
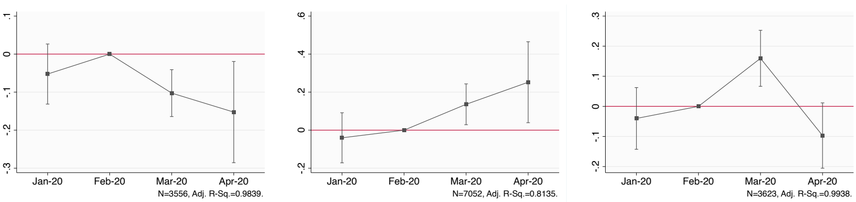


Figure 13: Event Studies, by sector: Number of Transactions [Up]

(a) Supermarkets (b) Trad. and Grocery stores (c) Pharmacies and Drugstores



We begin with the sectors that had an increase in purchases. Our findings show that people optimized their visits to hyper and supermarkets, as the number of transactions decreased at the same time that average transactions increased substantially. This is evidence that the consumers optimize by going less often and buying more each time they go to the supermarket, which could be suggestive of stockpiling behavior or just the fact that individuals want to minimize exposure to the health risk.[24] Nevertheless, these last results should be interpreted with a grain of salt as the parallel trend assumption does not hold, using a confidence interval at 95%, in this case.

The result for supermarkets contrasts with that of traditional retail and grocery stores, where the number of transactions increased. This fact can be explained by a higher sense of relative proximity and safety, given the smaller average size and density of clients shopping at the same time in these stores. Pharmacies and drugstores experienced an increase in the average transaction in March and April and an increase in the number of transactions only in March. One possible explanation for this fact is the need for masks and other protection equipment.

[24] Santos and Gonçalves (2018) showed that Portuguese consumers, when confronted with the introduction of a tax on sugar sweet beverages in 2017, stockpiled these products in the quarter before the implementation of the reform.

Covid Economics 28, 12 June 2020: 119-158

Figure 14: Event Studies, by sector: Average Transaction [Down]

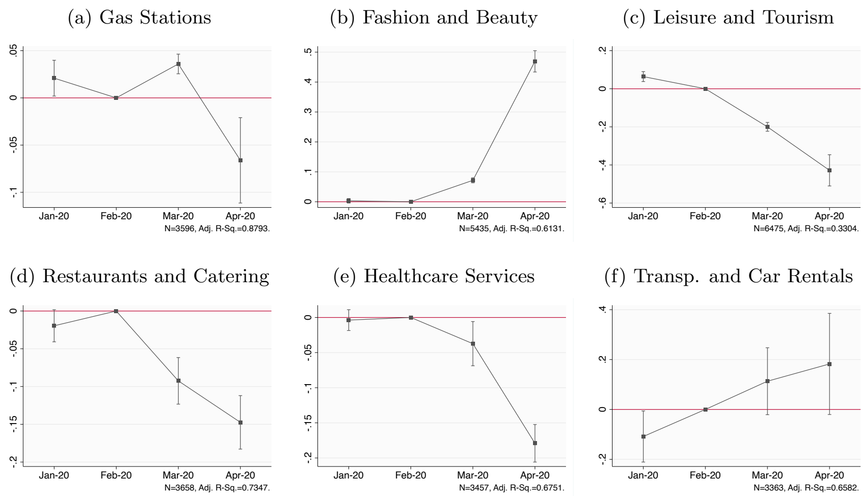
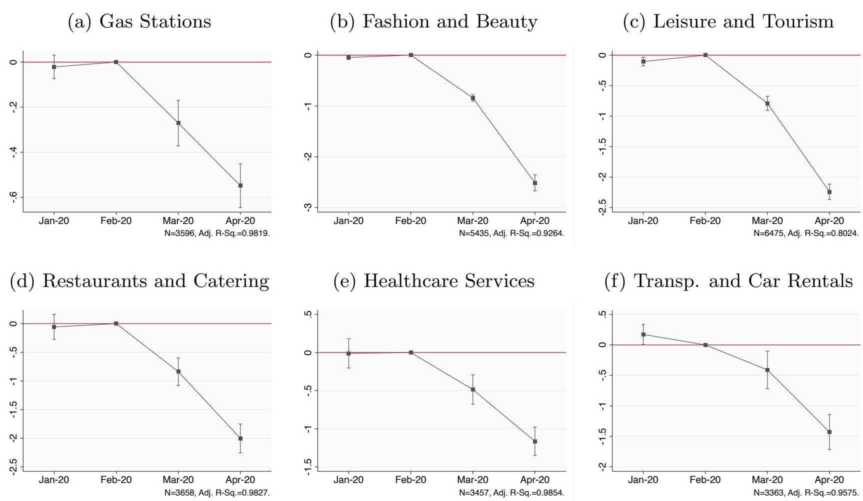


Figure 15: Event Studies, by sector: Number of Transactions [Down]



We next focus on sectors with negative impacts. Fashion and Beauty displays an interesting pattern, because of the sizeable increase in the average transaction. The gross growth rate is 65% above what it would have been in the absence of the lockdown. This is possibly driven by an increase in on-line purchases, as all shopping centers and small businesses were closed in late March and throughout April. Gas stations display a small increase in March, reflecting some limited initial stockpiling of gasoline in the beginning of the confinement. The great lockdown does not seem to impact average purchase in Transportation and Car Rentals. All the remaining sectors reported in Figure 14 suffered a sizeable drop on the average purchase.

One can see in Figure 15 that, for all selected sectors, consumers' transactions significantly decreased. As mentioned before, Google Mobility Report data highlights the magnitude of the Confinement.

In tandem with the Leisure and Tourism sector, Restaurants and Catering experienced a sharp decline in the number and in average transactions.

7 Concluding remarks

Evaluating the tremendous speed and magnitude of the economic effects of the Covid-19, a once in a century pandemic, is a necessary tool to design appropriate policy responses and raise awareness about the disruptive shocks and invest in preparedness to accommodate this ever more frequent tsunamis (Sands, 2017).

In this paper, we explore purchasing behavior of individuals in the first two months of the Covid-19 meltdown in the Portuguese economy. We use transaction data on monthly electronic payments disaggregated by sector and municipality, both on-site and on-line, from the largest player in the market for electronic payments in Portugal. We identify the causal impact of the pandemic shock by implementing a difference-in-differences event study. Our identification strategy relies on the assumption that, in the absence of the pandemic, monthly evolution in the first four months of 2020 would be the same as the equivalent months of the two previous years. We identify a massive causal impact of the shock on overall purchases, i.e., from a baseline growth rate of 10% to a decrease of 45%. We document an increase on the purchases of essential goods, contrasting with severe contractions in sectors that were closed by government order or depend heavily on tourism. We find evidence that the lockdown led people to postpone or forego essential expenditures related to their health and relationship with the state. Gas stations display a small contraction compared to transportation, probably reflecting a preference for private cars. We find that buyers adjust their shopping strategies in rational ways to minimize public health risks, since they go less often to supermarkets and buy more each

Covid Economics 28, 12 June 2020: 119-158

time, and visit local groceries more. We do not find evidence of heterogeneous effects across municipal characteristics, except for purchases in supermarkets in poorer, more remote and older municipalities. We show that supermarkets and groceries in municipalities whose economies depend more on foreign tourists face a decrease in purchases with foreign cards.

Our paper contributes to the nascent literature that uses transaction data to study the economics of the Great Lockdown. Transaction data has the potential to uncover economic effects with high frequency and low noise. Our data is comprehensive because it comprises all the transactions processed by the main player in the electronic payments market in Portugal. Its main drawback, however, is that the provider aggregates all individual transactions to municipal monthly data disaggregated by 39 sectors of activity. A possible avenue for future research would be to shed light on the differential impacts with respect to inequality concerns and further understand employment consequences.

Covid Economics 28, 12 June 2020: 119-158

References

Adams-Prassl, A., Boneva, T., Golin, M., and Rauh, C. (2020). Inequality in the Impact of the Coronavirus Shock: New Survey Evidence for the UK. *Cambridge-INET Working Paper Series*, (2020/09).

ADC (2018). Inovação Tecnológica e Concorrência no Setor Financeiro em Portugal. Technical report, Autoridade da Concorrência.

Adda, J. (2016). Economic activity and the spread of viral diseases: Evidence from high frequency data. *The Quarterly Journal of Economics*, 131(2):891–941.

Almond, D. (2006). Is the 1918 influenza pandemic over? Long-term effects of in utero influenza exposure in the post-1940 US population. *Journal of Political Economy*, 114(4):672–712.

Alstadsæter, A., Bratsberg, B., Eielsen, G., Kopczuk, W., Markussen, S., Raaum, O., and Røed, K. (2020). The First Weeks of the Coronavirus Crisis: Who Got Hit, When and Why? Evidence from Norway. Technical report, National Bureau of Economic Research.

Andersen, A. L., Hansen, E. T., Johannesen, N., and Sheridan, A. (2020a). Consumer responses to the COVID-19 crisis: Evidence from bank account transaction data. *Covid Economics*, 7:88–111.

Andersen, A. L., Hansen, E. T., Johannesen, N., and Sheridan, A. (2020b). Pandemic, Shutdown and Consumer Spending: Lessons from Scandinavian Policy Responses to COVID-19. *Working Paper*.

Baker, S. R., Farrokhnia, R. A., Meyer, S., Pagel, M., and Yannelis, C. (2020a). How does household spending respond to an epidemic? Consumption during the 2020 COVID-19 pandemic. Technical report, National Bureau of Economic Research.

Baker, S. R., Farrokhnia, R. A., Meyer, S., Pagel, M., and Yannelis, C. (2020b). Income, Liquidity, and the Consumption Response to the 2020 Economic Stimulus Payments. Technical report, National Bureau of Economic Research.

Bandiera, O., Buehren, N., Goldstein, M. P., Rasul, I., and Smurra, A. (2019). *The Economic*

Covid Economics 28, 12 June 2020: 119-158

Lives of Young Women in the Time of Ebola: Lessons from an Empowerment Program. The World Bank.

Barro, R. J., Ursúa, J. F., and Weng, J. (2020). The coronavirus and the great influenza pandemic: Lessons from the "spanish flu" for the coronavirus's potential effects on mortality and economic activity. Technical report, National Bureau of Economic Research.

Bartik, A. W., Bertrand, M., Cullen, Z. B., Glaeser, E. L., Luca, M., and Stanton, C. T. (2020). How are small businesses adjusting to COVID-19? Early evidence from a survey. Technical report, National Bureau of Economic Research.

Bertrand, M., Duflo, E., and Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *The Quarterly Journal of Economics*, 119(1):249–275.

Campante, F. R., Depetris-Chauvin, E., and Durante, R. (2020). The Virus of Fear: The Political Impact of Ebola in the US. Technical report, National Bureau of Economic Research.

Carvalho, V. M., Hansen, S., Ortiz, Á., Garcia, J. R., Rodrigo, T., Rodriguez Mora, S., and Ruiz de Aguirre, P. (2020). Tracking the COVID-19 Crisis with High-Resolution Transaction Data.

Chen, H., Qian, W., and Wen, Q. (2020). The impact of the COVID-19 pandemic on consumption: Learning from high frequency transaction data. *Available at SSRN 3568574*.

Christensen, D., Dube, O., Haushofer, J., Siddiqi, B., and Voors, M. (2020). Building Resilient Health Systems: Experimental Evidence from Sierra Leone and the 2014 Ebola Outbreak. *University of Chicago, Becker Friedman Institute for Economics Working Paper*, (2020-28).

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

Esselink, H. and Hernández, L. (2017). The use of cash by households in the euro area. *ECB Occasional Paper*, (201).

Harris, J. E. (2020). The subways seeded the massive Coronavirus epidemic in New York city. *NBER Working Paper*, (w27021).

Covid Economics 28, 12 June 2020: 119-158

Jordà, Ò., Singh, S. R., and Taylor, A. M. (2020). Longer-run economic consequences of pandemics. Technical report, National Bureau of Economic Research.

Karlsson, M., Nilsson, T., and Pichler, S. (2014). The impact of the 1918 Spanish flu epidemic on economic performance in Sweden: An investigation into the consequences of an extraordinary mortality shock. *Journal of Health economics*, 36:1–19.

Midoes, C. (2020). Social distancing: Did individuals act before governments? Retrieved April 25, 2020.

Rasul, I. (2020). The economics of viral outbreaks. *AEA Papers and Proceedings*, 110:265–68.

Rhodes, A., Ferdinande, P., Flaatten, H., Guidet, B., Metnitz, P., and Moreno, R. (2012). The variability of critical care bed numbers in Europe. *Intensive care medicine*, 38(10):1647–1653.

