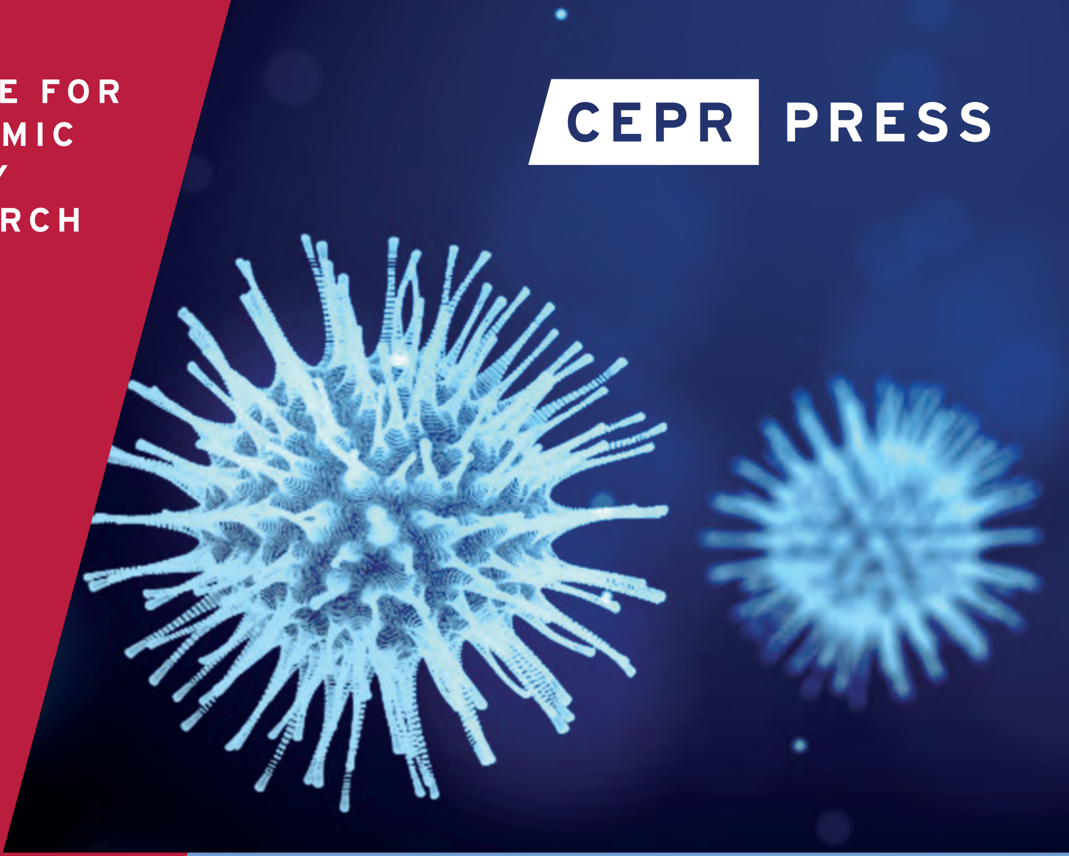
CENTRE FOR
ECONOMIC
POLICY
RESEARCH

CEPR PRESS



COVID ECONOMICS

VETTED AND REAL-TIME PAPERS

ISSUE 63
7 JANUARY 2021

THE ONLINE LABOUR MARKET
Frank Mueller-Langer
and Estrella Gomez-Herrera

WHAT WORKS?
Liming Chen, David Raitzer, Rana Hasan,
Rouselle Lavado and Orlee Velarde

HOUSEHOLD FINANCIAL VULNERABILITY
Catarina Midões and Mateo Seré

CORONA POPULISM
Patrick Mellacher

COMPLIANCE
Jacques Bughin, Michele Cincera,
Dorota Reykowska, Marcin Zyszkiewicz
and Rafal Ohme

FIRM AND HOUSEHOLD ELECTRICITY CONSUMPTION
Olympia Bover, Natalia Fabra, Sandra
García-Uribe, Aitor Lacuesta and Roberto
Ramos

CREDIT GUARANTEES IN JAPAN
Nobuyoshi Yamori and Tomoko Aizawa

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
*Econometrica**
Economic Journal
Economics of Disasters and Climate Change
International Economic Review
Journal of Development Economics
*Journal of Econometrics**
Journal of Economic Growth
Journal of Economic Theory
*Journal of the European Economic Association**
Journal of Finance
Journal of Financial Economics
Journal of International Economics
*Journal of Labor Economics**
Journal of Monetary Economics
Journal of Public Economics
Journal of Public Finance and Public Choice
Journal of Political Economy
Journal of Population Economics
Quarterly Journal of Economics
*Review of Corporate Finance Studies**
Review of Economics and Statistics
*Review of Economic Studies**
Review of Financial Studies

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

Covid Economics
Vetted and Real-Time Papers

Issue 63, 7 January 2021

Contents

Covid Economics **Issue 63, 7 January 2021**

Mobility restrictions and remote work: Empirical evidence on demand and supply on a European online labour market[1]

Frank Mueller-Langer[2] and Estrella Gomez-Herrera[3]

Date submitted: 12 December 2020; Date accepted: 15 December 2020

Intensified by the COVID-19 pandemic, online labour markets are at the core of the economic and policy debate about the future of work and the conditions under which we work online. We analyse the effects of COVID-19 related mobility restrictions on the demand, supply and hiring outcomes for remote work relative to on-site work. We benefit from the fact that the implementation of stay-at-home requirements varies by country, time and level. We use company data from a large European online labour market. Our results suggest that the stay-at-home requirements had a positive effect on the demand, supply and hiring of remote work relative to on-site work. We also find that the effect of the stay-at-home requirements on the demand, supply and hiring of remote work relative to on-site work varies substantially over time. Additional findings suggest that the stay-at-home effect is non-linear for the demand and supply of remote work and linear for the hiring of remote work. Overall, our results suggest that the flexibility provided by online labour markets may facilitate the adaptation of labour demand and labour supply to unpredicted situations where mobility is restricted.

Covid Economics 63, 7 January 2021: 1-34

1 Both authors contributed equally to this paper. Frank Müller-Langer gratefully acknowledges financial support from a research grant of the University of the Bundeswehr Munich granted by the Vice President for Research, Professor Eva-Maria Kern.
2 Department of Business Administration, University of the Bundeswehr Munich and Max Planck Institute for Innovation and Competition.
3 University of the Balearic Islands.

I. INTRODUCTION

Lockdown measures and mobility restrictions that were implemented due to the COVID-19 pandemic have challenged the labour market, transforming working patterns and working conditions. Recent empirical evidence suggests that the pandemic has negative short-term effects and caused massive job losses in several sectors (Brinca et al., 2020; Brodeur et al., 2020; Del Rio-Chanona et al., 2020; International Monetary Fund, 2020a, b; Papanikolaou and Schmidt, 2020). The latest ILO estimations reveal a decline in working hours of around 10.7 per cent relative to the last quarter of 2019, which is equivalent to 305 million full-time jobs.[1] Borjas and Cassidy (2020) explore the adverse effects of the pandemic-related mobility restrictions and lockdown measures on relative immigrant employment in the U.S. Their results suggest that immigrant workers are less likely to remain employed because they are less likely to have jobs that can be performed remotely.

In parallel, online labour markets (henceforth, OLMs) have recently gained substantial importance (Farrell and Greig, 2016; Pesole et al., 2018; Kässi and Ledhonvirta, 2018). OLMs are digital marketplaces that allow clients and freelancers to communicate, hire, and work remotely. They allow market participants to solve information problems and gain from trade in remote labour services. Intensified by the COVID-19 pandemic, OLMs are at the heart of the economic and policy debate about the future of work and the conditions under which we work online (Acemoglu and Autor, 2010; Balliester and Elshekhi, 2018; Berg, 2016; Berg et al., 2018; Codagnone et al., 2016; European Commission, 2016a, b; Gonzalez-Vazquez et al., 2019; Von der Leyen, 2019a, b).

Using company data from a large European OLM, we analyse the effects of stay-at-home requirements on the demand, supply and hiring outcomes for remote work relative to on-site work. We define “remote work” as projects that can be done remotely, e.g., online from the home office. In contrast, “on-site work” is given by projects that should be done on-site, e.g., on the clients’ premises. In the OLM under study, clients choose eligible freelancers to which they send projects requests (henceforth, also referred to as requests). The number of requests is our measure for demand.

Figure 1 illustrates the weekly number of requests by project type (remote vs. on-site) and year (2019 and 2020). The two upper solid lines indicate the number of requests for remote projects (2020: red, 2019: blue). The two lower dashed lines indicate the number of requests for on-site

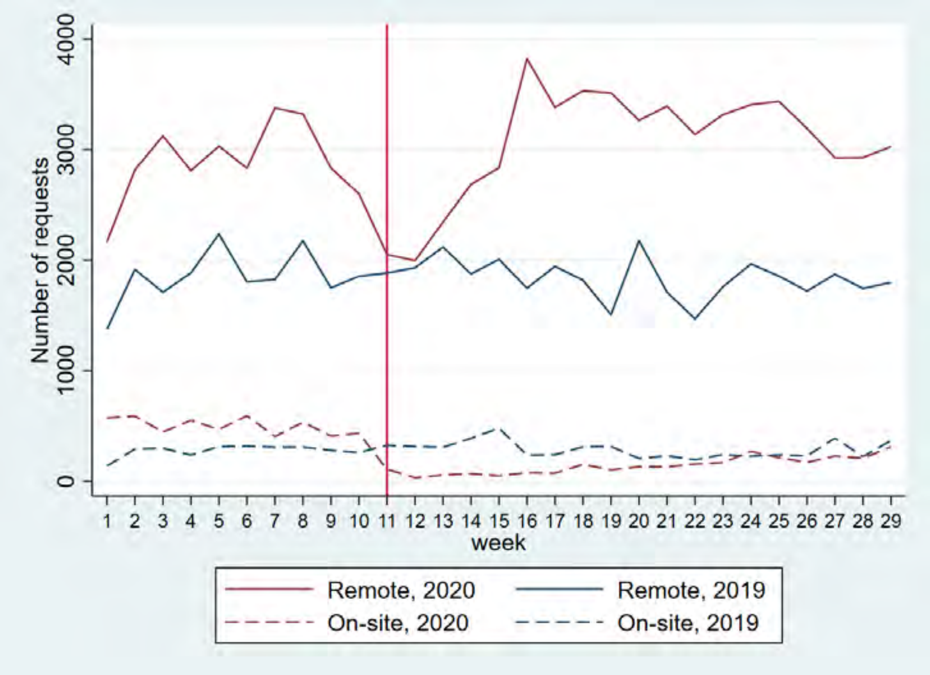
[1] ILO Monitor: COVID-19 and the world of work: https://www.ilo.org/global/about-the-ilo/newsroom/news/WCMS_743036/lang--en/index.htm (last accessed December 3, 2020).

Covid Economics 63, 7 January 2021: 1-34

projects (as before, 2020: red, 2019: blue). The vertical red line indicates 15 March 2020 in week 11, i.e., the day when most European countries started to implement their stay-at-home requirements.

Figure 1 suggests that there is no positive trend in the number of requests for remote projects before 15 March 2020 and a substantial increase afterwards.[2] It also suggests that the number of requests for on-site projects decreased after 15 March 2020. These findings contrast the results for 2019 where the numbers for both types of requests remain relatively stable over time.

Figure 1 | Weekly number of clients' requests for remote and on-site projects



Notes: Figure 1 illustrates the weekly number of requests by project type (remote vs. on-site) and year (2019 and 2020). The two upper solid lines indicate the number of requests for remote projects (2020: red, 2019: blue). The two lower dashed lines indicate the number of requests for on-site projects (as before, 2020: red, 2019: blue). The vertical red line indicates 15 March 2020 in week 11, i.e., the day when most European countries started to implement their stay-at-home requirements. Figure 1 suggests that there is no positive trend in the number of requests for remote projects before 15 March 2020 and a substantial increase afterwards. It also suggests that the number of requests for on-site projects has decreased after 15 March 2020. These findings contrast the results for 2019 where the numbers for both types of requests remain relatively stable over time.

Analysing the effects of stay-at-home requirements on demand, supply and hiring outcomes, we obtain the following main results. First, we find evidence for a positive effect of stay-at-home

[2] In Appendix Figures A1-A3, we include the country-level version of Figure 1 for the top-3 countries in the sample, i.e., France, Spain and Switzerland.

Covid Economics 63, 7 January 2021: 1-34

requirements on the demand for remote work relative to on-site work. Our results suggest that the share of clients' requests for remote projects on all requests increased by between 1.8 and 3.9 percentage points with the implementation or increase in intensity of the stay-at-home requirements.[3] Second, we provide evidence for a positive effect of the stay-at-home requirements on the supply for remote work relative to on-site work. The number of quotes that clients receive from freelancers for their projects – being our measure for supply – is 5.2 percentage points higher for remote projects after the implementation or increase in intensity of the stay-at-home requirements. Third, we find that stay-at-home requirements had a positive effect on the hiring of remote work relative to on-site work. Finally, our results suggest that the effect of the stay-at-home requirements on the demand, supply and hiring of remote work relative to on-site work varies substantially over time.[4]

The remainder of the paper is organized as follows. Section II provides an overview of the related literature. In Section III, we describe the data and empirical methodology. Section IV provides an analysis of the effects of stay-at-home requirements on remote work. In Section V, we provide additional results. Section VI discusses policy implications and concludes.

II. RELATED LITERATURE

Our paper is at the interface of three interrelated strands of literature: (1) online labour markets, (2) remote work, and (3) the impact of COVID-19 on online labour.

1. Online Labour Markets

OLMs are a growing field of research at the interface of platform economics and labour economics (Agrawal et al., 2013; Autor, 2001&2013; Chen and Horton, 2016; Dube et al., 2020; Goldfarb and Tucker, 2019; Horton and Tambe, 2015). Among other things, OLMs have been used to explore reputation systems (Benson et al., 2019; Kokkodis and Ipeirotism 2016), team production (Lyons, 2017), job referrals (Pallais and Sands, 2016), bidding cost (Snir and Hitt, 2003), outsourcing (Ghani et al., 2014), clients' recruiting invitations (Horton, 2019), hiring

[3] The main variable of interest in our panel regressions for demand, supply and hiring outcome is an ordinal variable which indicates the level of national stay-at-home requirements ranging from 0 (no stay-at-home requirements) to 3 (government requires not leaving the house with minimal exceptions). See Figure 3 below. See also Section V. "Additional Findings" where we explore whether the stay-at-home effects on demand, supply and hiring outcome are non-linear.

[4] In our demand, supply and outcome regressions, we include the time-variant number of confirmed COVID-19 cases to account for other COVID-related effects. We also include client-month fixed effects to control for other time-variant COVID-19 related effects at the level of individual clients not already controlled for by the number of COVID-19 cases.

preferences (Chan and Wang, 2018), and gender wage gaps (Gomez-Herrera and Mueller-Langer, 2019).[5] The OLM under study has several important characteristics. First, clients directly contact suitable freelancers by sending them project requests. Second, freelancers can send their quotes to prospective clients only upon request. Lastly, about 20% of the projects done on the studied OLM are on-site projects. The latter aspect is particularly important for our analysis as we analyse the effects of stay-at-home requirements on the demand, supply and hiring outcomes for remote work relative to on-site work.

2. Remote Work

Recent empirical evidence suggests that remote working increases worker productivity.[6] Bloom et al. (2015) use a field experiment at Ctrip, a large Chinese travel agency, where volunteers were randomly assigned to work from home. Bloom et al. (2015) find that working from home increased performance by 13 percentage points. Their results also suggest that working from home increased work satisfaction.[7] Mas and Pallais (2017) use a discrete choice experiment to explore the willingness of workers to pay for alternative work arrangements such as working from home or flexible scheduling. Overall, they find that most workers are not willing to pay for alternative work arrangements. However, their results also suggest that female workers have a higher willingness to pay for flexible work arrangements.[8]

Dingel and Neimann (2020) use surveys from the Occupational Information Network to explore which occupations can be done from home. Their index of suitability for remote work suggests that 37% of jobs in the US can be done from home. Bartik et al. (2020) argue that many firms could implement remote-work arrangements but refrain from doing so.

Using survey data from the U.S., Bick et al. (2020) provide evidence for the development of the share of the US workforce working from home over time. They find that this share increased by 27 percentage points from February 2020 to May 2020, i.e., the share increased from 8.2% to 35.2%. Their results also suggest that, in May 2020, 71.7% of workers for which home work was possible de facto worked from home. Adams-Prassl et al. (2020) use surveys from the U.S. and U.K. to explore the variation of work that can be performed from home. Their results suggest that, during the COVID-19 pandemic, the share of work that can be done from home increased

[5] See also Gomez-Herrera and Mueller-Langer (2019) and Gomez-Herrera et al. (2017) for an overview of the economic literature on OLMs.
[6] See Huws et al. (1990) on telework and Mokhtarian (1991) on telecommuting. See also Blinder (2009) and Blinder and Krueger (2013) on the offshorability of jobs and Oettinger (2011) on the growth of home-based work in the US from 1980 to 2000.
[7] See also Bloom (2014) on the productivity effects of working from home.
[8] See also Mas and Pallais (2020) for a thorough overview of the literature on alternative work arrangements. See Chen et al. (2019) on the value of flexible work.

Covid Economics 63, 7 January 2021: 1-34

most in occupations that had already shown high home-work shares before COVID-19. Finally, using American Time Use Survey data, Hensvik et al. (2020) provide evidence that, from 2011 to 2018, about 15% of working hours in the U.S. are done from home.

3. Impact of COVID-19 on Online Labour

Our paper is also related to a recent strand of empirical work on COVID-19 and online labour (Bartik et al., 2020a; Brynjolfsson et al., 2020; Stephany et al., 2020). Brynjolfsson et al. (2020) provide evidence on the effect of COVID-19 on the US labour market using Google Consumer Surveys. They find that about 35% of those who were employed before COVID-19 switched to working from home in April/May 2020. They also find that the share of workers working from home can be predicted by the COVID-19 incidence.

Stephany et al. (2020) use data from Kässi and Ledhonvirta's (2018) Online Labour Index and an interview-based panel of freelancers located in the US to explore the near-term effects of the COVID-19 pandemic on online labour demand and the livelihoods of freelancers. They find that online labour demand fell substantially for all occupations in early March 2020. Stephany et al. (2020) use the number of registered worker profiles as their measure for labour supply. However, they also state that this is "an imperfect proxy for the number of workers offering services through online labour platforms" (Stephany et al., 2020, p. 567). The company data that we use in our analyses allows us to exploit a different measure of labour supply, i.e., the number of quotes of workers to potential clients at the level of individual projects.

Our paper is also related to Bartik et al. (2020a) who provide evidence from two firm level surveys, i.e., the Alignable Network (AN) and the National Association of Business Economists (NABE), to explore the effect of COVID-19 on remote work in the US.[9] In the AN survey, 45% of the firms reported that any workers switched to remote work during the COVID-19 pandemic while in the NABE survey 50% of firms reported that more than 20 percent of their employees work remotely.

Our analysis contributes to these interrelated strands of literature in several important aspects. First, we use company data to explore the effect of stay-at-home requirements on remote work while the majority of prior works use survey data. Second, our data allows us to explore the effect of stay-at-home requirements on the share of remote work versus on-site work at the level of individual projects. In our panel regressions, we account for other COVID-19-related effects by including the time-variant number of COVID-19 cases and client-month fixed effects.

[9] See also Bartik et al. (2020) for an analysis of the impact of the COVID-19 pandemic on small businesses in the US.

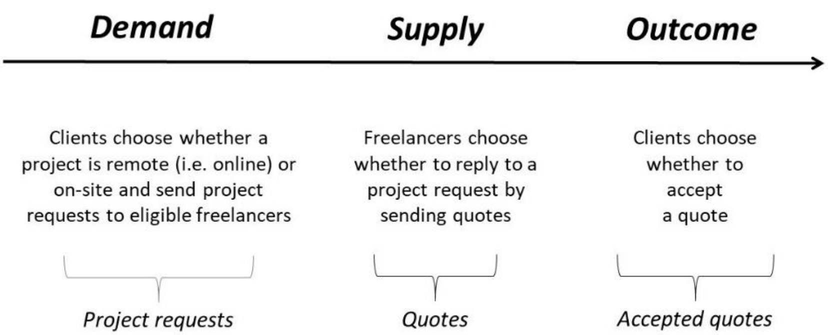
Third, our data allows us to observe the complete hiring process, i.e., demand, supply and outcome. Finally, our analysis focuses on the European labour market while the majority of prior works explores the US labour market.

III. DATA AND EMPIRICAL METHODOLOGY

1. Data

We use company data from a large European OLM that has more than 120,000 registered users in more than 120 countries around the world. Our data allows us to track the complete hiring process on the marketplace in real time starting in 1 January 2013 up to today. Figure 2 provides an overview of the timing of interactions on the studied OLM.

Figure 2 | Timing of interactions



The timing of interactions is as follows. First, the client chooses whether a given project should be performed on-site or remotely, e.g., at the client's offices or via online work in the home office, and chooses eligible freelancers[10] to which she sends a project request. Then, the contacted freelancers choose whether to reply to a project request by sending quotes to the clients, i.e., the price they charge to complete the project. Finally, the client chooses whether to accept a quote. We divide our empirical analysis into three parts according to the timing of interactions: demand, supply and outcome.

Our dataset contains information about clients' and freelancers' preferences about job location over time. Hence, it allows us to study the change in these preferences due to the implementation of stay-at-home requirements. We benefit from the fact that the stay-at-home

[10] Henceforth, we use the terms "freelancers" and "workers" interchangeably.

requirements differ by country, time and level (see Figure 3 below). We observe the city and country where the clients and freelancers are located. We also have detailed information on a large set of characteristics for more than 56,000 clients, 140,000 projects and 60,000 freelancers. Tables 1 and 2 provide summary statistics of the data at the client-day level and the project-day level, respectively.

Table 1 | Descriptive statistics for demand and outcome (Client-day level)

	N	mean	sd	min	max
Dependent variables					
Share of requests for remote projects over total (see demand analysis: Table 3)	138,563	0.821	0.124	0	1
Share of accepted quotes in remote projects over total (see outcome analysis: Table 5)	92,257	0.696	0.121	0	1
Main variables of interest					
Stay-at-home requirements, ordinal	138,320	0.168	0.505	0	3
Stay-at-home requirements level 1, binary	138,320	0.054	0.225	0	1
Stay-at-home requirements levels 2 or 3, binary	138,320	0.057	0.232	0	1
Cumulative number of confirmed COVID-19 cases, in 100,000	138,320	0.575	1.419	0	10.04
Project can be done remotely	138,563	0.726	0.446	0	1
Control variables					
Number of marketplace accounts in client company	131,573	3.909	11.24	1	158
Pricing plan 1: Low fees	138,563	0.737	0.440	0	1
Pricing plan 2: Intermediate fees	138,563	0.0894	0.285	0	1
Pricing plan 3: High fees	138,563	0.0983	0.298	0	1
Number of requests with at least one accepted quote	92,257	1.077	0.379	1	15
Number of quotes received	92,257	453.08	231.52	1	1,099
Client located in capital city	138,563	0.271	0.444	0	1
*Client countries**					
France	138,563	0.870	0.336	0	1
Spain	138,563	0.0634	0.244	0	1
Switzerland	138,563	0.0108	0.103	0	1
Germany	138,563	0.00632	0.0793	0	1
Belgium	138,563	0.00597	0.0770	0	1
Other country	138,563	0.176	0.381	0	1
Top 3 job categories#					
Software development	138,563	0.346	0.476	0	1
Graphic design	138,563	0.231	0.422	0	1
Marketing and communication	138,563	0.246	0.431	0	1

*Client countries are included in the regressions as fixed effects.
#Other job categories are Business consulting, Data, Industrial engineering, Picture sound, Project managers, Support functions, Videogames, and Other. Job categories are included in the regressions as fixed effects.

Table 2 | Descriptive statistics (Project-day level)

	N	mean	sd	min	max
Dependent variable					
Number of quotes received (see supply analysis: Table 4)	147,336	3.498	5.362	1	444
Main variables of interest					
Stay-at-home requirements, ordinal	147,072	0.169	0.506	0	3
Stay-at-home requirements level 1, binary	147,072	0.054	0.226	0	1
Stay-at-home requirements levels 2 or 3, binary	147,072	0.057	0.232	0	1
Cumulative number of confirmed COVID-19 cases, in 100,000	147,072	0.579	1.424	0	10.04
Project can be done remotely	147,336	0.716	0.451	0	1
Control variables					
Number of marketplace accounts in client company	140,102	4.252	12.26	1	158
Project request specified in fixed terms	147,336	0.989	0.103	0	1
Median daily rate of workers contacted for a project	147,330	371.3	188.9	25	8,000
Pricing plan 1: Low fees	147,336	0.728	0.445	0	1
Pricing plan 2: Intermediate fees	147,336	0.0921	0.289	0	1
Pricing plan 3: High fees	147,336	0.105	0.307	0	1
Client located in capital city	147,336	0.272	0.445	0	1
Client countries[*]					
France	147,336	0.871	0.335	0	1
Spain	147,336	0.0625	0.242	0	1
Switzerland	147,336	0.0110	0.104	0	1
Germany	147,336	0.00616	0.0783	0	1
Belgium	147,336	0.00607	0.0777	0	1
Top 3 job categories[#]					
Software development	147,336	0.345	0.475	0	1
Graphic design	147,336	0.230	0.421	0	1
Marketing and communication	147,336	0.248	0.432	0	1

[*]Client countries are included in the regressions as fixed effects.

[#]Other job categories are Business consulting, Data, Industrial engineering, Picture sound, Project managers, Support functions, Videogames, and Other. Job categories are included in the regressions as fixed effects.

Covid Economics 63, 7 January 2021: 1-34

CEPR PRESS

Our main variable of interest in the demand, supply and outcome analyses is the ordinal stay-at-home-requirement variable (see Table 3 below).[11] We obtain this variable from Hale et al. (2020a&b).

For clients, we observe the registration date, their country, the number of marketplace accounts in the company, their preference about job location, the number of project requests sent by day, and the pricing plan contracted in the OLM.[12]

For projects, we observe the location requirement (remote vs. on-site), the number of remote and on-site quotes received and accepted, the median expected wage of contacted freelancers, the job category, and whether a given project request is specified in fixed terms, i.e., the full amount to be paid is agreed upon before the project starts.

For freelancers, we observe the expected salary, their location (i.e., city and region), their preference with respect to remote work vs. on-site work, their registration date and their experience on the marketplace. Finally, we obtain the cumulative number of confirmed COVID-19 cases by country in a given day (in 100,000) from Hale et al. (2020a&b).

2. Empirical Methodology

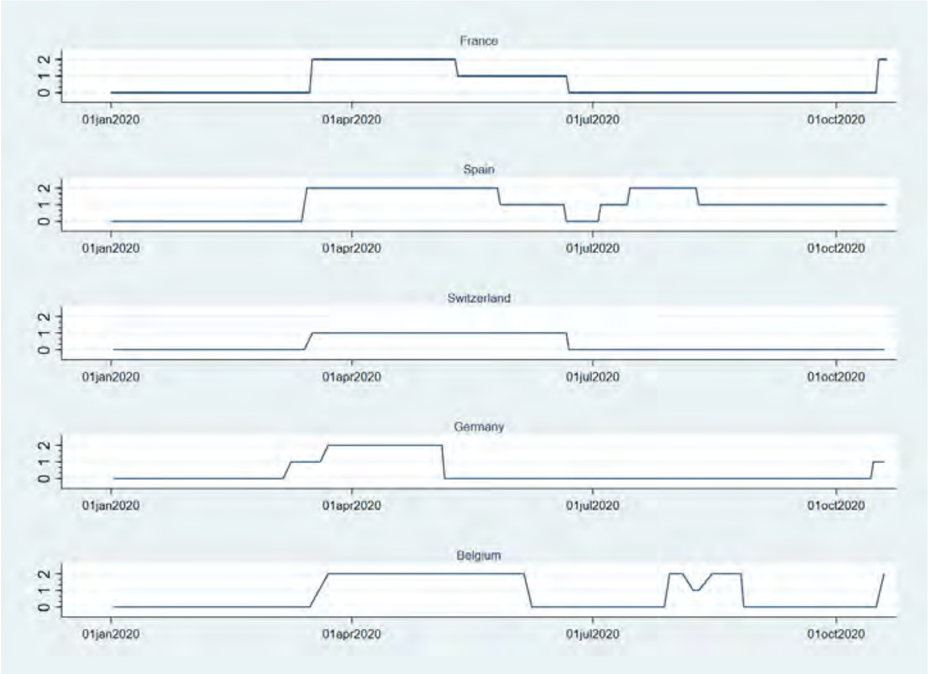
A. Stay-At-Home Requirements

Following Borjas and Cassidy (2020) and Del Rio-Chanona et al. (2020), our identification strategy takes advantage of the fact that local stay-at-home requirements vary by country, time and level.[13] Figure 3 illustrates the timing and levels of the implemented stay-at-home requirements for the five main countries in our sample, i.e., France, Spain, Switzerland, Germany and Belgium, which account for 97% of the sample.

Covid Economics 63, 7 January 2021: 1-34

[11] In Section V., we run our demand, supply and outcome regressions using separate dummy variables indicating the different levels of the stay-at-home requirements to explore possible non-linearities in the stay-at-home effects.
[12] These pricing plans differ in fees and services offered.
[13] See also Balleer et al. (2020).

Figure 3 | Stay-at-home requirements



Notes: Figure 3 illustrates the stay-at-home requirements by country and day. The ordinal variable takes value 0 when no restriction is imposed, 1 when the government recommends staying at home, 2 when the government makes it mandatory to stay at home with exceptions for daily exercise, grocery shopping, and 'essential' trips and 3 when the government requires not leaving the house with minimal exceptions. We obtain this variable from Hale et al. (2020a&b). We include the top 5 countries in the sample ranked by the number of project requests made. These top 5 countries account for 97% of the sample. Figure 3 suggests that there is substantial variation in the implementation of stay-at-home requirements by country, day and level. The maximum stay-at-home value in Figure 3 is 2 because restriction 3 was not applied in any of the top 5 countries.

The ordinal stay-at-home variable obtained from Hale et al. (2020a&b) takes value 0 when no restriction is imposed, 1 when the government recommends staying at home, 2 when the government makes it mandatory to stay at home with exceptions for daily exercise, grocery shopping, and 'essential' trips and 3 when the government requires not leaving the house with minimal exceptions (e.g., people are allowed to leave only once a week, or only one person can leave at a time, etc.). Figure 3 suggests that there is substantial variation in the implementation of stay-at-home requirements by country, time and level.

B. Demand for Online Labour

There are several potential mechanisms through which the stay-at-home requirements could cause a positive demand shock on online work (Del Rio-Chanona et al., 2020; Stephany et al., 2020).

First, due to stay-at-home requirements companies are likely to shift the work of their employees from office work to home-based remote work, i.e., remote work is a substitute for on-site work (Del Rio-Chanona et al., 2020; Stephany et al., 2020). Second, as Stephany et al. (2020, p. 563) put it, "remote-by-design online labour markets could be seeing a significant demand boost". Arguably, the COVID-19 pandemic has increased the interest of employers and clients in OLMs leading to a larger number of jobs posted on OLMs. That is, firms that are looking for new freelancers are likely to favour contracting freelancers via OLMs over on-site freelancers hired through conventional freelance intermediaries (Stephany et al., 2020). Third, companies may find it interesting to move existing (on-site) freelancing relationships to OLMs (Corporaal and Lehdonvirta, 2017; Braesemann et al., 2020).

However, there are also potential mechanisms through which the COVID-19 pandemic could cause a negative demand shock on online work. First, independent online freelancers are typically hired on a temporary basis (Stephany et al., 2020). Firms may have an incentive to terminate such non-standard work contracts before they lay-off employees to protect their core staff (Kalleberg, 2003). Arguably, the higher flexibility to react to changing demand is often an important reason for employers to prefer online freelancing over conventional employment arrangements. Based on this, firms may have an incentive to reduce non-essential spending such as the contracting of external online freelancers as a reaction to decreasing revenues due to the COVID-19 pandemic (Stephany et al., 2020).

Our data allows us to disentangle the effect of the stay-at-home requirements on the demand for online labour from the overall COVID-19 demand effect. That is, we account for possibly adverse COVID-19-related demand effects by including the time-variant number of COVID-19 cases in the demand regressions. In addition, we include client-month fixed effects to control for other time-variant COVID-19 related effects at the level of individual clients not already controlled for by the number of COVID-19 cases.

C. Supply of Online Labour

As for the potential effects of COVID-19 and stay-at-home requirements on the supply of labour on OLMs, Stephany et al. (2020) argue that the number of freelancers offering services on OLMs might increase as the COVID-19 pandemic and related mobility restrictions increased the number of unemployed workers (del Rio-Chanona et al., 2020). In addition to the potential increase in the number of (full-time) workers offering services on OLMs, freelancers that are already offering their services on OLMs in addition to a traditional employment relationship, also known as moonlighters, might have an incentive to increase the number of hours worked (Stephany et al., 2020).[14]

However, the COVID-19 pandemic and stay-at-home requirements might also have a negative effect on the supply of labour on OLMs. For instance, Stephany et al. (2020, p. 564) argue that workers that remain employed during the COVID-19 pandemic and that used to offer their services also on OLMs might decrease the number of hours worked on OLMs "to signal loyalty to their employers." Finally, the supply of labour on OLMs might also decrease because freelancers get sick or have increased duties at home because of the COVID-19 pandemic and related countermeasures (Kahn et al., 2020).

Based on the above-mentioned arguments, our paper is closely related to Stephany et al. (2020). Stephany et al. (2020, p. 567) use the number of registered worker profiles as a proxy for labour supply because the Online Labour Index that they use in their analysis does not provide them "with a direct measure of labour supply". Arguably, our data allows us to construct a "more direct" measure for online labour supply as we observe the number and the characteristics of the quotes that online freelancers send to potential clients at the level of individual projects. Finally, in a similar fashion as for the demand analysis, our data allows us to disentangle the effect of the stay-at-home requirements on the supply of online labour from the overall COVID-19 supply effect by including the time-variant number of COVID-19 cases and client-month fixed effects.

IV. ANALYSIS: STAY-AT-HOME REQUIREMENTS AND REMOTE WORK

1. Stay-at-home requirements and demand for remote work

We explore the impact of stay-at-home requirements on the demand for remote labour as given by the share of requests for remote projects over total by client and day. Using an unbalanced panel, we run the following regression at the client-day level:

[14] See Pesole et al. (2018) on moonlighting. See also Horton (2010).