Sands, P. (2017). *From Panic and Neglect to Investing in Health Security.* World Bank, Washington, DC.

Santos, J. P. d. and Gonçalves, J. (2018). Brown sugar, how come you taste so good? the impact of a soda tax on prices and consumption. Technical report, Gabinete de Estratégia e Estudos, Ministério da Economia.

Santos, J. P. d. and Tavares, J. (2018). European Funds and Firm Dynamics: Estimating Spillovers from Increased Access. Technical report, CEPR Discussion Papers.

Santos, J. P. d., Tavares, J., and Vicente, P. C. (2019). Can ATMs Get Out the Vote? Evidence from a Nationwide Field Experiment. Technical report, CEPR Discussion Papers.

Wong, G. (2008). Has SARS infected the property market? Evidence from Hong Kong. *Journal of Urban Economics*, 63(1):74–95.

Covid Economics 28, 12 June 2020: 119-158

Covid Economics 28, 12 June 2020: 119-158

A Additional Tables

Table A.1: Description of sectors of activity in SIBS dataset

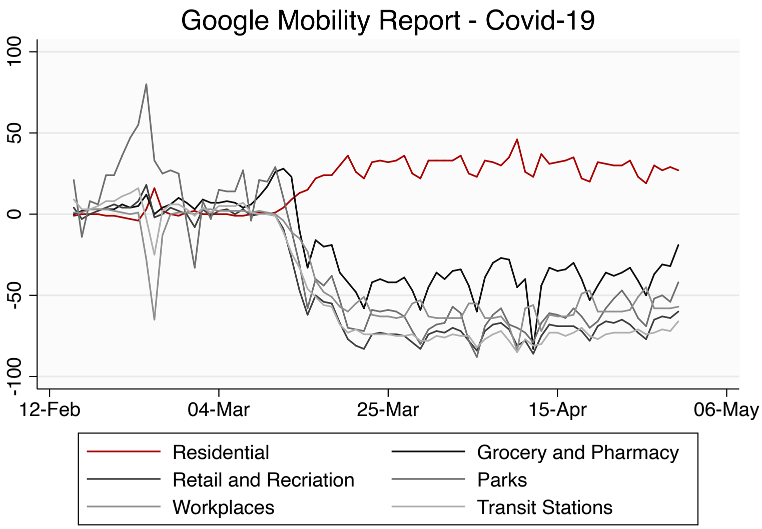
Sectors of Activity	Notes
Specialized Retail	
Tech, Culture and Entertainment	Includes appliances, electronics, computers, and books
Decor and Home Equipment	
Clothing, Footwear and Accessories	
Vehicles and related Accessories	Includes buses, vans, cars, motorbikes
Building and DIY materials	Includes hardware, paints and varnishes, textiles, and tiles
Toys and Childcare products	
Sports and Leisure gear	
Pharmacies and Drugstores	
Traditional Trade	Includes butchers, fish markets, breweries,
Fragrances and Beauty Products	
Gas Stations	
Other Retail	
Non-specialized retail	
Hyper and Supermarkets	
Grocery stores	
Other Non-specialized retail	
Wholesale	
Raw Materials	Includes fuels and derivatives, ironmongery, wood, and ores
Wholesale - Consumption Goods	Includes food, beverages, and tobacco
Wholesale Trade Agents	
Raw agricultural products and livestock	
IT Equipments	Includes computers, peripherals, and software
Machinery and equipments	Includes cranes, tractors, and agricultural machinery
Wholesale Trade	
Services	
Hotels and other lodging	
Education and Training	Includes public, private, and driving schools
Insurance and Financial Services	
Real Estate, Construction and Architecture	
Leisure and Travelling	Includes casinos, travel agencies, theater, and concerts
Press, Media and Advertising	Includes production of video, edition of books and newspapers
Restaurants and Catering	Includes bars and cafes
Healthcare Services	Includes hospital and clinical services
Transportation and Car Rentals	
Telecom and Utilities	
Social Services	Includes nursing homes and rehabilitation centres
Public Administration	Includes tax offices, courts, and social security
IT Services	Includes computer programming, and equipment repair
Other Services	
Production and Industry	
Agriculture, livestock, hunting, and fishery	
Mining and Quarrying	
Manufacturing	

Table A.2: Descriptive Statistics: Heterogeneity variables

Variable	Mean	Std Dev	Min	Q1	Q2	Q3	Max
Median net-at-source income (2017)	9442.33	1508.29	6740	8382.25	9216.5	10068.25	16323
Inequality P90/p10 (2017)	5.42	1.17	3.40	4.50	5.30	6.10	9.70
Unemployment Rate (2018)	5.41	2.06	2.4	3.8	5	6.5	12
Share of Permanent contracts (2018)	0.65	0.09	0.24	0.61	0.66	0.71	0.84
Population Density (2019)	292.44	807.72	3.9	25.275	67.45	175.075	7641.9
Share of Pop. above 65 years old (2019)	24.73	6.02	8.65	20.45	24.38	28.55	45.68
Overnight stays per 100 inhabitants (2018)	625.59	1622.28	2.50	95.20	221.80	451.00	20254.90

B Additional figures

Figure B.1: Google Mobility Report: Time Series

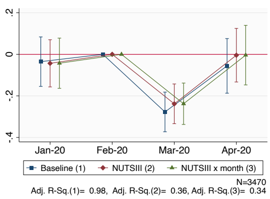


Covid Economics 28, 12 June 2020: 119-158

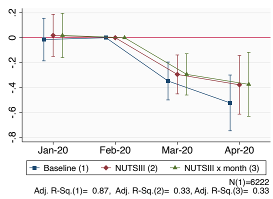
C Sector level robustness

Figure C.1: Value of purchases (Sectors): Changing Fixed Effects

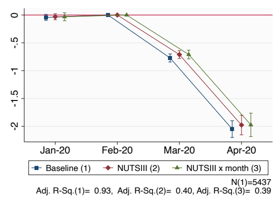
(a) Tech. and Entertainment



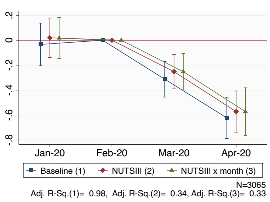
(b) Home Decoration and DIY



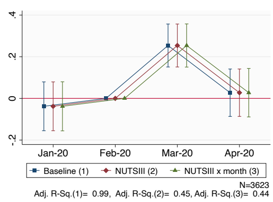
(c) Fashion and Beauty



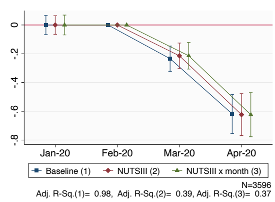
(d) Vehicles and Accessories



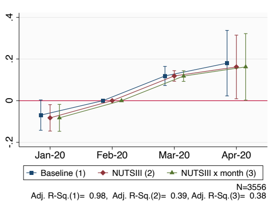
(e) Pharmacies and Drugstores



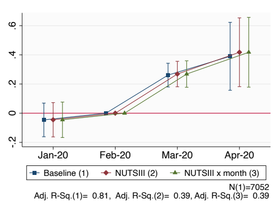
(f) Gas Stations



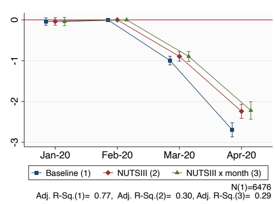
(g) Supermarkets



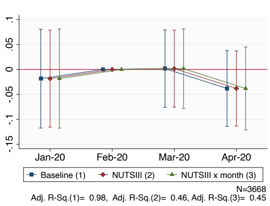
(h) Trad. and Grocery stores



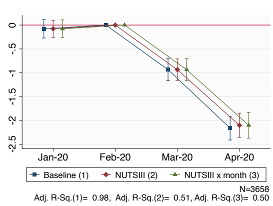
(i) Leisure and Tourism



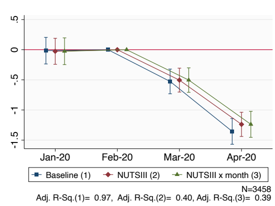
(j) Insurance and Fin. Services



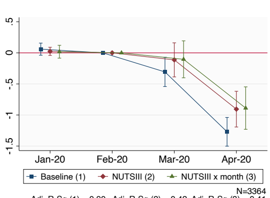
(k) Restaurants and Catering



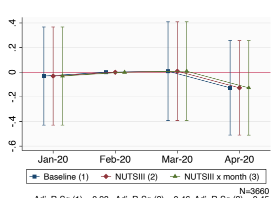
(l) Healthcare Services



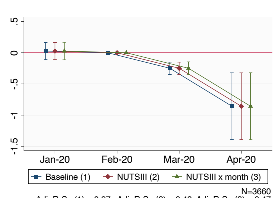
(m) Transp. and Car Rentals



(n) Telecom and Utilities

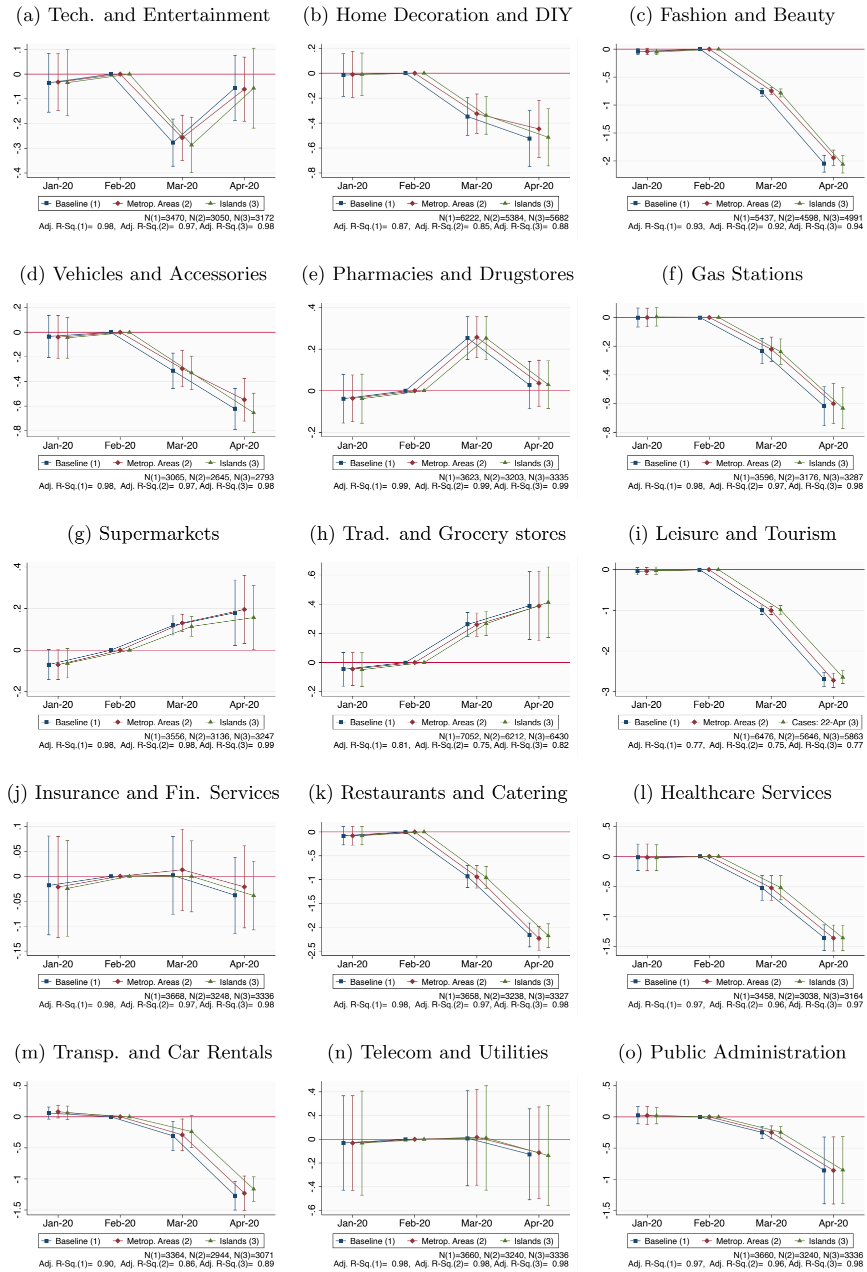


(o) Public Administration



Covid Economics 28, 12 June 2020: 119-158

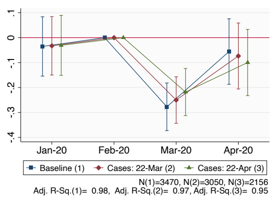
Figure C.2: Value of purchases (Sectors): Removing Metropolitan Areas and Islands