Covid Economics 63, 7 January 2021: 1-34

$$ShareRemoteRequests_{c,t} = \beta_0 + \beta_1 StayHome_{cc,t} + \beta_2\, CovidCases_{cc,t} + Z_c + \mu_{cat} + \mu_m + \mu_{cc} + \mu_c + \mu_{c,m} + \varepsilon_{c,t}\,. \quad (1)$$

The dependent variable is the share of requests for remote projects over total by client *c* and day *t*. It is our measure for remote labour demand. *StayHome* is the main variable of interest. It is an ordinal variable constructed by Hale et al. (2020a&b). It measures the four different levels of the stay-at-home requirements in the country where the client is located, *cc,* in day *t*.[15] We include the time-variant cumulative number of reported COVID-19 cases in country *cc*. Z_c is a vector of additional control variables at the client level. We also include job category fixed effects, μ_{cat}, month fixed effects, μ_m, client country fixed effects, μ_{cc}, client fixed effects, μ_c, and client-month fixed effects, $\mu_{c,m}$. The results are reported in Table 3.

We run the regressions using seven different specifications. Columns (1) and (2) – where we refrain from including any control variables or fixed effects – report the raw stay-at-home effect on labour demand.[16] In column (3), we add the cumulative number of confirmed COVID-19 cases. In column (4), we add a binary variable, which indicates whether the client is located in the national capital city, and additional control variables. In column (5), we add job category fixed effects, month fixed effects and client country fixed effects. In columns (6) and (7), we include client fixed effects and client-month fixed effects, respectively. R^2 increases substantially going from columns (1) to (7). Based on this, column (7) is our preferred specification.[17]

We obtain the following main results. First, our results provide evidence for a positive effect of *StayHome* on the demand for remote work. The coefficient is positive and statistically significant at the 1% level across all columns ranging from +0.018 in column (5) to +0.039 in columns (1) and (2). This means that the share of remote projects posted by client and day increases by between 1.8 and 3.9 percentage points when the level of stay-at-home requirements increases by one unit.

[15] This variable takes four different values according to Hale et al. (2020a&b): 0 – No measures; 1 – national government recommends not leaving the house; 2 – national government requires not leaving the house with exceptions for daily exercise, grocery shopping, and 'essential' trips; 3 – national government requires not leaving the house with minimal exceptions (e.g., it is allowed to leave the house only once a week, or only one person can leave the house at a time, etc.).

[16] The only difference between Columns (1) and (2) is that we use the *reg* command in Stata in column (1) while we use the *reghdfe* command in Stata in column (2). As results are the same, henceforth, we use the *reghdfe* command to be able to include high-dimensional fixed effects.

[17] For the five main countries, we ran the regressions with all possible *StayHome*Country* interactions. However, none of the interactions is statistically significant at least at the 5% level. These interactions are thus not reported in Table 3.

Table 3 | Effects of stay-at-home requirements on demand for remote work (Client-day level)

	(1) Share of requests for remote projects over total	(2) Share of requests for remote projects over total	(3) Share of requests for remote projects over total	(4) Share of requests for remote projects over total	(5) Share of requests for remote projects over total	(6) Share of requests for remote projects over total	(7) Share of requests for remote projects over total
Stay-at-home requirement, ordinal	0.039***	0.039***	0.037***	0.036***	0.018***	0.020***	0.021***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Cumulative number of confirmed			0.004***	0.004***	-0.002***	-0.002***	-0.002*
COVID-19 cases, in 100,00			(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Client located in capital city				-0.009***	-0.001*		
				(0.001)	(0.000)		
Job category FE	NO	NO	NO	NO	YES	NO	NO
Month FE	NO	NO	NO	NO	YES	YES	YES
Client country FE	NO	NO	NO	NO	YES	NO	NO
Client FE	NO	NO	NO	NO	NO	YES	YES
Client-month FE	NO	NO	NO	NO	NO	NO	YES
Control variables included#	NO	NO	NO	YES	YES	YES	YES
Constant	0.814***	0.814***	0.812***	0.818***	0.821***	0.822***	0.818***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
Observations	138,320	138,320	138,320	122,118	121,862	94,735	41,329
R-squared	0.026	0.026	0.028	0.029	0.707	0.762	0.790

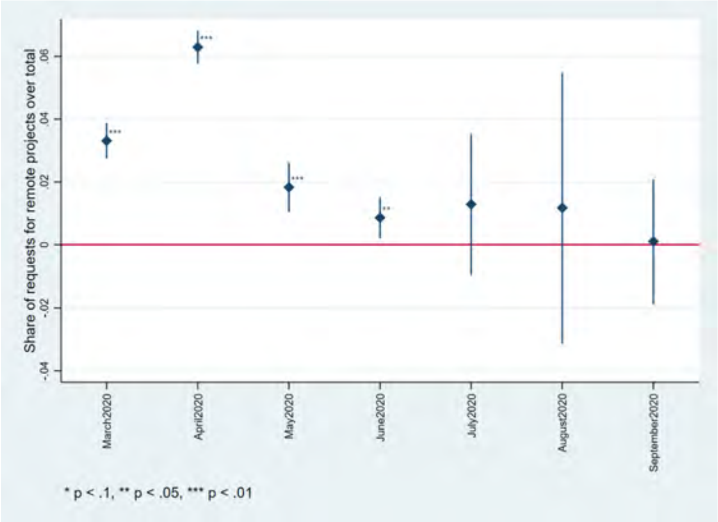
Notes: OLS regression coefficients reported. Regressions are run at the client-day level. We use the *reg* command in Stata in column (1). From column (2) on, we use the *reghdfe* command in Stata to be able to include high-dimensional fixed effects (Correia, 2017). According to Correia (2015), maintaining singleton groups in linear regressions where fixed effects are nested within clusters can overstate statistical significance and lead to incorrect inference. Due to this problem, the *reghdfe* package automatically drops singletons in columns (4) to (7). Robust standard errors clustered at client level in parentheses.
*** *p*<0.01, ** *p*<0.05, * *p*<0.1.
#Additional control variables included (results not reported): *Number of marketplace accounts in client company, Log median daily rate of freelancers contacted for a project, Pricing plans 1, 2 and 3.*
We run the regressions with all possible interactions of the stay-at-home variable with the five main countries (France, Spain, Switzerland, Germany and Belgium). None of these interactions is statistically significant at least at the 5% level.

Covid Economics 63, 7 January 2021: 1-34

Second, we find evidence for a negative correlation between the cumulative number of confirmed COVID-19 cases and the demand for remote work. While the coefficient is positive and statistically significant at the 1% level in columns (3) and (4), it is negative and statistically significant at the 1% level in columns (5) and (6) and negative and statistically significant at the 10% level in column (7). Note that R^2 increases from 0.029 in column (4) to 0.707 in column (5) and to 0.790 in column (7). Our results also suggest that the demand for remote work is smaller if clients are located in the capital city.

Figure 4 plots the interactions of the stay-at-home variable with month fixed effects using the preferred specification from Table 3 (column 7). It illustrates the effect of the stay-at-home requirements on the demand for remote work over time.

Figure 4 | Effect of *StayHome* on the demand for remote work over time



Notes: Figure 4 plots the interactions of the stay-at-home variable with month fixed effects using the preferred specification from Table 3 (column 7). Confidence intervals and statistical significance reported. Figure 4 indicates that the stay-at-home effect on the demand for remote work is heterogeneous. It reaches its maximum level in April 2020 and its minimum level in September 2020. The stay-at-home effect on the demand for remote work is positive and statistically significant at least at the 5% level from March to June 2020 while it not statistically significant from July to September 2020.

Figure 4 indicates that the stay-at-home effect on demand for remote work is heterogeneous. It reaches its maximum level in April 2020 and its minimum level in September 2020. The stay-at-home effect on the demand for remote work is positive and statistically significant at least at the 5% level from March to June 2020 while it is not statistically significant from July to September 2020.[18]

2. Stay-at-home requirements and labour supply

Besides estimating whether overall labour supply is different for different levels of the stay-at-home requirements, we explore whether the stay-home effect is different for remote work than for on-site work. We run the following regression at the project-day level:

$$\begin{aligned} LogQuotes_{p,t} = \beta_0 + \; & \beta_1 StayHome_{cc,t} + \; \beta_2 \, RemoteProject_p \\ & + \beta_3 \, CovidCases_{cc,t} + \gamma_1 StayHome_{cc,t} * RemoteProject_p \\ & + Z_p + \; \mu_{cat} + \; \mu_m + \mu_{cc} + \mu_c + \mu_{c,m} + \varepsilon_{p,t}. \end{aligned} \tag{2}$$

[18] We do not report the October-2020 interaction because Stata dropped it in the regressions.

The dependent variable is the log-transformed number of quotes that a project p receives in day t. It is our measure for labour supply. As before, *StayHome* is the main variable of interest. Hence, β_1 indicates the difference in total quotes (in terms of percentage points) when the level of the stay-at-home requirements increases by one unit. We interact *StayHome* with the indicator for remote projects. γ_1 indicates to what extent the stay-at-home labour supply effect is different for remote projects. Z_p is a vector of additional control variables at the project level. We also include job category fixed effects, μ_{cat}, month fixed effects, μ_m, client country fixed effects, μ_{cc}, client fixed effects, μ_c, and client-month fixed effects, $\mu_{c,m}$. The results are reported in Table 4.

We run the regressions using nine different specifications. Columns (1) and (2) report the raw stay-at-home effect on labour supply.[19] In columns (3) and (4), we add the remote-project indicator and the cumulative number of confirmed COVID-19 cases, respectively. In column (5), we add a binary variable, which indicates whether the client is located in the national capital city, and additional control variables. In column (6), we add job category fixed effects, month fixed effects and client country fixed effects. We include client fixed effects and client-month fixed effects in columns (7) and (8), respectively. R^2 increases substantially going from column (1) to (8). Based on this, column (8) is our preferred specification. In column (9), we include the interaction of the stay-at-home indicator with the indicator for remote work.[20]

We obtain the following main results. First, we find no evidence for a robust negative effect of the stay-at-home requirements on labour supply. The coefficient of *StayHome* ranges from -0.034 in column (9) to +0.013 in columns (1) and (2). Note that while the *StayHome* effect is positive and statistically significant at least at the 5% level in columns (1), (2) and (4) and negative and statistically significant at the 5% level in column (5), it is not statistically significant in all other columns, including our preferred column (8). Second, we provide evidence for a negative correlation between the cumulative number of confirmed COVID-19 cases and the supply of labour. The coefficient of the confirmed COVID-19 cases is negative and statistically significant at least at the 5% level across columns, with the exception of column (6) where it is negative and not statistically significant. The coefficient of confirmed COVID-19 cases increases substantially in magnitude going from column (7) to column (8) where we include client-month fixed effects,

[19] The only difference between Columns (1) and (2) is that we use the *reg* command in Stata in column (1) while we use the *reghdfe* command in Stata in column (2). As results are the same, henceforth, we use the *reghdfe* command to be able to include high-dimensional fixed effects.

[20] We ran the regressions with all possible *StayHome**RemoteProject*Country* interactions. However, none of these interactions is statistically significant at least at the 5% level and is, thus, not reported in Table 4.

i.e., it increases from -0.017 in column (7) to -0.119 in column (8). Third, we find that remote projects receive more quotes. The effect is positive, statistically significant at the 1% level and large in magnitude across columns ranging from 46.4 percentage points in column (5) to 53.9 percentage points in columns (3) and (4). Fourth, we find that the coefficient of the interaction *StayHome*RemoteProject* is positive and statistically significant at the 5% level in column (9). This suggests that the supply of remote work increases by 5.2 percentage points when the level of the stay-at-home requirements increases by one unit.

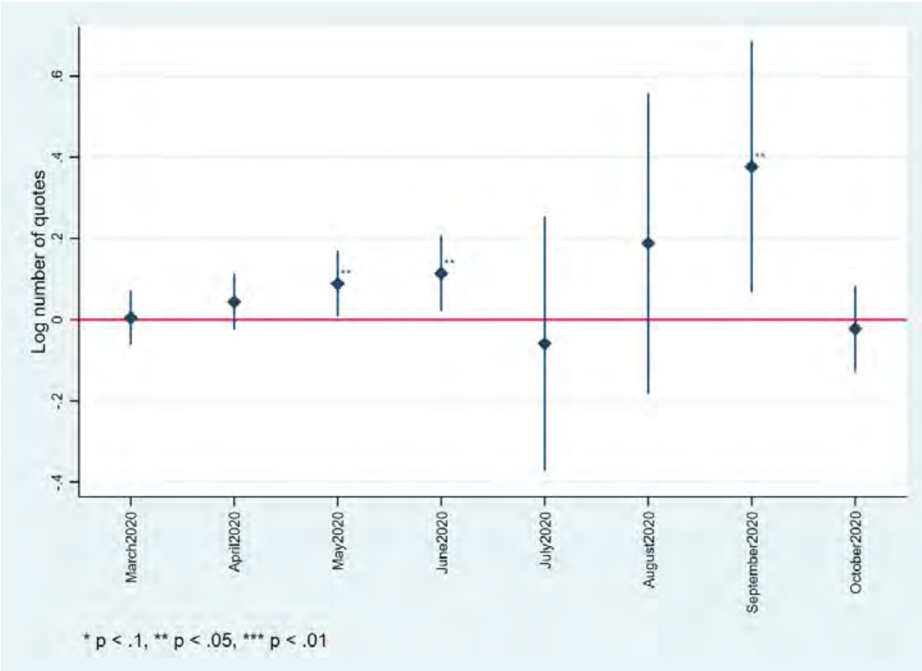
Table 4 | Effects of stay-at-home requirements on labour supply (Project-day level)

	(1) Log # quotes received	(2) Log # quotes received	(3) Log # quotes received	(4) Log # quotes received	(5) Log # quotes received	(6) Log # quotes received	(7) Log # quotes received	(8) Log # quotes received	(9) Log # quotes received
Stay-at-home requirements, ordinal	0.013***	0.013***	-0.000	0.009**	-0.010**	0.007	-0.005	-0.001	-0.034
	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.009)	(0.010)	(0.018)	(0.021)
Project can be done remotely			0.539***	0.539***	0.464***	0.486***	0.496***	0.511***	0.501***
			(0.004)	(0.004)	(0.005)	(0.005)	(0.008)	(0.013)	(0.013)
Cumulative number of confirmed COVID-19 cases, in 100,00				-0.014***	-0.012***	-0.010	-0.017**	-0.119***	-0.118***
				(0.002)	(0.002)	(0.006)	(0.008)	(0.016)	(0.016)
Client located in capital city					0.009*	-0.003			
					(0.005)	(0.005)			
Stay-at-home requirements interacted with:									
Project can be done remotely									0.052**
									(0.020)
Job category FE	NO	NO	NO	NO	NO	YES	NO	NO	NO
Month FE	NO	NO	NO	NO	NO	YES	YES	YES	YES
Client country FE	NO	NO	NO	NO	NO	YES	NO	NO	NO
Client FE	NO	NO	NO	NO	NO	NO	YES	YES	YES
Client-month FE	NO	NO	NO	NO	NO	NO	NO	YES	YES
Control variables included#	NO	NO	NO	NO	YES	YES	YES	YES	YES
Constant	0.790***	0.790***	0.406***	0.413***	0.835***	0.950***	0.497***	0.503***	0.509***
	(0.002)	(0.002)	(0.004)	(0.004)	(0.038)	(0.039)	(0.061)	(0.094)	(0.094)
Observations	147,072	147,072	147,072	147,072	130,139	129,863	103,252	51,874	51,874
R-squared	0.000	0.000	0.076	0.077	0.084	0.112	0.429	0.616	0.616

Notes: OLS regression coefficients reported. Regressions are run at the project-day level. We use the *reg* command in Stata in column (1). From column (2) on, we use the *reghdfe* command in Stata to be able to include high-dimensional fixed effects (Correia, 2017). According to Correia (2015), maintaining singleton groups in linear regressions where fixed effects are nested within clusters can overstate statistical significance and lead to incorrect inference. Due to this problem, the *reghdfe* package automatically drops singletons in columns (5) to (9). Robust standard errors clustered at project level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.
#Additional control variables included (results not reported): *Number of marketplace accounts in client company, Project request specified in fixed terms, Log median daily rate of freelancers contacted for a project, Pricing plans 1, 2 and 3.*
For the five main countries, we run the regressions with all possible interactions of *StayHome*RemoteProject*Country*. None of these interactions is statistically significant at least at the 5% level.

Figure 5 plots the triple interaction of the stay-at-home variable with the remote-project dummy and month dummies using the preferred specification from Table 4 (column 8). It indicates that the effect of the stay-at-home requirements on the supply of remote work is positive and statistically significant at the 5% level in May, June and September 2020. It also shows that the magnitude of the stay-home supply effect varies substantially over time.

Figure 5 | Effect of *StayHome* on the supply of remote work over time



Notes: Figure 5 plots the triple interaction of the stay-at-home variable with the remote-project dummy and month dummies using the preferred specification from Table 4 (column 8). Confidence intervals and statistical significance reported. Figure 5 indicates that the effect of the stay-at-home requirements on the supply of remote work is positive and statistically significant at the 5% level in May, June and September 2020. It also shows that the magnitude of the stay-home supply effect varies substantially over time.