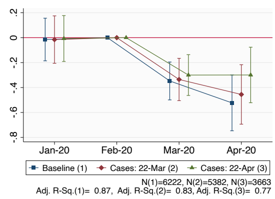
Covid Economics 28, 12 June 2020: 119-158

Figure C.3: Value of purchases (Sectors): Below Median of Covid-19 cases

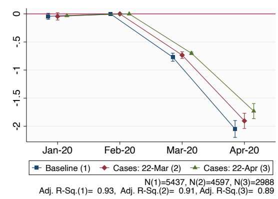
(a) Tech. and Entertainment



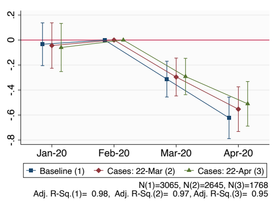
(b) Home Decoration and DIY



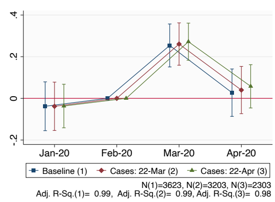
(c) Fashion and Beauty



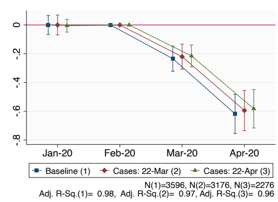
(d) Vehicles and Accessories



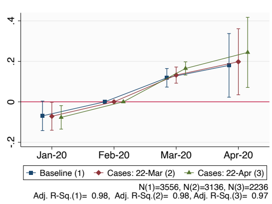
(e) Pharmacies and Drugstores



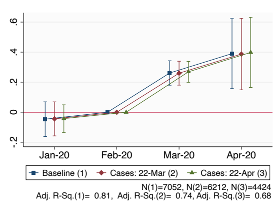
(f) Gas Stations



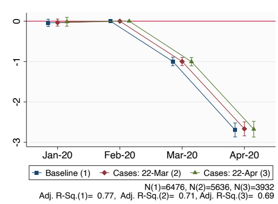
(g) Supermarkets



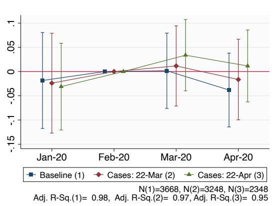
(h) Trad. and Grocery stores



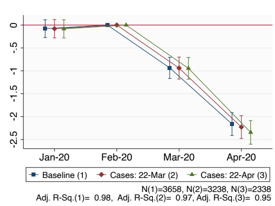
(i) Leisure and Tourism



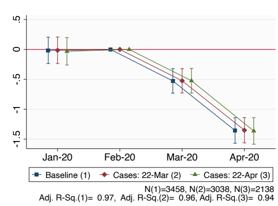
(j) Insurance and Fin. Services



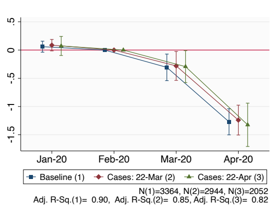
(k) Restaurants and Catering



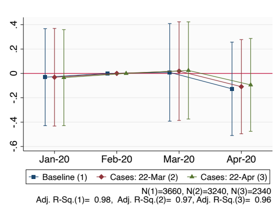
(l) Healthcare Services



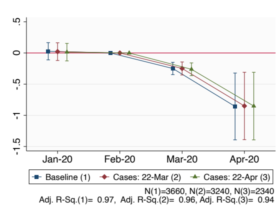
(m) Transp. and Car Rentals



(n) Telecom and Utilities



(o) Public Administration



Covid Economics 28, 12 June 2020: 119-158

Covid Economics Issue 28, 12 June 2020

Promoting social distancing in a pandemic: Beyond the good intentions[1]

Paolo Falco[2] and Sarah Zaccagni[3]

Date submitted: 21 May 2020; Date accepted: 23 May 2020

Reminders to promote social distancing have been ubiquitous throughout the COVID-19 crisis, but little is known about their effectiveness. Existing studies find positive impacts on intentions to comply, but no evidence exists of actual behavioural change. We conduct a randomised controlled trial with a representative sample of Danish residents, who receive different versions of a reminder to stay home as much as possible at the height of the crisis. We measure impacts on both intentions to comply and on actions in the following days (i.e., whether subjects report having stayed home in a follow-up survey). We find that the reminder significantly increases people's intentions to stay home when it emphasises the consequences of non-compliance for the respondent or his/her family, while it has no impact when the emphasis is on other people or the country as a whole. Changes in intentions, however, translate into weaker changes in actions that are not statistically significant, despite potential concerns of self-reported compliance being overstated. This is consistent with the existence of important intention-to-action gaps. Only people who are in relatively poor health are significantly more

1 We are grateful to Marco Piovesan, Alexander Sebald, Claus Thustrup Kreiner, Rudi G.J. Westendorp, Laus Hvast Mortensen, Davide Dragone, Pol Campos-Mercade, Christina Gravert, Mauro Caselli, Stefano Caria, Magnus Johansson, and all participants in the University of Copenhagen COVID-19 Seminar for their helpful comments. We are indebted to Bo Lønberg Bilde and his colleagues from DST Survey (Statistics Denmark) for their invaluable assistance and great efforts. We thank the Department of Economics, the Center for Economic Behaviour and Inequality (CEBI), the Department of Public Health, and the Centre for Healthy Ageing (CEHA) at the University of Copenhagen for their financial support. The activities of CEBI are funded by the Danish National Research Foundation. We are thankful to Arash Bal, Gan Khoon Lay, Nikita Kozin, and Priyanka from the Noun Project for some of the graphics used in our charts. All errors are our own.

2 Assistant Professor, Dept. of Economics, University of Copenhagen.
3 Post-doctoral Fellow, Dept. of Economics and Center for Economic Behaviour and Inequality, University of Copenhagen.

Covid Economics 28, 12 June 2020: 159-195

CEPR PRESS
COVID ECONOMICS
VETTED AND REAL-TIME PAPERS

likely to stay home after receiving the reminder with an emphasis on personal and family risks. This shows that while reminders may be useful to protect groups at risk by increasing their own compliance with social distancing, such a tool has no significant impact on the behaviour of those who face limited personal risks but could spread the disease.

Covid Economics 28, 12 June 2020: 159-195

Covid Economics 28, 12 June 2020: 159-195

1. Introduction

In the first months of 2020, a new type of coronavirus named SARS-CoV-2 spread like wildfire from China to the rest of the world. By mid-March, it reached the status of a global pandemic. By early June, over 6 million people had been infected and nearly 400,000 had died from the disease worldwide.[1]

In the absence of a cure or a vaccine, fighting a pandemic requires people to abide by certain norms of behaviour [(12)] and to follow the guidelines of authorities in a coordinated fashion [(13)]. Such recommendations span several domains, from personal hygiene to spending more time at home and avoiding contact with people who face the greatest risks [(14)] [(15)].

Social distancing - the practice of maintaining a physical distance between people and reducing the number of times people come into close contact with each other - is the most effective way of reducing contagion [(16)] [(17)] [(18)]. It is also difficult to enforce. In its most extreme form, social distancing implies that people should remain in their homes and avoid contact with others, unless strictly necessary. Such strict forms of distancing have been applied in countries like Italy and France. Milder forms of social distancing have been encouraged across the globe.

Since social distancing is disruptive for people's lives, authorities have been struggling to find ways of promoting it [(19)]. Awareness campaigns have been numerous in many countries and reminders of different sorts have been used, ranging from social media campaigns to SMSs like those sent by the Danish Police to every mobile user (March, 22nd)[2] or the British government to every UK resident (March, 24th)[3]. In other contexts, such as smoking cessation, medical adherence

[1] Source: Worldometers website [link]
[2] Source: The Local DK (March 24th 2020) [link]
[3] Source: UK Government website (March 24th 2020) [link]

[20] [21] [22] [23], physical activity [24], seat belt usage [25], take-up of social benefits [26], electricity consumption [27] [28], and giving to charitable organizations [29] [30] [31], reminders have been shown to cause behavioural change [32].

Do messaging campaigns to promote social distancing work during a pandemic? While few studies have shown that reminders affect people's intentions [1] [2] [4] [5], we know little about whether such intentions translate into changes in behaviour. In light of the large literature documenting intention-to-action gaps and time inconsistency across a wide range of domains [6] [7] [8] [9] [10] [11] [33], discrepancies between intended and actual behaviour deserve investigation. To the authors' knowledge, this is the first paper to test the impacts of reminders to promote social distancing *on both intentions and actions*. As argued below, while the behaviour we study is self-reported, we believe this does not pose a threat to our conclusions, since one would expect compliance to be over-stated when self-reported.[4]

By focusing on the decision to stay home, our study tests the effectiveness of one of the key recommendations provided by health authorities. From the UK Prime Minister[5], to the President of the United States[6], to the Queen of Denmark[7], the advice to stay home as much as possible has been ubiquitous during the COVID-19 pandemic. Yet, convincing people to follow this recommendation is difficult, since it implies major changes to their routine and can be perceived as a severe limitation of individual freedom.

[4] Despite that, we find no impact of the reminder on behaviour.
[5] Source: BBC (March 23rd 2020) [link]
[6] Source: The Washington Times (March 31st 2020) [link]
[7] Source: The Local DK (March 18th 2020) [link]

Covid Economics 28, 12 June 2020: 159-195

2. A randomised messaging campaign

We conduct a pre-registered randomised controlled trial with Danish residents aged 18-69.[8] We expose different groups to different variations of a recommendation to "stay home as much as possible" and we test the impact of the treatment on both respondents' intentions to stay home the following day and on their subsequent behaviour (i.e., whether the person reports having stayed home). Our data, described below, closely track widely used mobility measures based on mobile-phone data, corroborating the reliability of the information on respondents' behaviour.

We test four alternative ways of framing the recommendation, extending previous research that investigates self-interested versus prosocial motives as drivers of compliance with health recommendations [(34) (35) (36) (37)]. The first frame ("you") focuses on the potential consequences of the subject's behaviour for himself/herself. The second frame ("family") focuses on the consequences for his/her family. The third frame ("others") focuses on the consequences for other people in general. The fourth frame ("country") focuses on the broader consequences for the country as a whole by emphasising the risk of overloading the health system. This approach builds on existing studies showing that emotional proximity (whether the person affected by one's decision is a stranger or a friend) is an important determinant of people's choices [(38) (39)].

For each of the four treatments we test two variations. The first one, in the loss domain*,* emphasises the *risks of not complying* with the recommendation (for the respondent, the family, others, and the country). The second, in the gain domain*,* emphasises the *benefits of complying* with the recommendation. This approach builds on insights from prospect theory [(40)] and borrows from a vast literature that has tested framing effects in a number of contexts [(41) (42) (43) (44)].

---

[8] Registry number AEARCTR-0005582 [link]

CEPR PRESS

Covid Economics 28, 12 June 2020: 159-195

In addition to these four framed messages, we send a generic reminder to stay home as much as possible without any framing. This is akin to the simple appeals made by health authorities and politicians in televised speeches and social media campaigns. Finally, a control group receives no reminder. Table 1 reports a summary of the treatments, including the text of the reminders. Each treatment appeared to the respondents as a text box with the message on a red background (see Appendix B).

3. Data collection and summary

The study covers the period between March 25 and April 7, 2020, a time when the crisis was at its peak and financial markets in turmoil, causing authorities to adopt the most stringent measures applied in Denmark (including the closure of non-essential economic activities and of the borders). Appendix G provides a detailed timeline of the crisis in Denmark and shows that our study falls within the most critical period.

FRAME	DOMAIN	REMINDER
You	*Loss*	*"If you go outside and become infected, you may get very serious respiratory problems. Stay home as much as possible."*
	Gain	*"If you stay home, you protect yourself from the risk of getting very serious respiratory problems. Stay home as much as possible."*
Family	*Loss*	*"Think of your loved ones. If you go outside and become infected, you may infect them, and they may get very serious respiratory problems. Stay home as much as possible."*
	Gain	*"Think of your loved ones. If you stay home, you protect them from the risk of getting very serious respiratory problems. Stay home as much as possible."*
Others	*Loss*	*"If you go outside and become infected, you may infect others, who may get very serious respiratory problems. Stay home as much as possible."*
	Gain	*"If you stay home, you protect others from the risk of getting very serious respiratory problems. Stay home as much as possible."*
Country	*Loss*	*"If you go outside and become infected, you may contribute to an overloading of the Danish health care system. Stay home as much as possible."*
	Gain	*"If you stay home, you reduce the risk of an overloading of the Danish health care system. Stay home as much as possible"*
Generic		*"Stay home as much as possible."*

Table 1. The framing of reminders. The table provides an overview of the reminders we sent. We tested four frames with a focus on "you", "family", "others", and "country", respectively. Approximately 6,000 subjects were assigned to each frame. They were equally split between two variants of the frame (loss versus gain domain). In addition, 3,000 subjects received a generic reminder with no framing and 3,000 subjects in the control group received no reminder.