3. Stay-at-home requirements and hiring of remote work

We explore the effects of the stay-at-home requirements on the hiring of remote work as given by the share of accepted quotes in remote projects over total quotes. Using an unbalanced panel, we run the following regression at the client-day level:

$$\begin{aligned} ShareAcceptedQuotesRemote_{c,t} \\ = \beta_0 + \beta_1 StayHome_{cc,t} + \beta_2\, CovidCases_{cc,t} + Z_c \\ + \mu_{cat} + \mu_m + \mu_{cc} + \mu_c + \mu_{c,m} + \varepsilon_{c,t}. \end{aligned} \tag{3}$$

The dependent variable is the share of accepted quotes in remote projects over total accepted quotes for client *c* in day *t*. *StayHome* is the main variable of interest. β_1 indicates the difference in the share of accepted quotes for remote projects over total when the level of the stay-at-home requirements increases by one unit. Z_c is a vector of additional control variables at the client level. We also include job category fixed effects, μ_{cat}, month fixed effects, μ_m, client

Covid Economics 63, 7 January 2021: 1-34

country fixed effects, μ_{cc}, client fixed effects, μ_c, and client-month fixed effects, $\mu_{c,m}$. The results are reported in Table 5.

Table 5 | Effects of stay-at-home requirements on outcome (Client-day level)

	(1) Share of accepted quotes in remote projects over total	(2) Share of accepted quotes in remote projects over total	(3) Share of accepted quotes in remote projects over total	(4) Share of accepted quotes in remote projects over total	(5) Share of accepted quotes in remote projects over total	(6) Share of accepted quotes in remote projects over total	(7) Share of accepted quotes in remote projects over total
Stay-at-home requirements,	0.013***	0.013***	0.012***	0.009***	0.004***	0.005***	0.008***
ordinal	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Cumulative number of confirmed			0.001**	-0.001***	-0.003***	-0.005***	-0.006***
COVID-19 cases, in 100,00			(0.000)	(0.000)	(0.001)	(0.001)	(0.002)
Client located in capital city				-0.007***	-0.001		
				(0.001)	(0.001)		
Job category FE	NO	NO	NO	NO	YES	NO	NO
Month FE	NO	NO	NO	NO	YES	YES	YES
Client country FE	NO	NO	NO	NO	YES	NO	NO
Client FE	NO	NO	NO	NO	NO	YES	YES
Client-month FE	NO	NO	NO	NO	NO	NO	YES
Control variables included#	NO	NO	NO	YES	YES	YES	YES
Constant	0.694***	0.694***	0.694***	0.625***	0.770***	0.754***	0.760***
	(0.001)	(0.001)	(0.001)	(0.012)	(0.008)	(0.009)	(0.015)
Observations	92,090	92,090	92,090	85,972	85,761	67,351	27,593
R-squared	0.003	0.003	0.003	0.011	0.475	0.573	0.654

Notes: OLS regression coefficients reported. Regressions are run at the client-day level. We use the *reg* command in Stata in column (1). From column (2) on, we use the *reghdfe* command in Stata to be able to include high-dimensional fixed effects (Correia, 2017). According to Correia (2015), maintaining singleton groups in linear regressions where fixed effects are nested within clusters can overstate statistical significance and lead to incorrect inference. Due to this problem, the *reghdfe* package automatically drops singletons in columns (4) to (7). Robust standard errors clustered at client level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.
#Additional control variables included (results not reported): *Number of marketplace accounts in client company, Pricing plans 1, 2 and 3, Log number of quotes received, Log number of requests made.*
We run the regressions with all possible interactions of the stay-at-home variable with the five main countries (France, Spain, Switzerland, Germany and Belgium). None of these interactions is statistically significant at least at the 5% level.

We run the regressions using seven different specifications. Columns (1) and (2) – where we refrain from including any control variables or fixed effects – report the raw stay-at-home effect on the hiring of remote work.[21] In column (3), we add the cumulative number of confirmed COVID-19 cases. In column (4), we add a binary variable, which indicates whether the client is located in the national capital city, and additional control variables. In column (5), we add job category fixed effects, month fixed effects and client country fixed effects. In columns (6) and

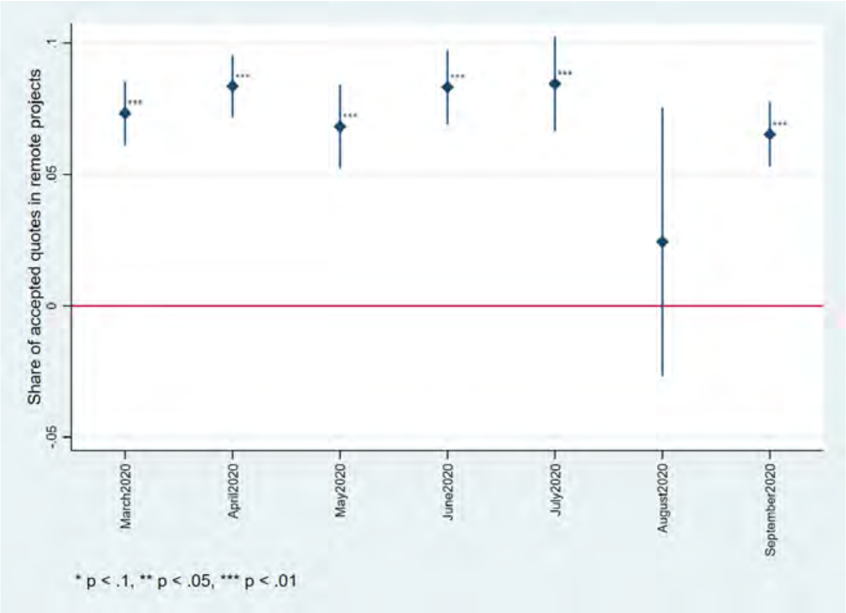
[21] The only difference between Columns (1) and (2) is that we use the *reg* command in Stata in column (1) while we use the *reghdfe* command in Stata in column (2). As results are the same, henceforth, we use the *reghdfe* command to be able to include high-dimensional fixed effects.

Covid Economics 63, 7 January 2021: 1-34

(7), we include client fixed effects and client-month fixed effects, respectively. R^2 increases substantially going from columns (1) to (7). Based on this, column (7) is our preferred specification.[22]

We obtain the following main results. We find evidence for a robust positive effect of the stay-at-home requirements on the hiring of remote work relative to on-site work. The coefficient of *StayHome* is positive and statistically significant at the 1% level across columns ranging from +0.004 in column (5) to +0.013 in columns (1) and (2). Based on our preferred specification (7), we find that a one-unit increase in the level of the stay-at-home requirements increases the share of accepted quotes in remote projects over total by 0.8 percentage points. In addition, we provide evidence for a negative correlation between the cumulative number of confirmed COVID-19 cases and the share of accepted quotes in remote projects over total. The coefficient of the confirmed COVID-19 cases is negative and statistically significant at the 1% level in all columns but column (3).

Figure 6 | Effect of *StayHome* on the hiring of remote work over time



Notes: Figure 6 plots the interactions of the stay-at-home variable with month fixed effects using the preferred specification from Table 5 (column 7). Confidence intervals and statistical significance reported. Figure 6 indicates that the stay-at-home effect is positive and statistically significant at the 1% level for all *StayHome*-month interactions, except for August 2020. It also indicates that the *StayHome* effect varies over time.

[22] For the give main countries, we ran the regressions with all possible *StayHome*Country* interactions. However, none of the interactions is statistically significant at least at the 5% level. These interactions are thus not reported in Table 5.

Figure 6 plots the interactions of the stay-at-home variable with month fixed effects using the preferred specification from Table 5 (column 7). It indicates that the stay-at-home effect is positive and statistically significant at the 1% level for all *StayHome*-month interactions, except for August 2020. It also indicates that the *StayHome* effect varies over time.[23]

V. ADDITIONAL FINDINGS

In this section, we explore whether the stay-at-home effects on demand, supply and hiring of remote work are non-linear. Arguably, the magnitude of the stay-at-home effects may depend on the level or intensity of the stay-at-home requirements. For instance, going from no restrictions to level-1 restrictions implies that the government *recommends* staying at home. In contrast, going from level-1 restrictions to level-2 or level-3 restrictions implies that the government makes it *mandatory* to stay at home with some exceptions. To control for this effect, we include two separate dummy variables in our regressions; one variable for *StayHome level 1* and another for *StayHome level 2 or 3*.[24] In the demand, supply and hiring outcome regressions, we use the case of no stay-at-home restrictions as the base.

1. Demand for remote work: Potential non-linear effects of stay-at-home requirements

We explore whether the stay-at-home effects on the demand for remote labour are non-linear. Using the level-1 and level-2-or-3 stay-at-home variables instead of the ordinal stay-at-home variable, we run the same demand regressions as reported in Table 3. Results are reported in Table 6.

We obtain the following main results. First, our results provide evidence for a non-linear effect of the stay-at-home requirements on the demand for remote work. The coefficient of *StayHome_Level_1* is positive and statistically significant at the 1% level across columns ranging from 1.4 percentage points in column (5) to 4.8 percentage points in columns (1) and (2). In contrast, the positive and statistically significant coefficient of *StayHome_Level_2_or_3* is higher in magnitude across all columns ranging from 3.7 percentage points in column (5) to 7.5 percentage points in columns (1) and (2). In our preferred specification (7), the effect of *StayHome_Level_2_or_3* is more than twice as large in magnitude as the effect of *StayHome_Level_1,* i.e., 4.4 percentage points vs. 1.7 percentage points. These results suggest

[23] We do not report the October-2020 interaction because Stata dropped it in the regressions.

[24] We merge the level-2 and level-3 restrictions in a single binary variable for the following reasons. First, under both restrictions staying at home is mandatory, i.e., they only differ slighly in the extent of the exceptions. Second, less than 0.03 percent of our observations (in total, 37 observations) are level-3 observations. Third, more than half of the few level-3 observations are from a single country, i.e., 21 level-3 observations are from China.

that the demand effect of mandatory stay-at-home requirements is larger in magnitude than the one of recommended staying-at-home. Second, we find evidence for some heterogeneity of the *StayHome_Level_1* effect at the country level.[25] The coefficient of the interaction *StayHome_Level_1*Germany* is positive and statistically significant at the 1% level as reported in column (8). While the same is true for *StayHome_Level_1*Belgium* (see column (9)), the interaction effect is larger in magnitude for Belgium than for Germany.

Table 6 | Non-linear effects of stay-at-home requirements on demand for remote work (Client-day level)

	(1) Share of requests for remote projects over total	(2) Share of requests for remote projects over total	(3) Share of requests for remote projects over total	(4) Share of requests for remote projects over total	(5) Share of requests for remote projects over total	(6) Share of requests for remote projects over total	(7) Share of requests for remote projects over total	(8) Share of requests for remote projects over total	(9) Share of requests for remote projects over total
Stay at home, level 1, binary	0.048***	0.048***	0.042***	0.041***	0.014***	0.016***	0.017***	0.017***	0.017***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Stay at home, levels 2 or 3, binary	0.075***	0.075***	0.072***	0.070***	0.037***	0.041***	0.044***	0.044***	0.044***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Cumulative number of confirmed COVID-19 cases, in 100,000			0.004***	0.004***	-0.002***	-0.002***	-0.002*	-0.002*	-0.002*
			(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Client located in capital city				-0.009***	-0.001*				
				(0.001)	(0.000)				
Level-1 stay-at-home requirements interacted with:									
Client from Germany								0.009***	
								(0.002)	
Client from Belgium									0.099***
									(0.024)
Job category FE	NO	NO	NO	NO	NO	YES	NO	NO	NO
Month FE	NO	NO	NO	NO	NO	YES	YES	YES	YES
Client country FE	NO	NO	NO	NO	NO	YES	NO	NO	NO
Client FE	NO	NO	NO	NO	NO	NO	YES	YES	YES
Control variables included#	NO	NO	NO	NO	YES	YES	YES	YES	YES
Constant	0.814***	0.814***	0.812***	0.818***	0.821***	0.820***	0.816***	0.816***	0.816***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Observations	138,563	138,563	138,320	122,118	121,862	94,735	41,329	41,329	41,329
R-squared	0.026	0.026	0.028	0.029	0.707	0.762	0.790	0.790	0.790

Notes: OLS regression coefficients reported. Regressions are run at the client-day level. We use the *reg* command in Stata in column (1). From column (2) on, we use the *reghdfe* command in Stata to be able to include high-dimensional fixed effects (Correia, 2017). According to Correia (2015), maintaining singleton groups in linear regressions where fixed effects are nested within clusters can overstate statistical significance and lead to incorrect inference. Due to this problem, the *reghdfe* package automatically drops singletons in columns (4) to (9). Robust standard errors clustered at client level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.
#Additional control variables included (results not reported): *Number of marketplace accounts in client company, Log median daily rate of freelancers contacted for a project, Pricing plans 1, 2 and 3*.
We run the regressions with all possible interactions of the stay-at-home variables with the five main countries (France, Spain, Switzerland, Germany and Belgium). We report the results for only those cases where the respective interaction is statistically significant at least at the 5% level.

[25] We run the regressions with all possible interactions of the two stay-at-home variables with the five main countries (France, Spain, Switzerland, Germany and Belgium). In Table 6, we report the results for only those cases where the respective interaction is statistically significant at least at the 5% level.

Covid Economics 63, 7 January 2021: 1-34

2. Supply of remote work: Potential non-linear effects of stay-at-home requirements

We explore whether the effects of the stay-at-home requirements on the supply of remote labour are non-linear. We use the level-1 and level-2-or-3 stay-at-home variables instead of the ordinal stay-at-home variable in the supply regressions (see Table 4). Results are reported in Table 7.[26] We find that the coefficient of *StayHome_Level_1*RemoteProject* is positive and statistically significant at the 1% level as reported in column (9). It is large in magnitude, i.e., 0.122. In addition, the coefficient of *StayHome_Level_2_or_3*RemoteProject* is positive and not statistically significant as reported in column (10). It is smaller in magnitude than the coefficient of *StayHome_Level_1*RemoteProject.* These results suggest that the effect of the stay-at-home requirements on the supply of remote work is non-linear.

Table 7 | Non-linear effects of stay-at-home requirements on labour supply (Project-day level)

	(1) Log number of quotes received	(2) Log number of quotes received	(3) Log number of quotes received	(4) Log number of quotes received	(5) Log number of quotes received	(6) Log number of quotes received	(7) Log number of quotes received	(8) Log number of quotes received	(9) Log number of quotes received	(10) Log number of quotes received
Stay at home, level 1,	0.020**	0.020**	0.001	0.024**	0.000	0.033*	0.005	0.049	-0.034	0.050
binary	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.017)	(0.021)	(0.034)	(0.042)	(0.034)
Stay at home, levels 2 or 3,	0.021**	0.021**	-0.001	0.012	-0.025**	0.008	-0.013	-0.011	-0.011	-0.046
binary	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)	(0.018)	(0.021)	(0.037)	(0.037)	(0.043)
Project can be done remotely			0.539***	0.539***	0.464***	0.486***	0.496***	0.511***	0.503***	0.507***
			(0.004)	(0.004)	(0.005)	(0.005)	(0.008)	(0.013)	(0.013)	(0.013)
Cumulative number of confirmed				-0.014***	-0.012***	-0.010	-0.017**	-0.118***	-0.119***	-0.118***
COVID-19 cases, in 100,000				(0.002)	(0.002)	(0.006)	(0.008)	(0.016)	(0.016)	(0.016)
Client located in capital city					0.009*	-0.003				
					(0.005)	(0.005)				
Remote project interacted with:										
Stay-at-home requirements,									0.122***	
level 1									(0.043)	
Stay-at-home requirements,										0.056
levels 2 or 3										(0.043)
Job category FE	NO	NO	NO	NO	NO	YES	NO	NO	NO	NO
Month FE	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES
Client country FE	NO	NO	NO	NO	NO	YES	NO	NO	NO	NO
Client FE	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES
Client-month FE	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES
Control variables included#	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES
Constant	0.790***	0.790***	0.406***	0.413***	0.834***	0.948***	0.496***	0.500***	0.504***	0.502***
	(0.002)	(0.002)	(0.004)	(0.004)	(0.038)	(0.039)	(0.061)	(0.094)	(0.094)	(0.094)
Observations	147,336	147,336	147,336	147,072	130,139	129,863	103,252	51,874	51,874	51,874
R-squared	0.000	0.000	0.076	0.077	0.084	0.112	0.429	0.616	0.617	0.616

Notes: OLS regression coefficients reported. Regressions are run at the project-day level. We use the *reg* command in Stata in column (1). From column (2) on, we use the *reghdfe* command in Stata to be able to include high-dimensional fixed effects (Correia, 2017). According to Correia (2015), maintaining singleton groups in linear regressions where fixed effects are nested within clusters can overstate statistical significance and lead to incorrect inference. Due to this problem, the *reghdfe* package automatically drops singletons in columns (5) to (10). Robust standard errors clustered at project level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.
#Additional control variables included (results not reported): *Number of marketplace accounts in client company, Project request specified in fixed terms, Log median daily rate of freelancers contacted for a project, Pricing plans 1, 2 and 3.* For the two binary stay-at-home variables and the five main countries, we run the regressions with all possible interactions of *StayHome*RemoteProject*Country*. None of these interactions is statistically significant at least at the 5% level.

[26] For the two binary stay-at-home variables and the five main countries, we run the regressions with all possible interactions of *StayHome*RemoteProject*Country*. None of these interactions is statistically significant at least at the 5% level and is, therefore, not reported in Table 7.