Covid Economics 28, 12 June 2020: 159-195

The different reminders were randomised within a representative sample of 29,756 Danish residents between the age of 18 and 69, who represent close to 1% of the population. Statistics Denmark (the national statistical office) carried out the randomisation and distributed the treatment via e-Boks - the official system of communication used by public authorities in Denmark, which is akin to a personal email account.[9] Respondents received a message inviting them to participate in a survey to investigate people's habits at the time of the COVID-19 crisis. Those who agreed to participate landed on a dedicated webpage where they were first shown the reminder (if they were in one of the treated groups) and then answered eight questions (control subjects only saw the questions). About 42% of contacted respondents completed the first questionnaire and received a second one in the coming days. Approximately 50% of them responded. The balanced sample used in most of the analysis contains $N = 5{,}310$ observations (the data-cleaning process is described in the "Methods" section). Attrition is balanced across treatment groups and does not depend on the kind of reminder respondents receive (see Appendix H). As a result, covariates are balanced across treatments (see Table 2 in Appendix A).

While the first questionnaire asked about intentions to stay home the day after, the second questionnaire asked about whether the respondent went out the day before (both questionnaires are available in Appendix C). Specifically, we asked respondents how long they were planning to spend (first questionnaire) or did spend (second questionnaire) outside their home, and we treated positive answers as instances of not staying home.[10] While the information on actual behaviour is

---

[9] By focusing on the general population of Danish residents, we avoid having to rely on selected panels of respondents on dedicated survey platforms, who may have been solicited frequently during the COVID-19 crisis and may be subject to fatigue [(49) (50)].

[10] We believe this is a preferable strategy to asking whether respondents were planning to go out (a "Yes/No" question), since it induced more careful reflection. The results are robust to treating respondents who only went out for a very short time (e.g., less than 5, 10, or 20 minutes) as having stayed home.

self-reported, it tracks "objective" measures of mobility obtained from mobile phone data for the same population[11], as detailed in the "Methods" section and in Appendix G (Figure 5).[12]

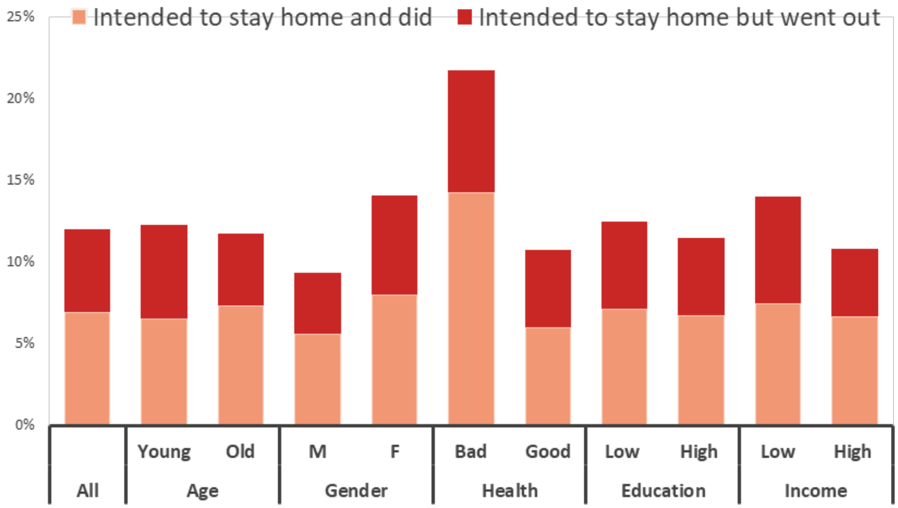


Figure 1. The gap between intentions and actions. 42% of the respondents who intend to stay home do not follow their intentions and go out instead. Intentions to stay home are higher among women and lower-income households, while they do not change significantly by age or education levels. People with relatively poor health conditions are the most likely to stay home and the least likely to deviate from such an intention. The sample for this figure is restricted to respondents whose answers to the first and the second questionnaires refer to the same day, since we are interested in documenting inconsistencies (N = 3,032). The subsequent analysis of treatment effects can rely on a larger sample since we do not need an exact match between the days. The different categories are defined as follows: young: < 50; low education: < post-secondary degrees; low income: household disposable income per capita < 250,000 DKK (approx. 36,000 USD).

A summary of our data shows that less than 15% of respondents intend to stay home the next day during the most critical period of the crisis, and 42% of them do not follow the declared intentions and go out instead (Figure 1). Intentions to stay home are higher among women and lower-income households, while they do not change significantly by age or education levels. People with

[11] Source: Mobility Trends Report by Apple Inc. [link]
[12] Specifically, we show a tight fit between data from our survey on the distance the respondents travelled outside their homes and data from Apple Inc., obtained from routing requests made to Apple web mapping service.

relatively poor health conditions are the most likely to stay home and the least likely to deviate from such an intention.

4. Impacts on intentions and actions

To measure the effects of the reminders, we compare the probability of going out in each of our treatment groups with the probability of going out among respondents in the control group that received no treatment (the estimation strategy is outlined in the "Methods" section).[13]

Our first finding is that the reminder significantly increases respondents' *intentions* to stay home when it is framed with respect to personal consequences and consequences for one's family. Figure 2 summarises the results (while Table 6 in Appendix D shows the full set of estimates). For simplicity, it reports them as percent increases relative to the share of people who stay home in the control group, which is just below 15% (i.e., an effect of 20 percent amounts to a 3-percentage point increase in the share of people who stay home, or 3 people out of 100). With both the "you" and the "family" framing, the treatment effect amounts to an increase in the share of people who intend to stay home of about 46% (p = 0.007 and p = 0.008, respectively) compared to the control group. On the other hand, the reminders have insignificant effects on intentions to stay home when they are framed with respect to the consequences for other people in general (12% with p = 0.459) and for the country as a whole (26.6% with p = 0.11). Similarly, the reminder with no framing - akin to the slogans commonly seen on social media (e.g., #STAYHOME) and promoted by governments around the world (e.g., the SMS sent by the UK government and the Danish Police[14])

[13] We test the null hypothesis of no difference between the control and each treatment group using standard significance testing. To this end, we estimate the empirical model outlined in the Methods section and report the resulting regression coefficients (and standard errors) in Appendix D. For ease of exposition, in the text we report treatment effects as percentage changes relative to the control group, together with the corresponding p-values and F-statistics.

[14] Source: The Local DK (March 24th 2020) [link]; UK Government website (March 24th 2020) [link]

- has a statistically insignificant effect (26%, p = 0.19). These findings are in line with the hypothesis that emotional proximity to the people affected by the respondent's actions plays a strong role in determining the success of a message. They are also consistent with recent evidence on prosocial motivation as an important driver of intentions to practice social distancing [(5)]. We shed new light on those findings by showing that prosocial motives are driven by an interest in protecting one's family rather than others in general.

Our second result is that when we further break down the most effective treatments ("you" and "family") and look at the sub-treatments in the gain and loss domain separately, we find very similar impacts independently of the domain. The estimated treatment effect on intentions ranges from 42% (p = 0.044) for the "family" treatment in the gain domain to 49% (p = 0.017) for the "family" treatment in the loss domain. The other treatments ("others" and "country") have no statistically significant impacts on intentions neither in the gain nor in the loss domain. The full set of results is available in Table 6 in Appendix D.

Our third result is that changes in intentions do not translate into sizeable changes in actions. The two most effective treatments identified above ("you" and "family") - with effects on intentions of over 45% - only result into a 19.7% (p = 0.127) and a 14.9% (p = 0.251) increase in the share of subjects who actually stay home relative to the control group. The other treatments, which had lower insignificant impacts on intentions have even lower impacts on actions.[15] When we test the joint hypothesis that all the reminders have an effect on actions equal to zero, we cannot reject it ($F(5, 5299) = 0.75$, p = 0.589).[16] Coupled with the first result, this evidence confirms that

[15] Since detecting the potential significance of lower effects on actions is statistically more difficult, we run some robustness checks by aggregating affine treatments (as detailed at the end of Appendix E). Even then, we are unable to detect significant impacts on behaviour.

[16] We also cannot reject the joint hypothesis that all the sub-treatments (considering the loss and the gain domain separately) have no impact on actions ($F(9, 5295) = 0.75$, p = 0.659).

Covid Economics 28, 12 June 2020: 159-195

Covid Economics 28, 12 June 2020: 159-195

intention-to-action gaps can limit the effectiveness of messaging campaigns of this kind [10] [45], a possibility that has been overlooked by the existing literature on the impact of reminders during the COVID-19 pandemic [1] [2] [3] [4] [5] .[17] In Appendix E, we run a battery of robustness checks to further test the validity of our conclusions.

One concern with the results is that the drop in sample size from baseline to follow-up makes it difficult to detect effects on actions due to a reduction in statistical power. While we acknowledge this possibility, it is important to remark that the effects we detect are small, since compliance in the control group is low. An increase of approximately 20% in the probability of staying home corresponds to a change of less than 3 percentage points (or 3 people every 100), since the share of people who stay home in the control group is below 15%. Detecting such a small impact poses a statistical challenge. On the other hand, it seems reasonable to argue that an effect of such magnitude would be considered of limited societal relevance by many policy-makers, even if estimated more precisely. This reinforces our conclusions on the limited effectiveness of reminders in changing behaviour.

Finally, our conclusions are robust to the possibility that respondents may over-report staying home due to experimenter demand effects. Indeed, despite such potential over-reporting, we are unable to detect sizeable impacts on behaviour.

[17] Such gaps may be due to systematic behavioural biases (e.g., time inconsistency) or idiosyncratic shocks forcing people to deviate from their intentions. While explaining such mechanisms is beyond the scope of this paper, documenting the divergence between intentions and actions is crucial for our understanding of how effective reminders are.

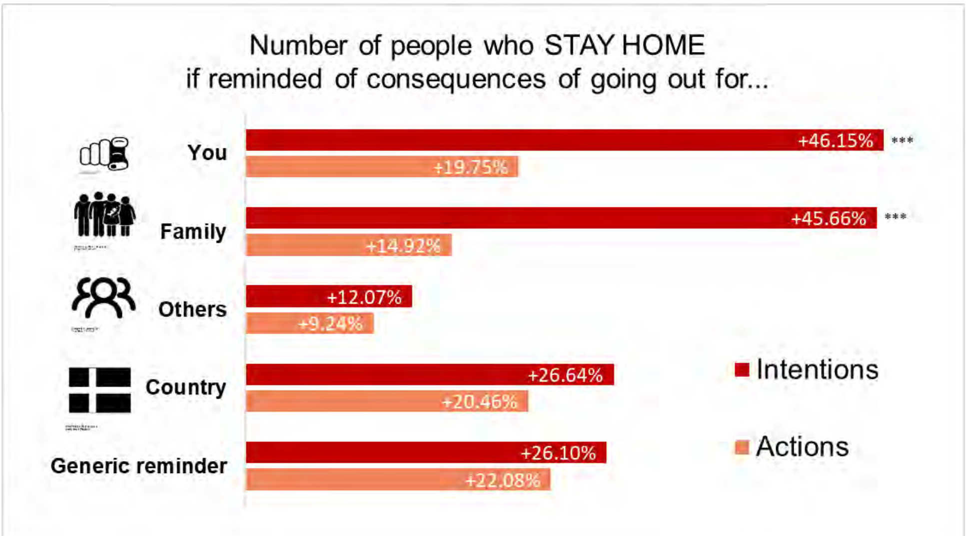


Figure 2. The effects of different reminders on intentions and actions. The effects are percentage changes relative to the share of people who intend to stay home or stayed home in the control group (i.e., the regression coefficients in Table 6 in Appendix D are divided by the share of people who intend to stay home (intentions) and stayed home (actions) in the control group). Intentions refer to the day after the first interview, actions refer to the day before the follow-up interview. The reminder increases respondents' intentions to stay home by 46% when it is framed with respect to personal consequences (p = 0.007) and consequences for one's family (p = 0.008). It has a lower insignificant effect on intentions when it refers to consequences for other people in general (p = 0.459), for the country as a whole (p = 0.110), and when it has no specific framing (p = 0.190). Changes in intentions do not translate into sizeable changes in actions. The reminders with a focus on personal consequences and consequences for one's family only increase the share of people who stay home by 19.7% (p = 0.127) and 14.9% (p = 0.251), respectively. As for intentions, the reminders have no significant impact on actions when they focus on "others" (p = 0.467), "country" (p = 0.113), or have no framing (p = 0.15). Respondents who referred to a weekday in the first interview and to a weekend day in the follow-up interview (and vice-versa) are dropped from the sample to avoid inconsistencies. The resulting sample size is N = 5,310. Stars reported at the top of the bars express the level of significance of the coefficient (*** p<0.01, ** p<0.05, * p<0.1).

5. Healthier people are harder to convince

The effects of the reminders may vary across social groups and many would argue that, in order to increase their effectiveness, they should be targeted at those who are least likely to comply with the recommendation. Previous research, for instance, finds that people who face the lowest risks from being infected are the most likely to diverge from social distancing measures during the COVID-19 pandemic [1]. Are such groups responsive to the reminders? To answer this question,

Covid Economics 28, 12 June 2020: 159-195

we split subjects according to their health status and repeat the analysis on separate samples.[18] Figure 3 shows the results for the two most powerful treatments. Table 8 in Appendix F reports the full set of estimates.

The results indicate that respondents who are in worse health conditions and face the greatest risks from an infection are the most affected by the treatments. Being reminded of the risks of going out for themselves and their families more than doubles their intended probability to stay home (p = 0.052 and p = 0.036, respectively) and increases their probability of actually staying home by over 80% (p = 0.067 and p = 0.034, respectively).[19] The strong effect of the "family" reminder among people in bad health may be due to the fact that it reminds them of the burden and suffering that a worsening of their health conditions would impose on their loved ones. Another plausible explanation is that subjects in poor health live with other people in similar health conditions (e.g., older couples).

On the other hand, people with better health, who face the lowest risks from an infection (and are the ones who go out of their homes the most) are less affected by the reminders. The share among them who declare an intention to stay home increases by 36.5% when the reminder is about personal risks and 38.2%, when the reminder is about risks for others, but the effects are only significant at the 10% level (p = 0.099 and p = 0.089, respectively). On the other hand, we are unable to reject the joint hypothesis that all the reminders have no effect on actions among people in good health ($F(9, 4689) = 0.70$, p = 0.711). These results show that reminders may help to

[18] The lowest two (out of five) values of a variable indicating health status are considered bad health conditions for the purpose of this analysis (this is the categorisation that appears to be most sensible, since only considering in bad health those with the lowest value would leave us with a very small sample size).

[19] These effects are even stronger if we focus on people with poor health who are relatively old (50 and above). Not shown for conciseness.

Covid Economics 28, 12 June 2020: 159-195

CEPR PRESS

Covid Economics 28, 12 June 2020: 159-195

protect groups at risk by increasing their likelihood of staying home, while they do not increase compliance among those who face limited personal health risks but may spread the disease.

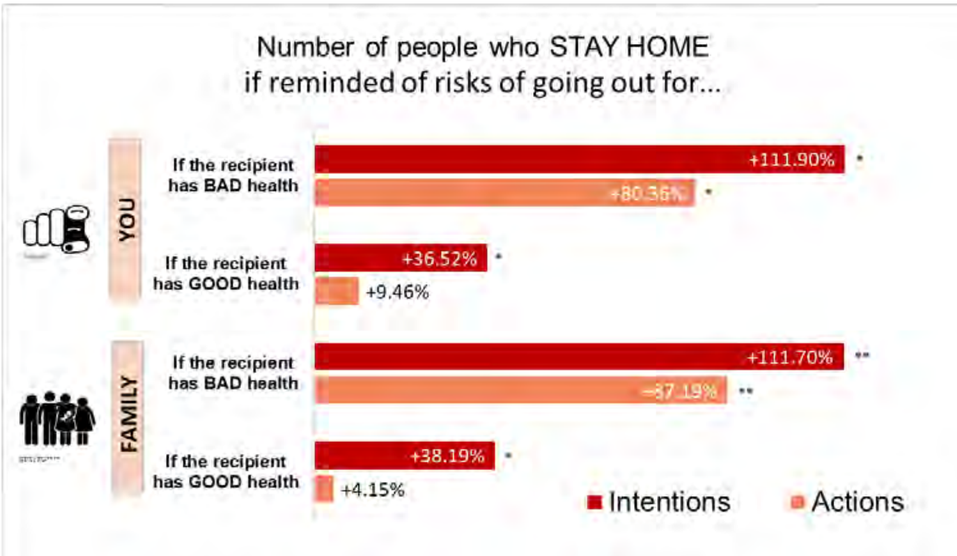


Figure 3. Treatment effects of the most effective reminders by the health status of the respondent. The effects are percentage changes relative to the probability of staying home in the control group, which receives no reminder (i.e., the regression coefficients in Table 8 in Appendix F are divided by the probability of staying home in the control group). Among respondents who are in bad health conditions (N = 603), the share of those who declare they will stay home more than doubles after receiving a reminder that emphasises personal risks (p = 0.052) and risks for family (p = 0.036), and the share of those who actually stay home increases by 80% (p = 0.067 for "you" and p = 0.034 for "family). Among respondents who are in good health (N = 4,704), the reminder increases intentions to stay home by 36.5% when framed with respect to personal risks and by 38.2% when framed with respect to risks for family, but the results are only significant at the 10% level (p = 0.099 for "you" and p = 0.089 for "family"). The share of respondents in good health who do stay home increases by less than 10% after receiving those reminders and the effect is not statistically significant (p = 0.564 for "you" and p = 0.8 for "family"). Respondents classify their health status on a 5-point scale. The lowest two values are considered bad health conditions for the purpose of this analysis (health information is missing for 3 observations used in the main regressions). Stars reported at the top of the bars express the level of significance of the coefficient (*** p<0.01, ** p<0.05, * p<0.1).

Covid Economics 28, 12 June 2020: 159-195

6. Discussion

This paper sheds new light on the effectiveness of messaging campaigns in promoting social distancing during the COVID-19 pandemic. It reveals that while reminders may be effective in changing people's intentions, those intentions are not matched by sizeable behavioural changes. The conclusion is robust to the possibility that respondents may over-report compliance, since that should facilitate detecting an effect that we do not find. Concerns about statistical power should be assessed in light of the fact that the effect sizes are small (the 20% increase in compliance induced by the most powerful treatment translates into fewer than 3 more people staying home out of 100), making precise identification challenging but also indicating the limited impacts on behaviour of such interventions.

Our evidence indicates that intention-to-action gaps may be an important obstacle in the promotion of social distancing during a pandemic and that messaging campaigns are unlikely to be effective unless they tackle such gaps. This could be achieved, for instance, by increasing the frequency of reminders to reduce the burden of time inconsistency, though the benefits of such a strategy should be weighed against the risk of habituation.

We also show that reminders are most effective in inducing behavioural change among people in relatively poor health, while subjects who are in good health are not affected. This is consistent with the idea that reminders are meant to leverage people's prior convictions, rather than changing people's minds. This suggests that in order to induce behavioural change, reminders should be targeted at specific audiences.

Our findings bear important lessons for the international community. Messaging campaigns like the one we tested have been used extensively across the world and our findings are applicable beyond the context of our experiment, as indicated by the tight fit between our data and widely used measures of social distancing from mobile-phone signals. In the absence of a vaccine or a cure for COVID-19, promoting social distancing will remain a top policy priority for the foreseeable future. Yet, as some governments begin to relax the initial restrictions, keeping people alert will become progressively more difficult, and intention-to-action gaps will only exacerbate the problem. Well-designed reminder campaigns can make a difference.

Covid Economics 28, 12 June 2020: 159-195

METHODS

I. Data cleaning

Out of the 29,756 subjects contacted by Statistics Denmark, a total of 12,573 (42,2%) completed the first survey. Out of those, 6,681 (22.3%) completed the second survey.[20] We drop 2 respondents whose answers to the questions on time spent home exceed 24 hours and 7 observations in which the follow-up refers to the day before the treatment occurred (which was the result of a technical problem). Furthermore, since some of the participants responded with some delay, it is possible that the answers to the follow-up questionnaire do not refer to the same day as the answers to the first questionnaire. To prevent major inconsistencies, we drop from the analysis respondents whose answers to the first questionnaire referred to a weekday, while their answers to the follow-up questionnaire referred to a day of the weekend, and vice-versa. This makes our results more precise, but does not change them qualitatively (as discussed below). This leaves us with a balanced panel of 5,310 respondents, which we use for the analysis.

II. Using mobile data to validate our measures

The information on actions (i.e., whether a person stayed home) is self-reported by the respondent in our follow-up survey. To validate the reliability of this measure, we use the data released by Apple Inc. on mobility trends during the COVID-19 pandemic.[21] Apple publishes daily reports on mobility trends based on mobile phone data, in countries and cities around the world. We extract the data for Denmark and we compare them with the distance that the subjects declared to have travelled the day before in our follow-up survey. To make the two series comparable, we calculate

[20] The first questionnaire was sent to respondents on March 25 and the last responses to the second questionnaire were received on April 7.

[21] Source: Mobility Trends Report by Apple Inc. [link]

Covid Economics 28, 12 June 2020: 159-195

CEPR PRESS

Covid Economics 28, 12 June 2020: 159-195

percentage changes in mobility compared to the first day for which we have information in our dataset. The results are reported in Appendix G.

III. Estimation strategy

To measure the effects of our treatments, we estimate the following econometric model:

$$Y_i = \beta_0 + \beta_1 T_{i,1} + \beta_2 T_{i,2} + \beta_3 T_{i,3} + \beta_4 T_{i,4} + \beta_5 T_{i,5} + \gamma \mathbf{X}_i + \varepsilon_{i,}$$

where Y_i is a dummy capturing whether the respondent stays home and equal to 1 when the respondent answers 0 to a question on the amount of time spent outside home[22]. We estimate the same model twice, first on intended outcomes from the baseline survey and then on realised outcomes from the follow-up. $T_1 - T_5$ are dummies equal to 1 if subject i was randomly assigned to each of the 5 treatments ($T_{i,1}$ = You, $T_{i,2}$ = Family, $T_{i,3}$ = Others, $T_{i,4}$ = Country, T_5 = No framing/ Generic), and $\varepsilon_{i,}$ is the error term. The first four dummies are further split in two when we separate the gain from the loss domain ($T_{i,1L}$ = You (Loss), $T_{i,1G}$ = You (Gain), $T_{i,2L}$ = Family (Loss),…, T_5 = No frame/ Generic) . $\mathbf{X}_i$ is a vector of covariates used at the randomisation stage to ensure balance between the groups. The variables included are gender, age, education, region, and household disposable income per capita. The control group is composed of people who do not receive any reminder. Hence, β_0 captures the proportion of people in the control group who intend to stay home (in the estimation on intentions) or actually do (in the estimation on actions). When we split the analysis by the health status of respondents, we divide the sample in two groups and estimate the model above separately on each of them.

[22] The question specifies that by ”outside one’s home” it means “outside one’s property”. Being in the home garden, for instance, should not be considered being out of one’s home.