3. Hiring of remote work: Potential non-linear effects of stay-at-home requirements

We explore the potential non-linear effects of the stay-at-home requirements on the hiring of remote labour. We use the level-1 and level-2-or-3 stay-at-home variables instead of the ordinal stay-at-home variable in the outcome regressions (see Table 5). Results are reported in Table 8.[27]

Table 8 | Linear effects of stay-at-home requirements on outcome (Client-day level)

	(1) Share of accepted proposals in remote projects over total	(2) Share of accepted proposals in remote projects over total	(3) Share of accepted proposals in remote projects over total	(4) Share of accepted proposals in remote projects over total	(5) Share of accepted proposals in remote projects over total	(6) Share of accepted proposals in remote projects over total	(7) Share of accepted proposals in remote projects over total
Stay at home, level 1, binary	0.010***	0.010***	0.009***	0.003***	0.008***	0.011***	0.017***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)
Stay at home, levels 2 or 3, binary	0.027***	0.027***	0.026***	0.020***	0.008***	0.010***	0.014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)
Cumulative number of confirmed COVID-19 in 100,000			0.001***	-0.001***	-0.003***	-0.005***	-0.006***
			(0.000)	(0.000)	(0.001)	(0.001)	(0.002)
Client located in capital city				-0.007***	-0.001		
				(0.001)	(0.001)		
Job category FE	NO	NO	NO	NO	YES	NO	NO
Month FE	NO	NO	NO	NO	YES	YES	YES
Client country FE	NO	NO	NO	NO	YES	NO	NO
Client FE	NO	NO	NO	NO	NO	YES	YES
Client-month FE	NO	NO	NO	NO	NO	NO	YES
Control variables included#	NO	NO	NO	NO	YES	YES	YES
Constant	0.694***	0.694***	0.694***	0.624***	0.769***	0.754***	0.759***
	(0.001)	(0.001)	(0.001)	(0.012)	(0.008)	(0.009)	(0.015)
Observations	92,257	92,257	92,090	85,972	85,761	67,351	27,593
R-squared	0.003	0.003	0.003	0.011	0.475	0.573	0.654

Notes: OLS regression coefficients reported. Regressions are run at the client-day level. We use the *reg* command in Stata in column (1). From column (2) on, we use the *reghdfe* command in Stata to be able to include high-dimensional fixed effects (Correia, 2017). According to Correia (2015), maintaining singleton groups in linear regressions where fixed effects are nested within clusters can overstate statistical significance and lead to incorrect inference. Due to this problem, the *reghdfe* package automatically drops singletons in columns (4) to (7). Robust standard errors clustered at client level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.
#Additional control variables included (results not reported): *Number of marketplace accounts in client company, Pricing plans 1, 2 and 3, Log number of quotes received, Log number of requests made.*
We run the regressions with all possible interactions of the stay-at-home variables with the five main countries (France, Spain, Switzerland, Germany and Belgium). None of these interactions is statistically significant at least at the 5% level.

We obtain the following main results. First, the coefficient of *StayHome_Level_1* is positive and statistically significant at the 1% level across all columns ranging from 0.3 percentage points in column (4) and 1.7 percentage points in column (7). In addition, the coefficient *StayHome_Level_2_or_3* is positive and statistically significant at the 1% level across all columns

[27] We run the regressions with all possible interactions of the stay-at-home variables with the five main countries (France, Spain, Switzerland, Germany and Belgium). None of these interactions is statistically significant at least at the 5% level. These interactions are, therefore, not reported in Table 8.

Covid Economics 63, 7 January 2021: 1-34

ranging from 0.8 percentage points in column (5) and 2.7 percentage points in columns (1) and (2). The effect of *StayHome_Level_2_or_3* is larger in magnitude than the one of *StayHome_Level_1* in columns (1) to (4). In contrast, the two effects are similar in magnitude in columns (5) to (7). In our preferred specification (7), the coefficient of *StayHome_Level_2_or_3* is 0.014 and the coefficient of *StayHome_Level_1* is 0.017. These results suggest that the outcome effect of mandatory stay-at-home requirements is similar in magnitude as the one of recommended staying-at-home. Based on this, we argue that the effects of the stay-at-home requirements on the hiring of remote labour are linear.

VI. POLICY IMPLICATIONS AND CONCLUSIONS

In this paper, we explore the impact of local stay-at-home requirements on workers' and clients' preferences for remote work. We analyse company data from a large European OLM that facilitates on-site and remote work for clients and freelancers. Our results provide evidence of a reaction from both the demand and supply side to the stay-at-home requirements. From the demand perspective, we observe an increase in the proportion of remote activity as compared to on-site activity. More specifically, the share of clients' requests for remote projects increases in the intensity of the stay-at-home requirements.

From the supply side perspective, we find that the stay-at-home requirements have a positive effect on the supply of remote work relative to the supply of on-site work. In addition, the clients' hiring of remote work relative to on-site work increases in the intensity of the stay-at-home requirements. In our panel regressions for demand, supply and outcome, we account for other COVID-19 related effects by including the time-variant number of COVID-19 cases. We also include client-month fixed effects to control for other time-variant COVID-19 related effects at the level of individual clients not already controlled for by the number of COVID-19 cases. Finally, our additional findings suggest that the stay-at-home effect is non-linear for demand and supply of remote work and linear for the hiring of remote work.

This empirical exercise suggests that the flexibility provided by OLMs may facilitate the adaptation of labour demand and labour supply to unpredicted situations where mobility is restricted. In addition, bringing about and sustaining an employment-rich recovery is essential at this stage. The flexible ways of work that OLMs provide could facilitate this recovery. Arguably, OLMs could help to mitigate negative labour market effects due to the economic disruption during the COVID-19 pandemic. Hence, empirical evidence to better understand the role of OLMs in the ongoing crisis is an important input for evidence-based policy making. On top of that, the discovery of new working patterns in online work caused by stay-at-home requirements may help to improve freelancers' working conditions beyond the current crisis and establish new working habits in the long run.

REFERENCES

Acemoglu, D. and D. Autor (2010). Skills, Tasks and Technologies: Implications for Employment and Earnings, NBER Working Paper Series 16082.

Adams-Prassl, A., Boneva, T., Golin, M. and C. Rauh (2020). Work Tasks that Can Be Done from Home: Evidence on the Variation Within and Across Occupations and Industries. IZA Discussion Paper 13374.

Agrawal, A., Horton, J. H., Lacetera, N. and E. Lyons (2013). Digitization and the Contract Labor Market: A Research Agenda. NBER Working Paper No. 19525.

Autor, D. H. (2001). Wiring the Labor Market. Journal of Economic Perspectives, 15(1), 25-40.

Autor, D. H. (2013). The “Task Approach” to Labor Markets: An Overview. Journal for Labour Market Research, 1-15.

Balleer, A., Zorn, P., Link, S., and M. Menkhoff (2020). Demand or Supply? Price Adjustment during the Covid-19 Pandemic. COVID Economics, 31, 59-102.

Balliester, T. and A. Elshekhi (2018). The Future of Work: A Literature Review. ILO Research Department Working Paper No. 29.

Bartik, A. W., Bertrand, M., Cullen, Z. B., Glaeser, E. L., Luca, M. and C. T. Stanton (2020). The Impact of COVID-19 on Small Business Outcomes and Expectations. The Proceedings of the National Academy of Sciences, 117(30), 17656–17666.

Bartik, A. W., Cullen, Z. B., Glaeser, E. L., Luca, M. and C. T. Stanton (2020a). What Jobs are Being Done at Home During the Covid-19 Crisis? Evidence from Firm-Level Surveys, NBER Working Paper No. 27422.

Bartik, A. W., Cullen, Z. B., Glaeser, E. L., Luca, M. and C. T. Stanton (2020b). How the COVID-19 Crisis is Reshaping Remote Working. VoxEU Article, 19 July 2020.

Benson, A., Sojourner, A., and A. Umyarov (2019). Can Reputation Discipline the Gig Economy? Experimental Evidence from an Online Labor Market. Management Science, forthcoming.

Berg, J. (2016). Income Security in the On-demand Economy: Findings and Policy Lessons from a Survey of Crowd Workers. Geneva, Conditions of Work and Employment Series No. 74.

Berg, J., Furrer, M., Harmon, E. Rani, U. and M.S. Silberman (2018). Digital Labour Platforms and the Future of Work: Towards Decent Work in the Online World, Geneva: ILO.

Bick, A., Blandin, A. and K. Mertens (2020). Work from Home After the COVID-19 Outbreak. Federal Reserve Bank of Dallas Working Paper 2017.

Brodeur, A., Gray, D., Islam, A. and S. J. Bhuiyan (2020). A Literature Review of the Economics of COVID-19. IZA DP No. 13411.

Blinder, A. (2009). How Many US Jobs Might be Offshorable?. World Economics, 10(2), 41-78.

Blinder, A. and A. Krueger (2013). Alternative Measures of Offshorability: A Survey Approach. Journal of Labor Economics, 31(S1), 97-128.

Bloom, N. (2014). To Raise Productivity, Let More Employees Work from Home. Harvard Business Review, 92(1-2), 28-29.

Bloom, N., Liang, J., Roberts, J. and Z. J. Ying (2015). Does Working from Home Work? Evidence from a Chinese Experiment. Quarterly Journal of Economics, 130(1), 165-218.

Borjas, G. J. and H. Cassidy (2020). The Adverse Effect of the COVID-19 Labor Market Shock on Immigrant Employment. NBER Working Paper No. 27243.

Covid Economics 63, 7 January 2021: 1-34

Braesemann, F., Lehdonvirta V. and O. Kässi (2020). ICTs and the Urban-rural Divide: Can Online Labour Platforms Bridge the Gap? Information, Communication and Society, 1-21.

Brinca, P., Duarte, J. B., and M. Faria-e-Castro (2020). Measuring Sectoral Supply and Demand Shocks during COVID-19. COVID Economics, 20, 158-182.

Brynjolfsson, E., Horton, J.J., Ozimek, A., Rock, D., Sharma, G. and H.-Y. TuYe (2020). COVID-19 and Remote Work: An Early Look at US Data. The National Bureau of Economic Research, 1-16.

Chan, J. and J. Wang (2017). Hiring Preferences in Online Labor Markets: Evidence of a Female Hiring Bias. Management Science, 64(7), 2973-2994.

Chen, K. M., Chevalier, J. A., Rossi, P. E. and E. Oehlsen (2019). The Value of Flexible Work: Evidence from Uber Drivers. Journal of Political Economy, 127(6), 2735-2794.

Chen, D. and J. J. Horton (2016). Are Online Labor Markets Spot Markets for Tasks? A Field Experiment on the Behavioral Response to Wage Cuts. Information Systems Research, 27(2), 219-470.

Codagnone, C, Abadie, F. and F. Biagi (2016). The Future of Work in the 'Sharing Economy'. Market Efficiency and Equitable Opportunities or Unfair Precarisation? Joint Research Centre Working Paper JRC101280.

Corporaal, G.F. and V. Lehdonvirta (2017). Platform Sourcing: How Fortune 500 Firms are Adopting Online Freelancing Platforms. Oxford: Oxford Internet Institute.

Correia, S. (2015). Singletons, Cluster-robust Standard Errors and Fixed Effects: A Bad Mix. Technical Note, Duke University.

Correia, S. (2017). reghdfe: Stata module for linear and instrumental-variable/gmm regression absorbing multiple levels of fixed effects. Statistical Software Components s457874, Boston College, Department of Economics.

Del Rio-Chanona, R. M., Mealy, P., Pichler, A., Lafond, F. and J. D. Farmer (2020). Supply and Demand Shocks in the COVID-19 Pandemic: An Industry and Occupation Perspective. Oxford Review of Economic Policy, 36, S94–S137.

Dingel, J. and B. Neiman (2020). How Many Jobs Can be Done at Home?. Journal of Public Economics, 189, 1-8.

Dube, A., Jacobs, J. Naiduand, S. and S. Suri (2020). Monopsony in Online Labor Markets. American Economic Review: Insights, 2(1), 33-46.

European Commission (2016a). A European Agenda for the Collaborative Economy (COM/2016/0356). European Commission, Brussels.

European Commission (2016b). Commission Staff Working Document accompanying a European Agenda for the Collaborative Economy – Supporting Analysis. SWD (2016) 184 final, European Commission, Brussels.

Farrell, D. and F. Greig (2016). Paychecks, Paydays, and the Online Platform Economy. JPMorgan Chase Institute.

Ghani, E., Kerr, W. R. and C. Stanton (2014). Diasporas and Outsourcing: Evidence from oDesk and India. Management Science, 60 (7), 1677-1697.

Goldfarb, A. and C. Tucker (2019). Digital Economics. Journal of Economic Literature, 57(1), 3-43.

Gomez-Herrera, E., Martens, B. and F. Mueller-Langer (2017). Trade, Competition and Welfare in Global Online Labour Markets: A "Gig Economy" Case Study. Digital Economy Working Paper 2017-05, JRC Technical Reports.

Covid Economics 63, 7 January 2021: 1-34

Gomez-Herrera, E. and F. Mueller-Langer (2019). Is There a Gender Wage Gap in Online Labor Markets? Evidence from Over 250,000 Projects and 2.5 Million Wage Bill Proposals, CESifo Working Paper No. 7779.

Gonzalez-Vazquez, I., et al. (Eds.) (2019). The Changing Nature of Work and Skills in the Digital Age. (eds.), EUR 29823 EN, Publications Office of the European Union, Luxembourg.

Hale, T., Angrist, N., Cameron-Blake, E., Hallas, L., Kira, B., Majumdar, S., Petherick, A., Phillips, T., Tatlow, H. and S. Webster (2020a). Oxford COVID-19 Government Response Tracker, Blavatnik School of Government. Available: www.bsg.ox.ac.uk/covidtracker

Hale, T., Angrist, N., Cameron-Blake, E., Hallas, L., Kira, B., Majumdar, S., Petherick, A., Phillips, T., Tatlow, H. and S. Webster (2020b). Variation in Government Responses to COVID-19. Version 8.0. Blavatnik School of Government Working Paper.

Hensvik, L., Le Barbanchon, T. and R. Rathelot (2020). Which Jobs Are Done from Home? Evidence from the American Time Use Survey. IZA Discussion Papers 13138.

Horton, J. J. (2010). Online Labor Markets. In: International Workshop on Internet and Network Economics. Springer, Berlin, Heidelberg, 515-522.

Horton, J. J. and P. Tambe (2015). Labor Economists Get Their Microscope: Big Data and Labor Market Analysis. Big Data, 3(3), 130-137.

Horton, J. J. (2019). Buyer Uncertainty about Seller Capacity: Causes, Consequences, and a Partial Solution. Management Science, 65(8), 3518-3540.

Huws, U., Korte, W. B. and S. Robinson (1990), Telework: Towards the Elusive Office. Hoboken, NJ: John Wiley & Sons.

International Monetary Fund (2020a). World Economic Outlook, April 2020: The Great Lockdown. IMF.

International Monetary Fund (2020b). World Economic Outlook Update, June 2020: A Crisis Like No Other, An Uncertain Recovery. IMF.

Kahn, L. B., Lange F. and D. Wiczer (2020). Labor Supply in the Time of COVID19. Cahiers de recherche 06-2020, CIREQ.

Kalleberg, A. L. (2003). Flexible Firms and Labour Market Segmentation: Effects of Workplace Restructuring on Jobs and Workers. Work and Occupations, 30, 154-175.

Kässi, O. and V. Lehdonvirta (2018). Online Labour Index: Measuring the Online Gig Economy for Policy and Research. Technological Forecasting and Social Change, 137, 241-248.

Kokkodis, M. and P.G. Ipeirotis (2016). Reputation Transferability in Online Labor Markets. Management Science 62(6), 1687-1706.

Lyons, E. (2017). Team Production in International Labor Markets: Experimental Evidence from the Field. American Economic Journal: Applied Economics, 9(3), 70-104.

Mas, A. and A. Pallais (2020). Alternative Work Arrangements. Annual Review of Economics, 12, 631-658.

Mas, A. and A. Pallais (2017). Valuing Alternative Work Arrangements. American Economic Review, 107(12), 3722-3759.

Mokhtarian, P.L. (1991). Defining Telecommuting. Transportation Research Record, 1305, 273-281.

Oettinger, G. S. (2011). The Incidence and Wage Consequences of Home-Based Work in the United States, 1980–2000. Journal of Human Resources, 46(2), 237-260.

Covid Economics 63, 7 January 2021: 1-34

Pallais, A. and E.G. Sands (2016). Why the Referential Treatment? Evidence from Field Experiments on Referrals. Journal of Political Economy, 124(6), 1793-1828.

Papanikolaou, D. and L. D. Schmidt (2020). Working Remotely and the Supply-side Impact of Covid-19. NBER Working Paper 27330.

Pesole, A., Urzi, C., Fernandez-Macias, E., Biagi, F. and I. Gonzalez-Vazquez (2018). Platform Workers in Europe. Evidence from the COLLEEM Survey, JRC Science for Policy Report.

Snir, E.M. and L. M. Hitt (2003). Costly Bidding in Online Markets for IT Services. Management Science, 49(11), 1504-1520.