References

1. *Evaluating COVID-19 Public Health Messaging in Italy: Self-Reported Compliance and Growing Mental Health Concerns.* . **Barari, S., Caria, S., Davola, A., Falco, P., Fetzer, T., Fiorin, S., ... & Kraft-Todd, G.** 2020, medRxiv.
2. *The effectiveness of moral messages on public health behavioral intentions during the COVID-19 pandemic.* **Everett, J. A., Colombatto, C., Chituc, V., Brady, W. J., & Crockett, M.** 2020.
3. *Adaptive and Dark Personality Traits in the Covid-19 Pandemic: Predicting Health-behavior Endorsement and the Appeal of Public-health Messages.* **Blagov, P. S.** 2020, PsyArXiv Preprints.
4. *Age-based messaging strategies for communication about COVID-19.* . **Utych, S. M., & Fowler, L.** 2020, Journal of Behavioral Public Administration, p. 3(1).
5. *Don't get it or don't spread it? Comparing self-interested versus prosocially framed COVID-19 prevention messaging.* **Jordan, J., Yoeli, E., & Rand, D.** 2020.
6. *What we can learn from five naturalistic field experiments that failed to shift commuter behaviour.* **Kristal, A.S., Whillans, A.V.** 2020, Nature Human Behaviour, pp. 4(2), 169-176.
7. *The role of attitudes, intentions and habit in predicting actual consumption of fat containing foods in Italy.* . **Saba, A., Vassallo, M., & Turrini, A.** 2000, European journal of clinical nutrition, , pp. 54(7), 540-545.
8. *Bridging the intention-behavior gap? The effect of plan-making prompts on job search and employment.* **Abel, M., Burger, R., Carranza, E., & Piraino, P.** 2019, American Economic Journal: Applied Economics, pp. 11(2), 284-301.
9. *Explaining the intention–behaviour gap in gluten-free diet adherence: The moderating roles of habit and perceived behavioural control.* **Kothe, E. J., Sainsbury, K., Smith, L., & Mullan, B. A.** 2015, Journal of health psychology, pp. 20(5), 580-591.
10. *Using text messages to bridge the intention-behavior gap? A pilot study on the use of text message reminders to increase objectively assessed physical activity in daily life.* . **Schwerdtfeger, A. R., Schmitz, C., & Warken, M.** 2012, Frontiers in psychology.
11. *School-level electronic cigarette use prevalence and student-level tobacco use intention and behaviours.* . **Chen, J., Ho, S. Y., Leung, L. T., Wang, M. P., & Lam, T. H.** 2019, Scientific reports, pp. 9(1), 1-7.
12. *Using social and behavioural science to support COVID-19 pandemic response.* **Bavel, J.J.V., Baicker, K., Boggio, P.S. et al.** 2020, Nature Human Behaviour, p. .
13. *Inviting free-riders or appealing to prosocial behavior? game-theoretical reflections on communicating herd immunity in vaccine advocacy.* . **Betsch, C., Böhm, R., & Korn, L.** 2013, Health Psychology, pp. 32(9), 978.
14. *Nonpharmaceutical interventions implemented by US cities during the 1918-1919 influenza pandemic.* . **Markel, H., Lipman, H. B., Navarro, J. A., Sloan, A., Michalsen, J. R., Stern, A. M., & Cetron, M. S.** 2007, Jama, pp. 298(6), 644-654.
15. *COVID-19 control in China during mass population movements at New Year.* . **Chen, S., Yang, J., Yang, W., Wang, C., & Bärnighausen, T.** 2020, The Lancet, pp. 395(10226), 764-766.
16. *Targeted social distancing designs for pandemic influenza.* . **Glass, R. J., Glass, L. M., Beyeler, W. E., & Min, H. J.** 2006, Emerging infectious diseases, pp. 12(11), 1671.
17. *Isolation and Quarantine: containment Strategies for SARS 2003.* **Cetron M, Maloney S, Koppaka R, et al.** 2004, National Academic Press (US).

Covid Economics 28, 12 June 2020: 159-195

18. **Ferguson, N., Laydon, D., Nedjati Gilani, G., Imai, N., Ainslie, K., Baguelin, M., ... & Dighe, A.** *Report 9: Impact of non-pharmaceutical interventions (NPIs) to reduce COVID19 mortality and healthcare demand.* 2020.
19. *Motivating social distancing during the Covid-19 pandemic: An online experiment.* **Lunn, P. D., Timmons, S., Barjaková, M., Belton, C. A., Julienne, H., & Lavin, C.** 2020.
20. *The effectiveness of interventions using electronic reminders to improve adherence to chronic medication: a systematic review of the literature.* . **Vervloet, M., Linn, A. J., van Weert, J. C., De Bakker, D. H., Bouvy, M. L., & Van Dijk, L.** 2012, Journal of the American Medical Informatics Association, pp. 19(5), 696-704.
21. *Nudges at the dentist.* . **Altmann, S., & Traxler, C.** 2014, European Economic Review, pp. 72, 19-38.
22. *Planning prompts as a means of increasing preventive screening rates.* . **Milkman, K. L., Beshears, J., Choi, J. J., Laibson, D., & Madrian, B. C.** 2013, Preventive Medicine, pp. 56(1), 92-93.
23. *Using implementation intentions prompts to enhance influenza vaccination rates.* . **Milkman, K. L., Beshears, J., Choi, J. J., Laibson, D., & Madrian, B. C.** 2011, Proceedings of the National Academy of Sciences, pp. 108(26), 10415-10420.
24. *Effective reminders.* . **Calzolari, G., & Nardotto, M.** 2017, Management Science, pp. 63(9), 2915-2932.
25. *An examination of the effects of delayed versus immediate prompts on safety belt use.* . **Austin, J., Sigurdsson, S. O., & Rubin, Y. S.** 2006, Environment and behavior, pp. 38(1), 140-149.
26. *Psychological frictions and the incomplete take-up of social benefits: Evidence from an IRS field experiment.* . **Bhargava, S., & Manoli, D.** 2015, American Economic Review, pp. 105(11), 3489-3529.
27. *Dynamic salience with intermittent billing: Evidence from smart electricity meters.* . **Gilbert, B., & Zivin, J. G.** 2014, Journal of Economic Behavior & Organization, pp. 107, 176-190.
28. *The short-run and long-run effects of behavioral interventions: Experimental evidence from energy conservation.* . **Allcott, H., & Rogers, T.** 2014, American Economic Review, pp. 104(10), 3003-37.
29. *Transactions costs in charitable giving: evidence from two field experiments.* **Huck, S., & Rasul, I.** 2010, The BE Journal of Economic Analysis & Policy, p. 10(1).
30. *On reminder effects, drop-outs and dominance: Evidence from an online experiment on charitable giving.* . **Sonntag, A., & Zizzo, D. J.** 2015, PloS one, p. 10(8).
31. *The hidden costs of nudging: Experimental evidence from reminders in fundraising.* **Damgaard, M. T., & Gravert, C.** 2018, Journal of Public Economics, pp. 157, 15-26.
32. *Preventive health behavior change text message interventions: a meta-analysis.* . **Armanasco, A. A., Miller, Y. D., Fjeldsoe, B. S., & Marshall, A. L.** 2017, American Journal of Preventive Medicine, pp. 52(3), 391-402.
33. *How big is the physical activity intention–behaviour gap? A meta-analysis using the action control framework.* . **Rhodes, R. E., & de Bruijn, G. J.** 2013, British journal of health psychology, pp. 18(2), 296-309.
34. *Vaccinating to help ourselves and others.* . **Vietri, J. T., Li, M., Galvani, A. P., & Chapman, G. B.** 2012, Medical Decision Making, pp. 32(3), 447-458.
35. *Stimulating influenza vaccination via prosocial motives.* **Li, M., Taylor, E. G., Atkins, K. E., Chapman, G. B., & Galvani, A. P.** 2016, PloS one, p. 11(7).

Covid Economics 28, 12 June 2020: 159-195

36. *On the benefits of explaining herd immunity in vaccine advocacy.* . **Betsch, C., Böhm, R., Korn, L., & Holtmann, C.** 2017, Nature Human Behaviour, pp. 1(3), 1-6.
37. *Prosociality predicts health behaviors during the COVID-19 pandemic".* **Campos-Mercade P., Meier A., Schneider F., and Wengström E.** s.l. : Department of Economics, University of Zurich, Working Paper No. 346 , 2020.
38. *Social preferences under risk: the role of social distance* . **Montinari, N., & Rancan, M.** 2013, Jena Economic Research Papers, pp. (No. 2013-050).
39. *Social discounting and distance perceptions in costly altruism.* . **Vekaria, K. M., Brethel-Haurwitz, K. M., Cardinale, E. M., Stoycos, S. A., & Marsh, A. A.** 2017, Nature Human Behaviour, pp. 1(5), 1-7.
40. *Prospect theory: An analysis of decision under risk.* . **Tversky, A., & Kahneman, D.** 1979, Econometrica, pp. 47(2), 263-291.
41. *Deciding for others reduces loss aversion.* **Andersson, O., Holm, H. J., Tyran, J. R., & Wengström, E.** 2016, Management Science, pp. 62(1), 29-36.
42. *The systematic influence of gain-and loss-framed messages on interest in and use of different types of health behavior.* . **Rothman, A. J., Martino, S. C., Bedell, B. T., Detweiler, J. B., & Salovey, P.** 1999, Personality and Social Psychology Bulletin, pp. (11), 1355-1369.
43. *An affective booster moderates the effect of gain-and loss-framed messages on behavioral intentions for colorectal cancer screening.* . **Ferrer, R. A., Klein, W. M., Zajac, L. E., Land, S. R., & Ling, B. S.** 2012, Journal of behavioral medicine, pp. 35(4), 452-4.
44. *The neural basis of loss aversion in decision-making under risk.* **Tom, S. M., Fox, C. R., Trepel, C., & Poldrack, R. A.** 2007, Science, pp. 315(5811), 515-518.
45. *Bridging the intention–behaviour gap: Planning, self-efficacy, and action control in the adoption and maintenance of physical exercise.* . **Sniehotta, F. F., Scholz, U., & Schwarzer, R.** 2005, Psychology & Health, pp. 20(2), 143-160.
46. *The effects of on-screen, point of care computer reminders on processes and outcomes of care.* . **Shojania, K. G., Jennings, A., Mayhew, A., Ramsay, C. R., Eccles, M. P., & Grimshaw, J.** 2009, Cochrane Database of Systematic Reviews, p. (3).
47. *The roles of altruism, free riding, and bandwagoning in vaccination decisions.* . **Hershey, J. C., Asch, D. A., Thumasathit, T., Meszaros, J., & Waters, V. V.** 1994, Organizational behavior and human decision processes, pp. 59(2), 177-187.
48. *Human volition: towards a neuroscience of will.* . **Haggard, P.** 2008, Nature Reviews Neuroscience, pp. 9(12), 934-946.
49. *Multiple surveys of students and survey fatigue.* **Porter, S. R., Whitcomb, M. E., & Weitzer, W. H.** 2004, New directions for institutional research, pp. 2004(121), 63-73.
50. *Data collection in a flat world: The strengths and weaknesses of Mechanical Turk samples.* **Goodman, J. K., Cryder, C. E., & Cheema, A.** 2013, Journal of Behavioral Decision Making, pp. 26(3), 213-224.

Covid Economics 28, 12 June 2020: 159-195

Covid Economics 28, 12 June 2020: 159-195

Appendix A: Tests of balance

In Table 2, we test balance across treatments in the sociodemographic characteristics of respondents provided by Statistics Denmark. The sample is the one used for our main estimations (Figure 2 in the main text and Table 6 in Appendix D). For each covariate, we report the difference between its mean in the different treatment groups and the control mean (with standard errors in parentheses). The results show that covariates are balanced across treatment groups.