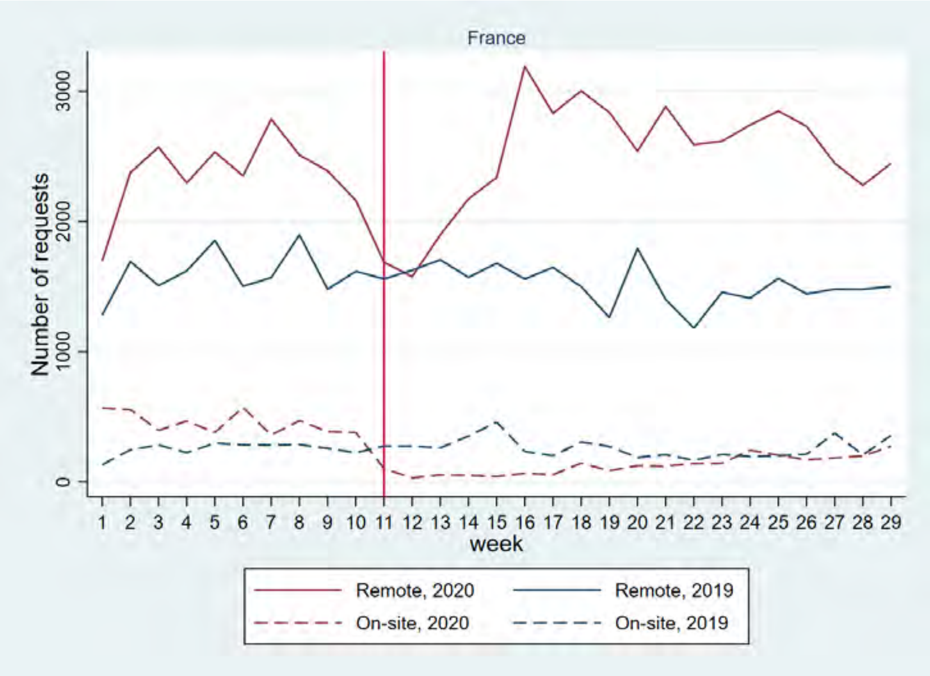
Stephany, F., Dunn, M. Sawyer, S. and V. Lehdonvirta (2020). Distancing Bonus Or Downscaling Loss? The Changing Livelihood of Us Online Workers in Times of COVID-19. Journal of Economic and Social Geography, 111(3), 561-573.

Von der Leyen, U. (2019a). A Union that Strives for More: My Agenda for Europe, Political Guidelines for the Next European Commission 2019-2024. European Commission, Brussels.

Von der Leyen, U. (2019b). Mission Letter to Margrethe Vestager, Executive Vice-President for A Europe Fit for the Digital Age. European Commission, Brussels.

Covid Economics 63, 7 January 2021: 1-34

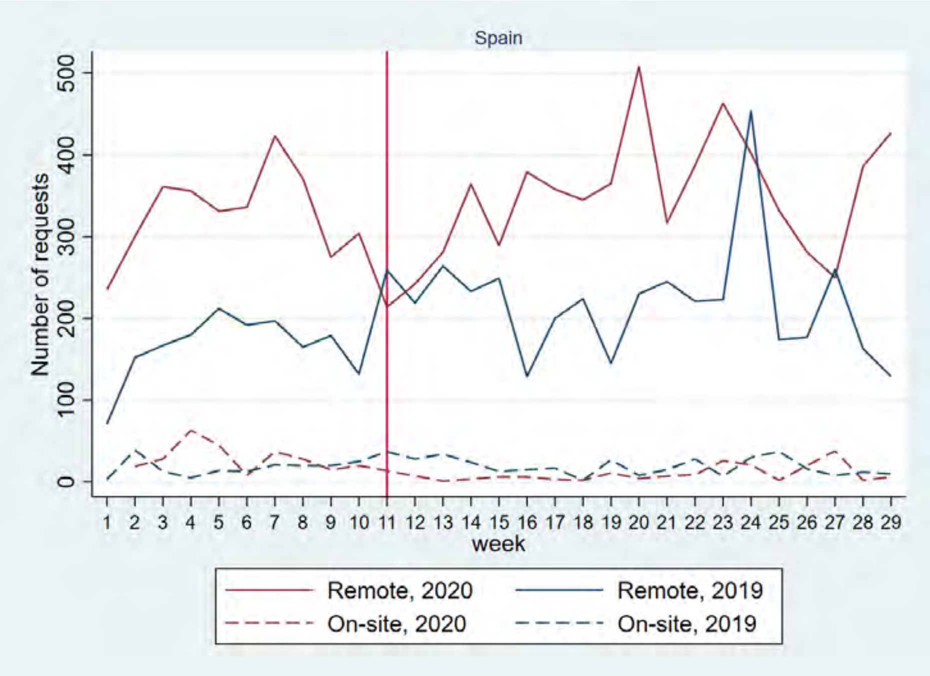
Figure A.1 | Weekly number of clients' requests for remote and on-site projects, France



Notes: Figure A.1 illustrates the weekly number of requests by project type (remote vs. on-site) and year (2019 and 2020) in France. The two upper solid lines indicate the number of requests for remote projects (2020: red, 2019: blue). The two lower dashed lines indicate the number of requests for on-site projects (as before, 2020: red, 2019: blue). The vertical red line indicates 11 March 2020 in week 11, i.e., the day when France started to implement the stay-at-home requirements. Figure A.1 suggests that there is no positive trend in the number of requests for remote projects before 11 March 2020 and a substantial increase afterwards. It also suggests that the number of requests for on-site projects has decreased after 11 March 2020. These findings contrast the results for 2019 where the numbers for both types of requests remain relatively stable over time.

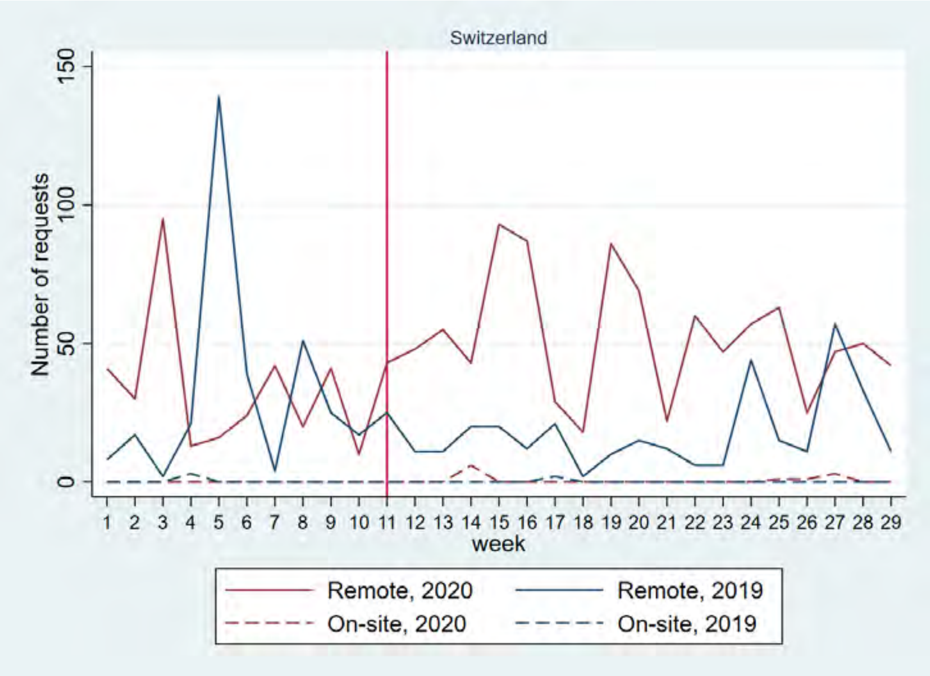
Covid Economics 63, 7 January 2021: 1-34

Figure A.2 | Weekly number of clients' requests for remote and on-site projects, Spain



Notes: Figure A.2 illustrates the weekly number of requests by project type (remote vs. on-site) and year (2019 and 2020) in Spain. The two upper solid lines indicate the number of requests for remote projects (2020: red, 2019: blue). The two lower dashed lines indicate the number of requests for on-site projects (as before, 2020: red, 2019: blue). The vertical red line indicates 15 March 2020 in week 11, i.e., the day when Spain started to implement the stay-at-home requirements. Figure A.2 suggests that there is no positive trend in the number of requests for remote projects before 15 March 2020 and a substantial increase afterwards. It also suggests that the number of requests for on-site projects has decreased after 15 March 2020. These findings contrast the results for 2019.

Figure A.3 | Weekly number of clients' requests for remote and on-site projects, Switzerland



Notes: Figure A.3 illustrates the weekly number of requests by project type (remote vs. on-site) and year (2019 and 2020) in Switzerland. The two upper solid lines indicate the number of requests for remote projects (2020: red, 2019: blue). The two lower dashed lines indicate the number of requests for on-site projects (as before, 2020: red, 2019: blue). The vertical red line indicates 17 March 2020 in week 12, i.e., the day when Switzerland started to implement the stay-at-home requirements. Figure A.3 suggests that there is no positive trend in the number of requests for remote projects before 17 March 2020 and a substantial increase afterwards. These findings contrast the results for 2019 where the numbers for remote requests remain relatively stable after March.

Covid Economics Issue 63, 7 January 2021

What works to control COVID-19? Econometric analysis of a cross-country panel[1]

Liming Chen,[2] David Raitzer,[3] Rana Hasan,[4] Rouselle Lavado[5] and Orlee Velarde[6]

Date submitted: 18 December 2020; Date accepted: 4 January 2021

Covid Economics 63, 7 January 2021: 35-72

We use cross-country panel data to examine the effects of a variety of nonpharmaceutical interventions used by governments to suppress the spread of coronavirus disease (COVID-19). We find that while lockdown measures lead to reductions in disease transmission rates as captured by the reproduction number, R_t, gathering bans appear to be more effective than workplace and school closures, both of which are associated with large declines in gross domestic product. Further, our estimates suggest that stay-at-home orders are less effective in countries with larger family size and in developing countries. We also find that incentives are very important, as efforts at ramping up testing and tracing COVID-19 cases are more effective in controlling the spread of disease in countries with greater coverage of paid sick leave benefits. As future waves of the disease emerge, the use of more targeted and better incentivized measures can help keep the epidemic controlled at lower economic cost.

1 The authors thank Yasuyuki Sawada for detailed comments and suggestions on an earlier draft, and Abdul Abiad, Matteo Lanzafame, and participants at the ADB Economics Seminar Series for constructive feedback. Ma. Adelle Gia Toledo Arbo and Xylee Javier provided excellent research assistance. The views expressed in this paper are those of the authors and do not necessarily reflect the views and policies of ADB or its Board of Governors or the governments they represent. ADB does not guarantee the accuracy of the data included in this paper, and accepts no responsibility for any consequence of their use.

2 Economic Research and Regional Cooperation Department, Asian Development Bank (ADB).
3 Economic Research and Regional Cooperation Department, ADB.
4 Economic Research and Regional Cooperation Department, ADB.
5 Economic Research and Regional Cooperation Department, ADB.
6 Economic Research and Regional Cooperation Department, ADB.

I. INTRODUCTION

On 23 January 2020, Wuhan in Hubei Province of the People's Republic of China (PRC) became the first city to implement a lockdown featuring strict restrictions on the movement of people as a tool for suppressing the spread of the novel coronavirus disease, COVID-19.[3] Since then lockdowns of varying stringency and duration, together with other types of nonpharmaceutical interventions (NPIs) such as mandates to wear masks and efforts to test, trace, and isolate individuals potentially exposed to COVID-19, have been implemented in many economies.[4] Starting late April, some economies or locations have gradually lifted or eased lockdown measures.[5] Yet, there are also examples of "re-locking" as COVID-19 cases reemerge in various locations.

While lockdowns are likely to have helped restrict COVID-19 transmission, they have taken a big toll on economic activity and people's livelihoods. A key question for policy makers everywhere is: How can economies be reopened while keeping this disease in check? Specifically, what types and combinations of NPIs are effective in containing the spread of COVID-19 and simultaneously entail lower disruption to economic activity?

There are many efforts underway to help address these questions. Broadly, there are two approaches used, one involving the use of mathematical epidemiological models of how infectious diseases spread and the other using empirical statistical approaches such as regression analysis.

Epidemiological models can enable the integration of key assumptions about COVID-19 and its spread into a cohesive framework in which forecasts can be made and simulations can be performed of options for epidemic control. However, such models are very reliant on assumptions, many of which concern matters where evidence is scarce, such as the relative infectivity of asymptomatic individuals. Such models also rely on untested assumptions about how human behavior is altered by policy measures. See Avery et al. (2020) for a review of models of the spread of the novel coronavirus epidemic, including those that have been used for informing policy decisions.

Regression models can reduce this reliance on assumptions by using real world observations and simplified "reduced form" approaches that minimize reliance on prespecification of parameters. In this paper, we use a cross-country regression framework and data from over 70 economies to examine the relationship between a variety of NPIs—such as workplace closures and gathering bans; the extent of testing, tracing, and isolation; and mandates on the use of masks—on both transmission rates of COVID-19 as captured by its reproduction number, R_t, as well as economic activity captured by estimates of quarterly gross domestic product (GDP). In this way, we are able to shed light on the question of how effective different control measures are, and which ones are associated with larger or smaller contractions in economic activity. Our regression analysis uses country fixed effects to control for all time-invariant, country-specific factors that may influence the spread of COVID-19 and GDP growth. Further, we include a linear time trend to capture unobserved temporal features of COVID-19 and the change in the share of time people spend at their residences relative to a pre-COVID-19 baseline. Increases in the latter should

3 The terms lockdown or shutdown are being used by many to describe relatively general and widespread restrictions on movement, work, and travel on people in a city, region, or country. They can be distinguished from quarantines, which involve separating and restricting people who have been exposed to a disease, such as COVID-19.

4 As noted by the United States Center for Disease Control, NPIs are "actions, apart from getting vaccinated and taking medicine, that people and communities can take to help slow the spread of" infectious diseases like COVID-19.

5 Lockdown measures were widely adopted in March, during the early phase of worldwide spread.

Covid Economics 63, 7 January 2021: 35-72

be associated with reductions in social contacts outside the home and thus in the spread of COVID-19. Only countries with more than 30 observations between January 2020 and June 2020 are included in our regression analysis.

The various COVID-19 control measures we use are guided by recent research, including ongoing work on the Philippines (Raitzer et al. forthcoming). Specifically, this research uses an age-structured susceptible, exposed, infected, and recovered (SEIR) model to examine COVID-19 transmission across scenarios that vary in terms of the nature and duration of lockdowns; extent of tracing, testing, and isolation; and paid sick leave (PSL) as a tool for encouraging self-isolation by workers potentially exposed to COVID-19. It also examines the costs and benefits associated with the alternative scenarios, factoring in health-related costs and benefits as well as the economic losses due to lockdowns.

The findings of Raitzer et al. (forthcoming) motivate crucial aspects of our cross-country regression analysis. A few key findings are worth noting. First, though effective in suppressing disease transmission, lockdowns involving workplace and school closures lead to large reductions in household income, resulting in relatively high costs for the benefits achieved. Second, an extensive system of testing, tracing, and isolation provides a far more economically viable basis for controlling the spread of COVID-19. Third, a PSL policy that encourages workers with COVID-19 or similar symptoms to isolate is not only an effective tool for controlling the disease, it is also a strong complement to tracing and isolation efforts and has a relatively low cost–benefit ratio.

These findings motivate two major ways in which our cross-country regression analysis departs from similar studies. First, in addition to examining the relationship between COVID-19 control measures and disease transmission, we also consider the relationship between the former and economic activity. Second, we consider a broader set of control measures, such as PSL, and also consider how certain country-specific features may affect the efficacy of control measures.

The rest of this paper is organized as follows. Section II goes over recent literature based on cross-country regression analysis and places our contributions in context. Section III describes our data and variable construction. Section IV covers the empirical framework, while section V provides the results of our analysis. Section VI compares our findings with those of other studies and also discusses some limitations of our analysis. Section VII concludes.

II. COVID-19 CONTROL: EVIDENCE FROM CROSS-COUNTRY REGRESSION ANALYSIS

A large and growing literature that examines the socioeconomic consequences of COVID-19, the policies and measures to control its spread, and their effectiveness has emerged since early 2020. It is beyond the scope of this section to describe this literature and readers are referred to a recent survey of the literature provided by Brodeur et al. (2020). Instead, we focus here on studies most closely related to ours—i.e., those using cross-country data to examine the relationship between COVID-19 outcomes and the

Covid Economics 63, 7 January 2021: 35-72

measures and policies governments have used to control COVID-19.[6] (Later, in section VI, we discuss our findings in the context of these studies.)

An early study is that of Bergman and Fishman (2020), who examine how declines in societal mobility are related to the spread of COVID-19. Mobility is captured using daily data from Google and Apple on travel and location, while COVID-19 transmission is captured using estimates of the effective reproduction number. Bergman and Fishman's reduced form regression estimates, based on panel data from 99 economies covering the period from late February and early May and controlling for country and date fixed effects, suggest that a 10 percentage point reduction in mobility is associated with a 0.04–0.07 reduction in R_t. Bergman and Fishman's focus on mobility leads them to avoid analyzing the effects of specific measures governments have taken to control COVID-19 spread. One reason they note is that lockdowns and reductions in mobility are closely though imperfectly related (for example, mobility can decline even without a lockdown as individuals become cautious about exposure to the virus in public spaces).