Table 2: Balance of covariates across treatments

Variable	Categories	Treatments					Control mean	N
		Personal	Family	Others	Country	Generic		
Gender	M	0.039	0.013	-0.019	0.022	0.032	0.423	5,310
		(-0.026)	(-0.026)	(-0.026)	(-0.026)	(-0.030)	(-0.021)	
	F	-0.039	-0.0132	0.0192	-0.0223	-0.0324	0.577	5,310
		(-0.026)	(-0.026)	(-0.026)	(-0.026)	(-0.030)	(-0.021)	
Age	18-29	0.00276	0.00437	0.0132	0.0166	-0.0111	0.144	5,310
		(-0.018)	(-0.019)	(-0.019)	(-0.019)	(-0.021)	(-0.015)	
	30-39	0.00342	0.00579	-0.0067	-0.0079	0.0119	0.138	5,310
		(-0.018)	(-0.018)	(-0.018)	(-0.018)	(-0.022)	(-0.015)	
	40-49	-0.0168	-0.017	-0.0236	-0.0026	-0.0253	0.205	5,310
		(-0.021)	(-0.021)	(-0.021)	(-0.021)	(-0.024)	(-0.017)	
	50-59	-0.0041	0.0125	0.0108	0.00833	0.0311	0.248	5,310
		(-0.023)	(-0.023)	(-0.023)	(-0.023)	(-0.027)	(-0.018)	
	60-69	0.0147	-0.0057	0.00637	-0.0144	-0.0066	0.264	5,310
		(-0.023)	(-0.023)	(-0.023)	(-0.023)	(-0.027)	(-0.019)	
Region	Nordjylland	-0.0164	-0.024	-0.0221	-0.0179	0.00645	0.121	5,310
		(-0.017)	(-0.017)	(-0.017)	(-0.017)	(-0.020)	(-0.014)	
	Midtjylland	-0.0243	-0.0349	-0.0306	-0.0266	-0.0167	0.261	5,310
		(-0.023)	(-0.023)	(-0.023)	(-0.023)	(-0.027)	(-0.019)	
	Syddanmark	0.00812	0.0523**	0.0206	0.0146	0.0185	0.192	5,310
		(-0.021)	(-0.022)	(-0.021)	(-0.021)	(-0.025)	(-0.017)	
	Hovedstaden	0.0217	0.00986	0.0336	0.0133	-0.04	0.308	5,310
		(-0.024)	(-0.025)	(-0.024)	(-0.024)	(-0.028)	(-0.020)	
	Sjælland	0.0109	-0.0033	-0.0014	0.0166	0.0317	0.119	5,310
		(-0.017)	(-0.017)	(-0.017)	(-0.017)	(-0.021)	(-0.014)	
Highest completed education	Elementary school	-0.0112	-0.0349*	-0.0057	0.00717	0.00461	0.167	5,310
		(-0.019)	(-0.019)	(-0.019)	(-0.020)	(-0.023)	(-0.016)	
	Youth Education	0.00224	0.00952	0.0186	0.00797	0.0432	0.388	5,310
		(-0.026)	(-0.026)	(-0.025)	(-0.026)	(-0.030)	(-0.021)	
	Short + Medium Long Ex.	-0.0056	0.0202	-0.0153	0.0205	-0.0331	0.273	5,310
		(-0.023)	(-0.024)	(-0.023)	(-0.024)	(-0.027)	(-0.019)	
	Long Higher education	0.0146	0.00526	0.00242	-0.0356*	-0.0146	0.171	5,310
		(-0.020)	(-0.020)	(-0.020)	(-0.019)	(-0.023)	(-0.016)	
Equivalent disposable income for the family	<150	-0.0175	-0.0074	-0.0003	-0.0045	-0.0199	0.155	5,310
		(-0.019)	(-0.019)	(-0.019)	(-0.019)	(-0.022)	(-0.015)	
	150-250	-0.0293	-0.0255	-0.0081	0.00487	-0.0093	0.255	5,310
		(-0.023)	(-0.023)	(-0.023)	(-0.023)	(-0.027)	(-0.019)	
	250-350	0.0265	0.0311	0.00189	0.0046	0.0723**	0.273	5,310
		(-0.024)	(-0.024)	(-0.023)	(-0.023)	(-0.028)	(-0.019)	
	>350	0.0203	0.00186	0.00656	-0.005	-0.0431	0.317	5,310
		(-0.025)	(-0.025)	(-0.024)	(-0.024)	(-0.028)	(-0.020)	

For each covariate we test the difference in means between the control group and the treatment groups. Each cell shows the difference with standard errors in parentheses. Confidence: *** p<0.01, ** p<0.05, * p<0.10.

Covid Economics 28, 12 June 2020: 159-195

Appendix B: Treatments

This section shows the reminders as they appeared to respondents. For each reminder, we indicate the main focus of the framing ("you", "family", "others", "country") and whether the message was framed in terms of the risks from not complying ("loss") or the benefits from complying ("gain") with the recommendation to stay home.

Table 3: Treatments

FRAME **(Consequences for…)**	**DOMAIN** **(Loss / Gain)**	**MESSAGE**
CONTROL GROUP		NO REMINDER
PERSONAL	Loss	IF YOU GO OUTSIDE AND BECOME INFECTED, **YOU MAY GET** VERY SERIOUS RESPIRATORY PROBLEMS STAY HOME AS MUCH AS POSSIBLE
	Gain	IF YOU STAY HOME, **YOU PROTECT YOURSELF** FROM THE RISK OF GETTING VERY SERIOUS RESPIRATORY PROBLEMS STAY HOME AS MUCH AS POSSIBLE

Covid Economics 28, 12 June 2020: 159-195

FAMILY	Loss	**THINK OF YOUR LOVED ONES** IF YOU GO OUTSIDE AND BECOME INFECTED, **YOU MAY INFECT THEM,** AND THEY MAY GET VERY SERIOUS RESPIRATORY PROBLEMS STAY HOME AS MUCH AS POSSIBLE
	Gain	**THINK OF YOUR LOVED ONES** IF YOU STAY HOME, **YOU PROTECT THEM** FROM THE RISK OF GETTING VERY SERIOUS RESPIRATORY PROBLEMS STAY HOME AS MUCH AS POSSIBLE
OTHERS	Loss	IF YOU GO OUTSIDE AND BECOME INFECTED, **YOU MAY INFECT OTHERS,** WHO MAY GET VERY SERIOUS RESPIRATORY PROBLEMS STAY HOME AS MUCH AS POSSIBLE

Covid Economics 28, 12 June 2020: 159-195

	Gain	IF YOU STAY HOME, **YOU PROTECT OTHERS** FROM THE RISK OF GETTING VERY SERIOUS RESPIRATORY PROBLEMS STAY HOME AS MUCH AS POSSIBLE
COUNTRY	Loss	IF YOU GO OUTSIDE AND BECOME INFECTED, **YOU MAY CONTRIBUTE TO AN OVERLOADING OF THE DANISH HEALTH CARE SYSTEM** STAY HOME AS MUCH AS POSSIBLE
	Gain	IF YOU STAY HOME, **YOU REDUCE THE RISK OF AN OVERLOADING OF THE DANISH HEALTH CARE SYSTEM** STAY HOME AS MUCH AS POSSIBLE

GENERIC WARNING	STAY HOME AS MUCH AS POSSIBLE

Covid Economics 28, 12 June 2020: 159-195

CEPR PRESS

Covid Economics 28, 12 June 2020: 159-195

Appendix C: Questionnaires

This section reports the questions that form part of the two questionnaires we administered. Respondents completed the first questionnaire immediately after reading the reminder. They received and completed the second questionnaire in the following days (no earlier than two days after completing the first questionnaire to prevent inconsistent answers).

First questionnaire

Table 4 reports the English translation of all the questions in the first questionnaire.

Table 4: First questionnaire

	QUESTION	OPTIONS
Q1	*On a scale from 1 to 5, how worried do you feel at the moment?*	*1-5*
Q2	*On a scale from 1 to 5, how sad do you feel at the moment?*	*1-5*
Q3	*How do you think your health is overall?*	- *Excellent* - *Very good* - *Good* - *Not very good* - *Bad* - *Do not know*
Q4	*For how long do you think you will go out of your house tomorrow?* *Please give your answer in minutes and/ or hours* *(If you are spending time in your own garden, it is seen as staying home, so you should not include this time in your answer)*	*Hours and Minutes*
Q5	*What is the maximum distance from home you are going to reach tomorrow?* *Please give your answer in meters and/or kilometers* *(If you are spending time in your own garden, it is seen as staying and you should answer "0")*	*Kilometers and Meters*
Q6	*For how long do you think, on average, other people in Denmark will go out tomorrow, on average?* *Please give your answer in minutes and/ or hours*	*Hours and Minutes*
Q7	*On a scale of 1 to 100%, how likely do you think it is that you will be infected with the Coronavirus?*	*1-100*

Q8	*To what extent do you trust the Danish government to take care of the citizens of the country in connection with the Corona situation?*	- *Strongly distrust* - *Somewhat distrust* - *Neither trust not distrust* - *Somewhat trust* - *Strongly trust* - *Refusing to answer* - *Do not know*

Follow-up questionnaire

Table 5: Follow-up questionnaire

	QUESTION	OPTIONS
Q1	*On a scale from 1 to 5, where 1 means very little and 5 means very much, how angry do you feel at the moment?*	*1-5*
Q2	*On a scale from 1 to 5, where 1 means very little and 5 means very much, how worried do you feel at the moment?*	*1-5*
Q3	*On a scale from 1 to 5, where 1 means very little and 5 means very much, how sad do you feel at the moment?*	*1-5*
Q4	*For how long did you leave your home yesterday?* *(If you are spending time in your own garden, it is seen as staying home, so you should not include this time in your answer)*	*Hours and Minutes*
Q5	*What was the maximum distance from home you reached yesterday?*	*Kilometers and Meters*
Q6	*What were the reasons for you to leave your home yesterday (check all that apply)?*	- *Work* - *Purchase* - *Physical activity (e.g., walking, running, cycling)* - *Medical treatment (e.g., in hospital or at own doctor)* - *Drugstore* - *Visiting / caring for relatives* - *Ventilate a pet* - *Meet with friends or family* - *Other:*
Q7	*Did someone else who lives with you go out yesterday?* *(If the individual was only in his/her own garden, it is seen as staying hope and you are asked to answer "no")*	- *Yes* - *No* - *Refusing to answer* - *Do not know*

Covid Economics 28, 12 June 2020: 159-195

Q8	*How much do you trust the Danish government to take care of its citizens?*	- *Strongly distrust* - *Somewhat distrust* - *Neither trust not distrust* - *Somewhat trust* - *Strongly trust* - *Refusing to answer* - *Do not know*
Q9	*On a scale from 0-100 how important do you think it is that everyone stays at home in Denmark?*	*0-100*
Q10	*On a scale from 0 - 100 how important do you think others believe it is to stay at home in Denmark?*	*0-100*
Q11	*How effective do you think the social distancing measures are in slowing down the spread of the coronavirus?*	- *Very effective* - *Effective* - *Neither effective nor ineffective* - *Not effective* - *Not effective at all* - *Do not know*
Q12	*Which of the following consequences of the epidemic are you most concerned about?*	- *Health system overload* - *Economic consequences of the shutdown for Denmark* - *Financial consequences of the shutdown for my family* - *The effect of isolation on my well-being* - *The impact on my social life and lifestyle* - *Other things*
Q13	*How strongly do you agree with the following statement?* *"The healthcare system will be overloaded by the COVID19 epidemic".*	- *Strongly agree* - *Agree* - *Neither agree or disagree* - *Disagree* - *Strongly disagree* - *Refusing to answer* - *Do not know*
Q14	*How many people in Denmark do you think will be infected (tested positive) with Coronavirus in a month?*	*0-…*

Covid Economics 28, 12 June 2020: 159-195

Appendix D: Table of main results

This section reports the full set of regression results from the estimation of the empirical model outlined in the "Methods" section and discussed in the article (see Figure 2).

Table 6: Effect of the treatments and sub-treatments on intentions and actions of staying home

	(1)	(2)	(3)	(4)
REMINDERS	Intention	Action	Intention	Action
You	0.044***	0.0288		
	(0.016)	(0.0188)		
Family	0.044***	0.0217		
	(0.016)	(0.0189)		
Others	0.012	0.0135		
	(0.016)	(0.0185)		
Country	0.025	0.0298		
	(0.016)	(0.0188)		
You loss			0.0449**	0.0273
			(0.0196)	(0.0223)
You gain			0.0432**	0.0302
			(0.0193)	(0.0221)
Family loss			0.0471**	0.0251
			(0.0198)	(0.0223)
Family gain			0.0398**	0.0183
			(0.0197)	(0.0223)
Others loss			0.00421	-0.000453
			(0.0181)	(0.0214)
Others gain			0.0181	0.0260
			(0.0181)	(0.0216)
Country loss			0.0270	0.0171
			(0.0185)	(0.0215)
Country gain			0.0237	0.0436*
			(0.0189)	(0.0227)
Generic	0.025	0.0322	0.0249	0.0322
	(0.019)	(0.0223)	(0.0190)	(0.0224)
Controls	Yes	Yes	Yes	Yes
Observations	5,310	5,310	5,310	5,310

Note: The table shows treatment effects relative to receiving no reminder. Control mean (intentions) = 0.0953; Control mean (actions) = 0.1457. Intentions refer to the day after the first interview, actions refer to the day before the follow-up interview. Respondents who referred to a weekday in the first interview and to a weekend day in the follow-up interview (and vice-versa) are dropped from the sample to avoid inconsistencies. The resulting sample size is $N = 5,310$. Controls include the following balancing covariates (used at the randomisation stage): gender, age, region, education, and household disposable income per capita. Robust standard errors in parentheses. Confidence: *** p<0.01, ** p<0.05, * p<0. 10.

Covid Economics 28, 12 June 2020: 159-195

Appendix E: Robustness checks

In this section, we document the results of a battery of robustness checks to test the sensitivity of our results with respect to some key choices made when defining the sample of interest. The results are reported in Table 7 below.

First, the sample for the analysis was limited to respondents who referred to a weekday or a weekend day both in the baseline and in the follow-up survey (Col.1-2). This is a reasonable approach, as not doing so would make the two answers incomparable. Nonetheless, we check the robustness of our results to reinstating all the observations we have. Upon doing that, we find that the magnitude of the effects of the most effective treatments ("you" and "family") decreases slightly, but treated subjects still declare an intention to stay home 31%[23] more than subjects in the control group (whose likelihood to stay home is 10.6%). Column 2 confirms the fact that there are no significant effects on the actions as discussed above.