Carraro, Ferrone, and Squarcina (2020) seek to estimate how NPIs affect the number of active COVID-19 cases using data on 166 economies spanning January 2020 to 15 May 2020. It regresses log differences of COVID-19 cases on 7- and 14-day lagged measures of NPIs and a variety of controls, such as population density and the share of the population over 65 years of age. The NPI measures are introduced separately. The study finds that measures such as school closures and lockdowns are highly effective in reducing growth of active COVID-19 cases. Brauner et al. (2020) assess NPIs for 41 economies using a Bayesian hierarchal model, and find significant effects of school closure, closure of high risk businesses and gathering bans, but smaller effects of other measures.

Islam et al. (2020) similarly use an interrupted time series model on data for 149 economies, in which log cases are the dependent variable, and a range of 7-day lagged NPIs are independent variables independently regressed, and synthesized via meta-analysis. Of the five control measures (transport closure, school closure, workplace closure, gathering bans, and lockdown) assessed, all but transport closure are found to be significant, with larger effects in high-income economies than low-income ones.

Demirgüç-Kunt, Lokshin, and Torre (2020) focus on the effects of NPIs on economic activity, as captured by high-frequency proxies such as daily electricity consumption and nitrogen dioxide emissions data in addition to mobility data for around 33 economies between January and April. A key finding, drawing on panel regressions that include country fixed effects, is that NPIs implemented in the early stages of the pandemic appear to have less adverse effects on short-term economic outcomes and lower cumulative mortality. To some extent, this is due to earlier implemented NPIs being less stringent.

In this paper, we extend these previous studies in several ways. First, given the large tradeoffs that may exist between the effects of some NPIs, especially lockdowns, on health outcomes versus economic activity, we assess the relationship between NPIs and both COVID-19 outcomes and economic activity. Second, given the various deficiencies in capturing the number of actual COVID-19 cases globally, we use estimates of the reproduction number (as do Bergman and Fishman 2020). Though still imperfect, this measure has several advantages (as noted below). Third, we allow relevant NPIs' effects on COVID-19 transmission to vary by relevant country characteristics. For example, lockdowns are supposed to suppress spread of disease by restricting physical contacts. However, large household sizes can lead lockdowns to have smaller effects on physical contacts. Utilizing appropriate interaction terms in our

6 A number of recent contributions use data from a single country and utilize subnational variations in COVID-19 outcomes and control measures. Brodeur et al. (2020) provide a useful discussion on these.

regressions of COVID-19 transmission help capture such relationships. Finally, we consider a potentially important measure of COVID-19 control that has so far been missed by the cross-country literature: the use of PSL benefits as a tool for incentivizing and enabling potentially infected workers to self-isolate.

Although widely viewed as a key element of social protection policies, PSL can also play an important role in controlling the spread of infectious diseases. Indeed, the effects of PSL on the spread of diseases such as influenza has been well demonstrated in the scientific literature (Kim 2017). Workers without PSL are more likely to report for work when contagious—a phenomenon often referred to as contagious presenteeism—leading to a spread of disease among coworkers and others. Conversely, providing workers access to PSL has been shown to reduce the spread of contagious diseases (e.g., Pichler, Wen, and Ziebarth 2020; Pichler and Ziebarth 2017).

While the inclusion of country fixed effects means that we cannot assess the independent effect of PSL on COVID-19 spread, we explore its effects indirectly. An important channel through which PSL is expected to influence COVID-19 is through the system of contact tracing, whereby people who have come in recent contact with a COVID-19 positive person are identified and requested to isolate. Especially since a large share of COVID-19 cases involve mild symptoms (or even no symptoms, but still infectious), a call for isolation is unlikely to be followed if doing so leads to a loss of income. Providing PSL can reduce such behavior and the negative externality associated with it by making contact tracing more effective. Appendix 1 describes a model that demonstrates that the mechanics of PSL works as a tool for controlling the spread of infectious diseases such as COVID-19.

Covid Economics 63, 7 January 2021: 35-72

III. DATA

A. Data Sources and Variable Construction

The dependent variables used in this study are the daily spread of COVID-19 and quarterly GDP growth rate. The principle explanatory variables are daily values of measures taken to control COVID-19 and the extent to which a population stays at home. All variables are measured at country level.

(1) Transmission of COVID-19

To measure COVID-19 spread, we use country-level effective reproductive rate, also known as R_t, from Abbott et al. (2020). R_t describes the average number of individuals infected by an infectious individual at time t. Using R_t has several advantages when measuring spread. Estimated R_t primarily uses data on confirmed cases from the European Centre for Disease Control and is further adjusted for delays in reporting, right-truncation of notification dates, delays between onset and infection, and the effects of testing procedures. Importantly, R_t provides a unit of measurement that avoids problems with other epidemic control measures. Raw numbers of cases are subject to large lag effects that confound identification of effects of specific control measures, and must be considered in relation to population to be comparable. R_t is inherently comparable and can be quicker to respond to policies. Mortality has both lag effects as well as dependence on treatment capacity, and is subject to inconsistencies in the classification of deaths. This said, it is worth noting that since R_t is estimated from reported cases, it cannot overcome problems shared with other COVID-19 measures, such as those arising from underreporting, changes in surveillance methods over time, differences in case definitions across economies, and conflating imported and local cases. We restrict our sample to countries with more than 30 days of R_t observations.

(2) GDP growth rate

To estimate the relationship between COVID-19 control measures and economic activity, we collect quarterly GDP growth data from 2018 to the second quarter of 2020 and compute the quarter-on-quarter growth rate for our dependent variable.[7] We use the total number of days each measure has been in place each quarter as the independent variables. We assume no measures were in place in before 2020.

(3) COVID-19 control measures

The NPI measures adopted by governments to combat COVID-19 spread can be largely categorized in two groups. The first group involves measures that aim to suppress the disease by restricting mobility through "lockdown" such as school closures, work closures, bans on public gatherings, the closure of public transport, etc. The second group includes mandates for wearing masks, mass testing, contact tracing, and isolation of those potentially infected with COVID-19, and the availability of PSL benefits.

We rely on the *Oxford COVID-19 Government Measure Tracker (*OxCGRT*)* (Hale et al. 2020) for a number of the control measures.[8] We construct an indicator of PSL using data on short-term paid sick leave from the World Policy Analysis Center.[9] The data contains information on PSL coverage, such as coverage by employment type and duration of PSL. In our baseline model, if an economy offers some duration of PSL and covers some self-employed and part-time workers, we treat it as offering PSL in our empirical model. We also test a specification with a stricter definition of PSL.

We construct the following daily variables from these data sources:

(i) School closure: 1 if closure is required for all school levels; 0 otherwise.
(ii) Workplace closure: 1 if closure is required for all but essential industries (e.g., grocery stores or health sector); 0 otherwise.
(iii) Public transport closure: 1 if public transport is closed or its use is prohibited for most citizens; 0 otherwise.
(iv) Small gathering ban: 1 if gatherings of more than 10 people are restricted; 0 otherwise.
(v) Large gathering ban: 1 if gatherings of more than 100 people are restricted; 0 otherwise.
(vi) Contact tracing: 1 if a government conducts comprehensive contact tracing for all identified cases; 0 otherwise.
(vii) Early contact tracing: number of days of implementation of contact tracing ahead of 100 cumulative cases.
(viii) Large scale testing: 1 if tests are conducted for anyone with COVID-19 symptoms.

Covid Economics 63, 7 January 2021: 35-72

---

7 Our sources for GDP growth rates include CEIC Data Company, Consensus Economics, Focus Economics, and the Organisation for Economic Co-operation and Development Database.

8 OxCGRT tracks the stringency measures imposed across economies each day. Each measure has corresponding ordinal and binary scales. The ordinal scale starts at 0 which refers to "no measure" having been imposed and it increases by one digit up to 3, 4, or 5 depending on the policy measure. The largest number is considered the most stringent measure imposed. The binary scale provides the geographic coverage of the measure whether it is targeted (0) or a general measure (1). The data was accessed at https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-measure-tracker.

9 The data was accessed on 2 July 2020 at WORLD Policy Analysis Center. Short-term Paid Sick Leave Data. https://www.worldpolicycenter.org/maps-data/data-download/short-term-paid-sick-leave-data.

(ix) Mask wearing[10]: 1 if wearing masks is mandatory or widely accepted.

(x) Paid sick leave: 1 if an economy offers some duration of PSL and covers some of self-employed and part-time workers.

The OxCGRT dataset also provides an overall policy stringency index. The index is a weighted sum of various individual policy measures. While the index is not directly involved in our regression analysis, we use it to provide descriptive analysis and proxy mobility trends for countries without mobility data.

(4) Change in time spent at home

To capture the *lack* of mobility or movement by people—something that can be important in reducing social contacts and thus the spread of COVID-19—we use the change in length of time people stay at their residences relative to a baseline as reported by Google COVID-19 Community Mobility Reports.[11] While these reports provide mobility trends for various locations, such as groceries and pharmacies, parks, transit stations, retail and recreational locations, and workplaces, we focus on trends involving the length of time spent at residential locations as this captures simultaneously the stringency of lockdown measures (such as stay-at-home orders) and voluntary reductions in travel by individuals motivated by preventive behavior. We use the term "time at home" to refer to a lack of mobility resulting from either reason.

The Google reports cover 75 countries in our sample. In countries without data from Google, we estimate changes in time at home using the overall stringency index from the OxCGRT dataset. [12] We run a pooled ordinary least squares (pooled-OLS) regression of time at home against the stringency index for countries with information on both variables, and use the estimated coefficients to extrapolate the change in time at home for places without Google data. We also test a specification only including countries with Google data in our econometric exercise.

(5) Other variables and controls

There are a few additional variables used in our analysis. We control for the daily maximum temperature to account for its potential effect on the spread of COVID-19.[13] Temperature has been hypothesized and been associated with COVID-19 transmission (see, for example, Xie and Zhu 2020). Temperature may also condition transmission by affecting the share of contacts that occur under outdoor or indoor conditions. For economies without information on daily temperature, we use temperature from locations with similar latitude as a proxy.

---

10 The data was compiled by #Masks4All team and accessible at https://masks4all.co/what-countries-require-masks-in-public/. The data provides information if the government requires wearing of masks across the country or just some parts of the country. Or, if it is a recommendation only or a universal practice in the country. It also provides the dates of implementation if the mask wearing is required and the links of the source of information. We fill in missing implementation dates by referring to various news articles provided by #Mask4All and other sources.

11 Google utilizes the location history of Google users to compile a dataset that provides aggregate information on how visits and length of stay at different places change each day compared to a baseline, which is the median value for the corresponding day of the week during the 5-week period from 3 January to 6 February 2020. The data refers to "change in duration" for residential locations, while it refers to "change in visitors" for other categories. Data was accessed through: https://www.google.com/covid19/mobility/.

12 The stringency index used is the overall policy stringency from OxCGRT. Change in time at home from seven countries are proxied by policy stringency.

13 We use maximum temperature from Land-Based Station Data of National Centers for Environmental Information. Data was accessed from https://www.ncdc.noaa.gov/data-access/land-based-station-data.

We collect household size from the United Nations Department of Economic and Social Affairs. In addition, the Nextstrain real time tracking database has been used to characterize the presence of genetic variations, or clades, of COVID-19 in particular countries at specific times (Hadfield et al. 2018). In total, our dataset consists of an unbalanced panel of 75 economies from 1 January 2020 to 17 June 2020.[14]

B. Descriptive Statistics

Table 1 provides summary statistics for the variables used in this study. The values taken by the various COVID-19 control measures across the 75 economies are diverse. On average, time at home increased by 15.8% over the baseline period, with a maximum increase of 55% for Singapore in early May. Among all the control measures, contact tracing is widespread. This is because some countries in the sample (especially in developed ones) had contact tracing mechanisms even before the pandemic instead of being introduced only in response to the pandemic. School closures are observed in 75.7% of observations, the second most widely adopted control measure. On average, countries implemented contact tracing 13.09 days after recording 100 cases. One-third of countries have PSL policies in place.

Table 1: Summary Statistics

Variables	N	Mean	Std Dev	Min	Max
R_t and daily control measures					
R_t	6,639	1.082	0.264	0.400	2.100
Change in time at home	6,639	15.770	9.789	−16	55
Small gathering ban	6,639	0.485	0.500	0	1
Large gathering ban	6,639	0.266	0.442	0	1
School closure	6,639	0.757	0.429	0	1
Workplace closure	6,639	0.347	0.476	0	1
Public transport closure	6,639	0.308	0.462	0	1
Mask use	6,639	0.432	0.495	0	1
Mass testing	6,639	0.523	0.500	0	1
Contact tracing	6,639	0.864	0.342	0	1
Time trend	6,639	54.380	31.230	3	170
Max temperature	6,639	22.600	9.399	−5.074	44.980
Household size	75	3.571	1.407	2.070	8.040
Paid sick leave	75	0.333	0.475	0	1
Early tracing	75	13.090	37.650	−107	78
Clade 19A presence	5,102	0.760	0.427	0	1
Clade 19B presence	5,102	0.400	0.490	0	1
Clade 20A presence	5,102	0.752	0.432	0	1
Clade 20B presence	5,102	0.617	0.486	0	1
Clade 20C presence	5,102	0.318	0.466	0	1
GDP growth and quarterly control measures					
GDP growth rate	899	1.754	4.719	−30.242	11.981
Workplace closure (ln days)	899	0.257	0.863	0	4.419
School closure (ln days)	899	0.436	1.165	0	4.522

continued on next page

[14] From 1 January to 14 February estimates of R_t were available only for the PRC. More economies started reporting COVID-19 cases and show up in our dataset on R_t from the middle of February.

Covid Economics 63, 7 January 2021: 35-72

Table 1 *continued*

Variables	N	Mean	Std Dev	Min	Max
Public transit closed (ln days)	899	0.129	0.631	0	4.522
Index of other measures (ln)	899	0.545	1.457	0	5.613
Days since first case (ln)	899	0.583	1.464	0	5.209
Quarter					
Q1 2018	899	0.108	0.310	0	1
Q2 2018	899	0.108	0.310	0	1
Q3 2018	899	0.108	0.310	0	1
Q4 2018	899	0.108	0.310	0	1
Q1 2019	899	0.108	0.310	0	1
Q2 2019	899	0.107	0.309	0	1
Q3 2019	899	0.107	0.309	0	1
Q4 2019	899	0.106	0.308	0	1
Q1 2020	899	0.083	0.277	0	1
Q2 2020	899	0.058	0.234	0	1

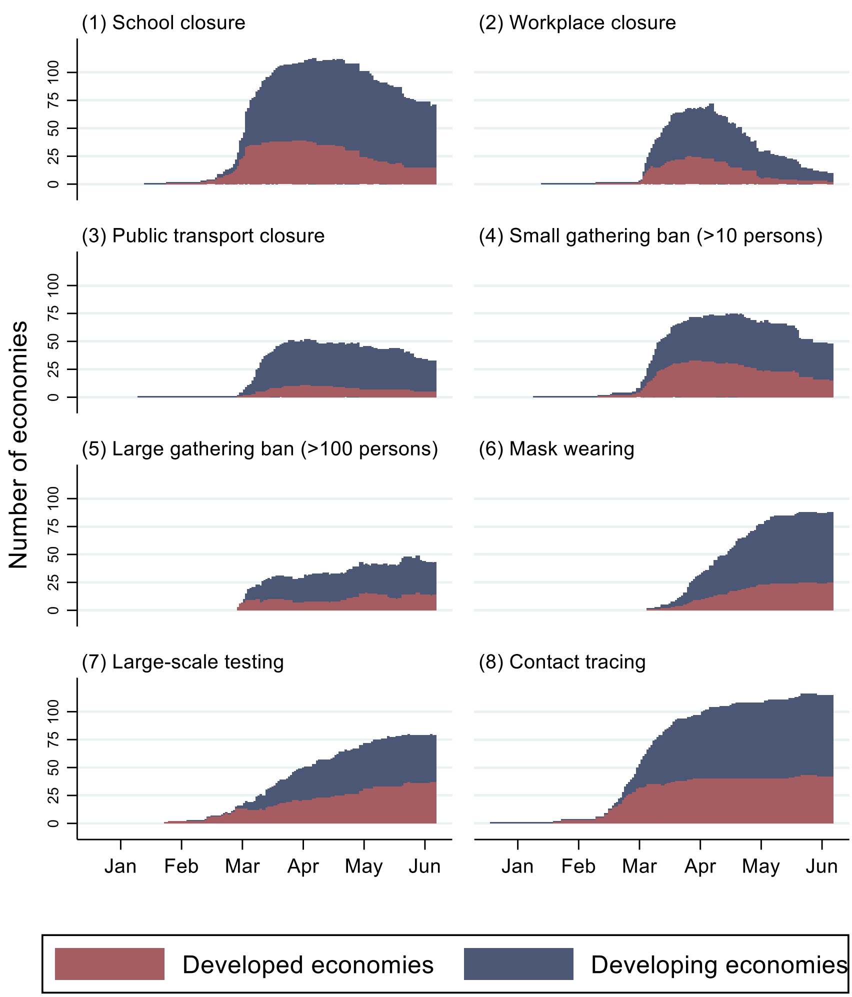
GDP = gross domestic product, ln = natural logarithm, Q = quarter.

Source: Authors' estimates.