Second, we test how our results change when we drop respondents who declared an intention to spend (or having spent) 24 hours outside their home (Col.3-4). Such responses are genuinely difficult to interpret. Those people may be away from their home for several days and may well have isolated themselves where they are (e.g., at a vacation house, which would not seem unlikely at the time of the experiment given the good weather), despite having reported being away from home for the entire day. Whether we drop such observations or code them as if the respondents stayed home, our results do not change.

Third, certain respondents answer the follow-up questionnaire with a significant delay after having responded to the baseline survey (Col.5-6). This poses a concern regarding the comparability of their answer in the first questionnaire with their answers in the second one. When we drop these

[23] "Family" treatment in the loss domain.

respondents from our sample, both the magnitude and the statistical significance of the estimated treatment effects increase slightly for the most effective treatments ("you" and "family"), but our conclusions do not change.

Since the COVID-19 crisis evolved very quickly and the situation changed between the first and the second week in our study period (as the Danish government gave the first signs of wishing to relax the restrictions it had imposed), we also test how the results change when we separate subjects who responded within the first week from the rest (Col. 7-8). When we drop the latter (who responded at a time when the situation was starting to become less tense in Denmark), our conclusions do not change. In fact, the effect on intentions of the treatment framed with respect to the dangers for one's family becomes even stronger and remains statistically significant despite the lower sample size. We still do not detect, however, significant impacts on actions, except for a positive effect of the "you" treatment in the gain domain, which is only significant at the 10% level.

Finally, since the treatment effects on actions appear to be generally smaller than those on intentions, detecting their statistical significance is naturally more difficult. In order to increase statistical power, we pool the "you" and the "family" treatment and re-run the analysis on both intentions and actions. Such a strategy is inspired by the conceptual affinity of those two treatments (both pertaining to the personal sphere) and is corroborated by the fact that they have very similar effects on both intentions and actions throughout the analysis. For simplicity, we also pool the other two framed treatments ("others" and "country"), which are also conceptually affine (whether we do that or not, however, does not change the results). Upon running such a test (Col.9-10), we are unable to detect significant effects of the aggregate treatments on actions, despite the increase in statistical power, and our conclusions do not change.

Covid Economics 28, 12 June 2020: 159-195

Covid Economics 28, 12 June 2020: 159-195

Table 7: Robustness checks

	Non-matching days included		Exclude subjects who spend 24h out of home		Excluded subjects who answered the follow-up later than 1 w after the first survey		First week only		Aggregate treatments	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
REMINDERS	Intention	Action	Intention	Action	Intention	Action	Intention	Action	Intention	Action
You loss	0.031*	0.0214	0.0441**	0.0281	0.0438**	0.0261	0.0254	0.0251		
	(0.018)	(0.0207)	(0.0197)	(0.0224)	(0.0198)	(0.0225)	(0.0226)	(0.0256)		
You gain	0.018	0.0106	0.0441**	0.0272	0.0412**	0.0301	0.0417*	0.0436*		
	(0.017)	(0.0201)	(0.0195)	(0.0221)	(0.0194)	(0.0223)	(0.0231)	(0.0259)		
Family loss	0.031*	0.0155	0.0462**	0.0236	0.0528***	0.0275	0.0575**	0.0315		
	(0.018)	(0.0205)	(0.0199)	(0.0223)	(0.0203)	(0.0228)	(0.0243)	(0.0261)		
Family gain	0.020	0.00403	0.0367*	0.0210	0.0414**	0.0196	0.0323	0.0325		
	(0.018)	(0.0204)	(0.0198)	(0.0225)	(0.0200)	(0.0226)	(0.0230)	(0.0260)		
Others loss	0.006	0.00507	0.00265	-0.000157	0.00576	-0.00813	0.00415	-0.0122		
	(0.017)	(0.0201)	(0.0182)	(0.0215)	(0.0184)	(0.0215)	(0.0218)	(0.0242)		
Others gain	0.017	0.00416	0.0192	0.0225	0.0198	0.0257	0.0132	0.0307		
	(0.017)	(0.0196)	(0.0183)	(0.0216)	(0.0184)	(0.0219)	(0.0214)	(0.0249)		
Country loss	0.019	0.0111	0.0272	0.0190	0.0289	0.0190	0.0180	0.00584		
	(0.017)	(0.0199)	(0.0187)	(0.0216)	(0.0187)	(0.0218)	(0.0219)	(0.0245)		
Country gain	0.027	0.0375*	0.0233	0.0448**	0.0219	0.0391*	0.00874	0.0311		
	(0.018)	(0.0209)	(0.0190)	(0.0228)	(0.0191)	(0.0229)	(0.0221)	(0.0260)		
You and Family									0.0438***	0.0253
									(0.0155)	(0.0178)
Others and Country									0.0183	0.0215
									(0.0155)	(0.0177)
Generic	0.017	0.00233	0.0238	0.0353	0.0253	0.0346	0.000467	0.0419	0.0249	0.0321
	(0.017)	(0.0199)	(0.0191)	(0.0225)	(0.0191)	(0.0227)	(0.0214)	(0.0259)	(0.0199)	(0.0228)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,674	6,674	5,249	5,249	5,159	5,159	3,843	3,843	5,310	5,310

Note: Intentions refer to the day after the first interview, actions refer to the day before the follow-up interview. Controls include the following balancing covariates (used at the randomisation stage): gender, age, region, education, and household disposable income per capita. Robust standard errors in parentheses. Confidence: *** p<0.01, ** p<0.05, * p<0.10.

Covid Economics 28, 12 June 2020: 159-195

Appendix F: Analysis of heterogeneous effects

This section reports the regression results from the estimation of the empirical model outlined in the "Methods" section on two distinct subsamples: people in good and bad health. The results are discussed in the article (see Figure 3).

Table 8: Heterogeneous effects by health status

	Good Health		Bad Health	
	(1)	(2)	(3)	(4)
REMINDERS	Intention	Action	Intention	Action
You loss	0.033*	0.0131	0.157*	0.161*
	(0.020)	(0.0227)	(0.0804)	(0.0877)
You gain	0.044**	0.0270	0.0410	0.0557
	(0.020)	(0.0229)	(0.0666)	(0.0762)
Family loss	0.034*	0.00574	0.156**	0.174**
	(0.020)	(0.0226)	(0.0742)	(0.0821)
Family gain	0.039*	0.0158	0.0490	0.0386
	(0.020)	(0.0232)	(0.0689)	(0.0775)
Others loss	-0.005	-0.0154	0.0856	0.124
	(0.018)	(0.0217)	(0.0704)	(0.0810)
Others gain	0.003	0.00900	0.129*	0.149*
	(0.018)	(0.0220)	(0.0672)	(0.0763)
Country loss	0.012	0.00916	0.113*	0.0541
	(0.019)	(0.0223)	(0.0668)	(0.0714)
Country gain	0.016	0.0302	0.0785	0.144*
	(0.019)	(0.0234)	(0.0693)	(0.0800)
Generic	0.017	0.0230	0.0747	0.0922
	(0.019)	(0.0231)	(0.0683)	(0.0755)
Controls	Yes	Yes	Yes	Yes
Observations	4,704	4,704	603	603

Note: The table shows treatment effects relative to receiving no reminder. Control mean - Good Health (intentions) = 0.089; Control mean - Good Health (actions) = 0.138; Control mean - Bad Health (intentions) = 0.14; Control mean - Bad Health (actions) = 0.2. Respondents classify their health status on a 5-point scale. The lowest two values are considered bad health conditions for the purpose of this analysis (focusing exclusively on those with the lowest value would leave us with little statistical power). Health information missing for 3 respondents. Controls include the following balancing covariates (used at the randomisation stage): gender, age, region, education, and household disposable income per capita. Robust standard errors in parentheses. Confidence: *** p<0.01, ** p<0.05, * p<0.10.

Appendix G: Timeline and Mobility Trends

In this section, we first report the timeline of the most salient events that occurred during the most critical period of the COVID-19 crisis in Denmark, up to the end of our study period (Figure 4).

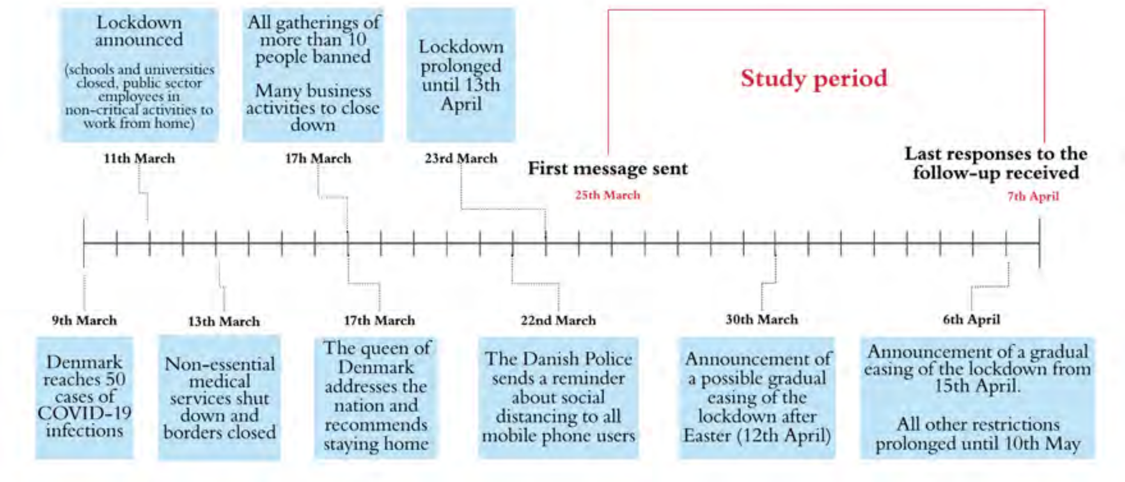


Figure 4. Timeline of relevant events related to the COVID-19 pandemic in Denmark. The figure shows that our intervention took place at the height of the crisis when maximum attention was placed on social distancing.

Covid Economics 28, 12 June 2020: 159-195

Next, we show that our data on respondents' mobility closely tracks a widely used measure of mobility based on Apple Inc.'s data from mobile-phone users in Denmark (Figure 4).

Figure 5. Mobility trends in Demark based on mobile data vs our survey. The figure shows data on how much people travel in Denmark over the period analysed. It compares data from a question on the distance travelled by the respondents in our survey with data from Apple Inc. obtained from routing requests made to Apple web mapping service (https://www.apple.com/covid19/mobility). For comparability, we plot percentage changes relative to the first date in the period. We exclude extreme values (top 1% largest distances) and individuals who travelled < 3km, since the respondents who are most likely to use a web mapping service (and to be comparable to those submitting routing requests to Apple) are the ones traveling outside their own neighborhood. If we relax this restriction, the results are similar, albeit less precise.

Covid Economics 28, 12 June 2020: 159-195

Appendix H: Attrition

In this section, we test whether the probability that a respondent drops out of the sample between the first survey and the follow-up survey correlates with assignment to treatment. The raw data in Table 9 show that attrition is strongly balanced across treatment groups.

Table 9: Number of respondents and attrition rate

GROUP	DOMAIN	Completed first survey	Completed follow-up survey	Attrition rate
Group 0		1,285	692	46%
Group 1		1,268	674	47%
Group 2	You	2,472	1,311	47%
Group 3	Family	2,480	1,264	49%
Group 4	Others	2,508	1,397	44%
Group 5	Country	2,560	1,343	48%
Total		12,573	6,681	47%

As a formal test, we regress the probability of dropping out of the sample on being in each of the treatment groups and we find no relationship (Table 10). When we run the same analysis for the sub-treatments, we reach the same conclusion (only the sub-treatment "Others" in the gain domain is associated with a lower probability of dropping out of the sample, but the result is only significant at the 10% level).

Table 10: Effect of the treatments on the attrition rate

REMINDERS	Attrition
Generic	0.005
	(0.019)
You	0.008
	(0.017)
Family	0.027
	(0.017)
Others	-0.019
	(0.017)
Country	0.011
	(0.017)
Constant	0.450
	(0.304)
Controls	Yes
Observations	12,573

Note: Attrition between the first and the second survey. Controls include the following balancing covariates (used at the randomisation stage): gender, age, region, education and household income. Robust standard errors in parentheses. Confidence: *** p<0.01, ** p<0.05, * p<0.1