Covid Economics 63, 7 January 2021: 35-72

Figure 1 describes the number of economies adopting each of the measures over time and by development level. There are several interesting features. First, lockdown measures were widely adopted in early March, roughly around the time when the World Health Organization declared COVID-19 to be a global pandemic (March 11), and began to be gradually relaxed starting late April. For example, while schools reopened and workplace closures were relaxed, the former was more common in developed economies. Second, more targeted NPI measures, such as the use of masks and large-scale testing and contact tracing have gained momentum gradually. More economies have allocated resources to enhance contact tracing and mass testing capacity; at the same time, such measures take time and institutional capacity, and the developing world shows up as being slower to put them in place. Compared to lockdown measures, these measures tend not to be phased out once in place.

Figure 1: Number of Economies Adopting Each Measure by Development Level

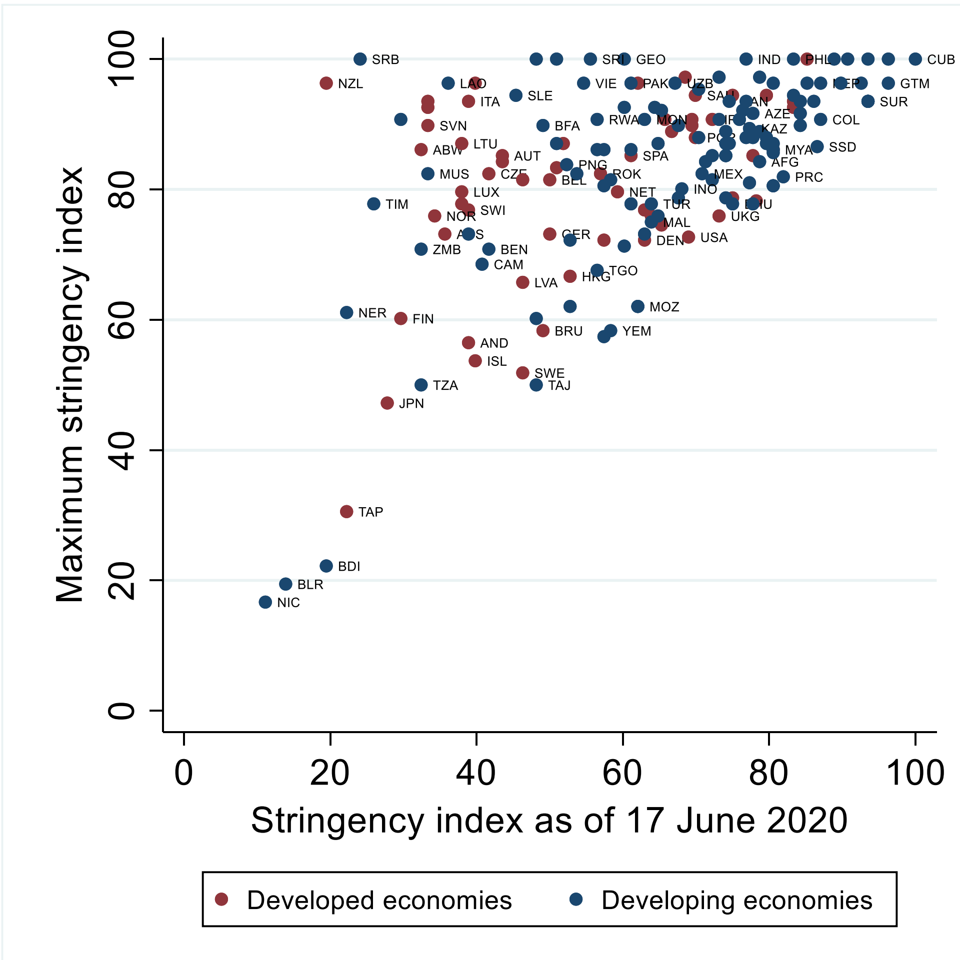


Notes: Developed economies refer to economies that belong to the high-income classification, while developing economies refer to economies that belong to the low-, lower-middle, and upper-middle income classification of the World Bank.

Source: Hale, Thomas, Noam Angrist, Emily Cameron-Blake, Laura Hallas, Beatriz Kira, Saptarshi Majumdar, Anna Petherick, Toby Phillips, Helen Tatlow, and Samuel Webster. 2020. Oxford COVID-19 Government Response Tracker, Blavatnik School of Government. https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker (accessed 30 June 2020).

Comparing the stringency of lockdown measures across economies reveals more variation in policy adoption. First, many economies have relaxed the overall lockdowns to some degrees since they were first introduced. Figure 2 compares the maximum value of the stringency index with the latest value as of 17 June 2020 using the OxCGRT stringency index. The economies on the 45-degree line maintained stringency index values at their respective maximums, while the economies on the top left half have more or less relaxed some control measures.

Figure 2: Stringency Index: Maximum and Latest Values



Notes: Developed economies refer to economies that belong to the high-income classification, while developing economies refer to economies that belong to the low-, lower-middle, and upper-middle income classification of the World Bank. Please refer to Appendix Table A2.2 for the definition of the three-letter codes. The maximum value of the stringency index is assessed between 1 January and 17 June 2020. The latest value of the stringency index is for 17 June 2020.

Source: Hale, Thomas, Noam Angrist, Emily Cameron-Blake, Laura Hallas, Beatriz Kira, Saptarshi Majumdar, Anna Petherick, Toby Phillips, Helen Tatlow, and Samuel Webster. 2020. Oxford COVID-19 Government Response Tracker, Blavatnik School of Government. https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker (accessed 30 June 2020).

Covid Economics 63, 7 January 2021: 35-72

Second, there is a large difference in stringency values and measures across economies. Figure 3 shows the maximum and latest values of the overall stringency index and selected control measures using the OxCGRT stringency index for various Asian economies. Georgia, India, the Philippines, and Sri Lanka implemented the most stringent measures (100) as of late March. Most economies have stringency index values above 70. Japan is among the most relaxed (less than 50) in Asia during the observation period.

Third, comparing specific measures across economies shows that school closure, prohibitions on public events, and border closures are the three most common restrictions imposed across the region (Figure 3). Workplace and public transport restrictions have been relaxed in most economies over time.

Figure 3: Stringency Index: Maximum and Latest Values

ADB Regional Members	Date when stringency index is highest	Stringency index (max)	Stringency index (as of June 17)	School closure	Workplace closure	Public events cancellation	Gatherings restriction	Public transport closure	Stay at home	Internal movement restriction	Border control
				(as of June 17)							
		0 to 100		0 to 4	0 to 4	0 to 3	0 to 5	0 to 3	0 to 4	0 to 3	0 to 4
Philippines	March 22	100	83								
India	March 22	100	77								
Georgia	March 31	100	60								
Sri Lanka	March 27	100	56								
Nepal	March 24	96	87								
Uzbekistan	April 28	96	67								
Pakistan	March 26	96	61								
Viet Nam	April 1	96	55								
Lao People's Democratic Republic	March 30	96	36								
New Zealand	March 26	96	19								
Bangladesh	April 11	94	75								
Kyrgyz Republic	March 25	92	76								
Azerbaijan	April 16	92	78								
Mongolia	May 5	91	63								
Kazakhstan	March 30	89	77								
Fiji	March 30	89	79								
Myanmar	April 17	86	81								
Singapore	April 14	85	78								
Afghanistan	April 12	84	79								
Papua New Guinea	April 16	84	52								
Republic of Korea	April 6	82	57								
Thailand	April 8	82	54								
People's Republic of China	March 26	82	82								
Indonesia	April 24	80	68								
Bhutan	March 27	78	75								
Timor-Leste	April 13	78	26								
Malaysia	May 23	75	64								
Australia	April 2	73	36								
Cambodia	April 9	69	41								
Hong Kong, China	April 6	67	53								
Brunei Darussalam	April 11	58	49								
Tajikistan	May 11	50	48								
Japan	April 16	47	28								
Taipei,China	February 2	31	22								

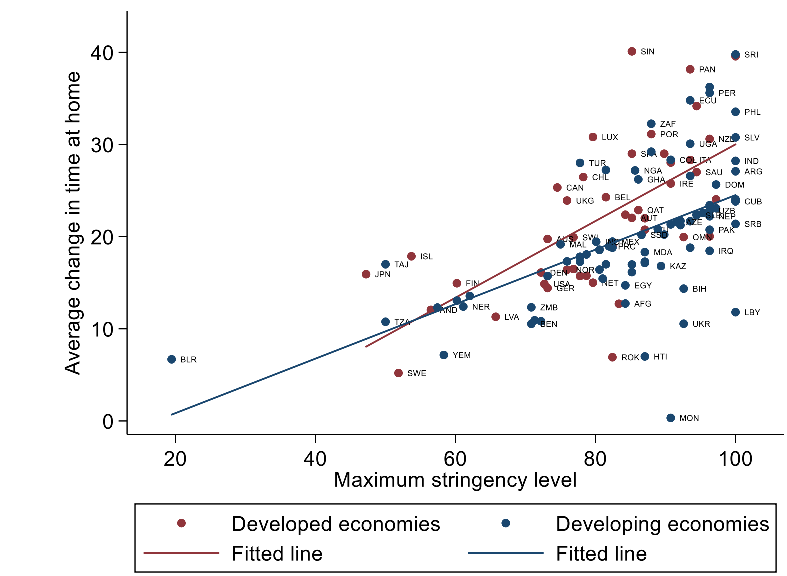
Notes: The maximum value of the stringency index is assessed between 1 January and 17 June 2020. The latest value of the stringency index is for 17 June 2020.

Source: Hale, Thomas, Noam Angrist, Emily Cameron-Blake, Laura Hallas, Beatriz Kira, Saptarshi Majumdar, Anna Petherick, Toby Phillips, Helen Tatlow, and Samuel Webster. 2020. Oxford COVID-19 Government Response Tracker, Blavatnik School of Government. https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker (accessed 30 June 2020).

Fourth, compared to developed economies, developing economies show relatively smaller increases in time spent at home even as more stringent lockdown measures were imposed. Figure 4 plots the maximum value of the stringency index imposed in each economy and the average changes in time spent at home during this period relative to the pre-COVID-19 baseline. There is no clear difference between changes in time at home by development level when the stringency index is moderate (less than 70). When the overall stringency index is high, developing economies show relatively smaller changes in time at home. A potential explanation for this is that people in developing economies simply cannot afford to stay at home for too long. For example, Dingel and Neiman (2020) show that emerging economies have a lower share of their labor force that can work from home.

Covid Economics 63, 7 January 2021: 35-72

Figure 4: Average Change in Time at Home during Period of Maximum Stringency



Notes: Developed economies refer to economies that belong to the high-income classification, while developing economies refer to economies that belong to the low-, lower-middle, and upper-middle income classification of the World Bank. Please refer to Appendix Table A2.2 for the definition of the three-letter codes. Average change in time at home indicates the average percentage change in time spent at home relative to a pre-COVID-19 baseline point of comparison during the period that an economy's stringency index is at its maximum value. Lines indicate linear fitted trends.

Source: Author's estimates.

IV. EMPIRICAL FRAMEWORK

We use panel regressions to estimate the relationship between R_t and COVID-19 control measures. Country fixed effects are included to account for time-invariant, or slow to change economywide features that may affect R_t, such as climate and geography, the nature and efficacy of the public health system, demographic characteristics, and prevalence of relevant comorbidities. A few time-invariant features are, however, introduced as interaction terms. We also include a linear time trend for days from outbreak in each country to absorb time-varying factors that affect R_t similarly across countries and day of week dummies to absorb cyclical patterns related to case reporting, as well as transmission risk contacts.

In principle, our approach is similar to using a difference-in-difference estimator and yields estimates of causal relationships, as long as the "parallel trends" assumption of similar changes over time in R_t in the absence of control measures of interest holds. Further, our use of a time trend that has a unique starting point per country based on when the pandemic emerged allows for control of R_t

reductions that occur naturally as the epidemic progresses and is an improvement over controls for time that are based solely on calendar dates.

We smooth our COVID-19 control measures and the time at home variable by using their corresponding 3-day moving average values. We then use 1-day lagged values of moving average as regressors to cover the periods up to that of the dependent variable.[15] R_t, as the dependent variable, is intended to be the instantaneous measure of how many individuals are being infected by the infectious on the given date, so that long lag effects are not needed, but there is also some imprecision in both the R_t measure and the policy implementation dates that the moving averages help to resolve.

Formally, we estimate the following model for R_t:

$$\begin{aligned} R_{t\,ct} = {} & \beta_M M_{c,t-1}^{ma(3)} + \beta_{MH} M_{c,t-1}^{ma(3)} \times HH_c \\ & + \beta_M Measure_{c,\,t-1}^{ma(3)} \\ & + \beta_{Tracing} Tracing_{c,\,t-1}^{ma(3)} \\ & + \beta_{EarlyT}\, Tracing_{c,\,t-1}^{ma(3)} \times EarlyT_c \\ & + \beta_{PSLT}\, Tracing_{c,\,t-1}^{ma(3)} \times PSL_c \\ & + \beta_{temp} Temp_{c,t-1}^{ma(3)} \\ & + \beta_t T \\ & + \beta_{wk} WK_t \\ & + \alpha_c + \epsilon_{ct} \end{aligned} \tag{1}$$

where $R_{t\,ct}$ is the reproduction number in country c on date t; $M_{c,t-1}^{ma(3)}$ is the 3-day moving average of changes in time at home on date $t-1$; HH_c is average household size and is interacted with time at home; $Measure_{c,t-1}^{ma(3)}$ is a vector of a series of 3-day moving average of country-specific control measures on date $t-1$ in country c, including school closure, workplace closure, public transport closure, small and large gathering ban, and large scale testing. $Tracing_{c,\,t-1}^{ma(3)}$ is the 3-day moving average of contact tracing measures on date $t-1$ in country c. $EarlyT_c$ is the number of days that contact tracing has been implemented prior to a country having 100 cumulative COVID-19 cases. It takes on negative values if tracing is implemented after 100 cumulative cases; PSL_c denotes the presence or absence of paid sick leave in country c; $Temp_{c,t-1}$ is the maximum temperature for country c on date $t-1$; T is linear time trend; WK_t is day of the week dummies; α_c is a country fixed effect; and ϵ_{ct} is the idiosyncratic error term for country c on date t.

To this regression we add a set of variables controlling for the timing of the appearance of genetic strains or clades of COVID-19 in selected runs. There has been speculation within the scientific community that new mutations have made COVID-19 more easily transmitted, and the inclusion of the variables helps to test this hypothesis.

To estimate the effects of COVID-19 control measures on GDP growth, we also use panel regression with country fixed effects to account for country-specific variations that could affect GDP growth. We also include quarter fixed effects in the specification, as well as the lagged effect of growth in

15 A range of lag structures and smoothing periods was tested, and the 3-day moving average with 1-day lag performed best in the regressions.

the same quarter in the previous year. Days since the first identified case in the country are also included to control for demand-side responses to the presence of the pandemic that may occur absent any control measures. The main independent variables are the natural log of the number of days that each control measure has been in place over each quarter. The control measures that can be included are constrained by correlations when summed to the quarterly level; thus those not expected to affect GDP (i.e., mask mandates, testing, and tracing) are summed to an index, whereas those expected to affect GDP are included separately.

Formally, we estimate the following model for GDP growth:

$$g_{cq} = \gamma_P lnDMeasure_{cq} + lnF_{cq} + \rho_q + g_{cq-4} + \delta_c + \varepsilon_{cq} \quad (2)$$

In equation (2), g_{cq} is the GDP growth rate of country c in quarter q; $DMeasure_{cq}$ is a vector of the total number of days various control measures have been implemented in country c in quarter q; F_{cq} is the number of days since the first COVID-19 case in the country; ρ_q is the quarter fixed effect; δ_c is a country fixed effect; ε_{cq} is the idiosyncratic error term for country c in quarter q.

Multicollinearity may be a concern that arises from the possible correlation of independent variables in the regression, as many countries have adopted a number of the control measures of interest. However, the data sources used indicate that the changes in these measures have not been simultaneous over time, so that it is possible to disentangle their effects with a two-way fixed effects model that focuses causal identification on differences in changes over time. Pairwise correlations in these differences are presented in Appendix Table A2.1.

V. RESULTS

A. Baseline Results of R_t and Measures

Table 2 presents our baseline results from equation (1). All specifications include day of the week fixed effects and country fixed effects.[16] Column (1) only includes change in time at home and its interaction with household size. Column (2) includes all COVID-19 control measures but does not control for time at home or PSL. Column (3) adds to Column (2) changes in time at home and Column (4) further adds an interaction of contact tracing and PSL. Column (4) is our preferred specification. There are several findings worth noting.

First, as expected, the coefficient on change in time at home is negative and significant. On average, a 1% increase in time at home leads to a 0.02 unit reduction in R_t. However, given the positive and significant coefficient on the change in time at home and household size interaction term, the effect is smaller if household size is larger. Compared to another country with one-unit smaller household size (i.e., on average, one fewer person per household), the effect of change in time at home and R_t reduction is 0.003 smaller (or 15% smaller on average). This implies that asking people to stay at home may be less

[16] We tested the specifications using pooled-OLS method. The large discrepancies of coefficients and level of significance of many independent variables (such as change in time at home, school closure, etc.) between pooled-OLS estimates and baseline results indicate missing variable bias when excluding country fixed effects. The pooled-OLS model also yields a much smaller explanatory power.

Covid Economics 63, 7 January 2021: 35-72

effective in reducing COVID-19 spread when household size is larger.[17] Including the mobility measure increases the explanatory power of the model substantially, indicating that it captures behavioral responses in addition to those dictated by the various control measures.

Second, the coefficients on lockdown measures included in the model are all negative and significant, except for closure of public transport, which is negative but not significant. Interestingly, the various lockdown measures lead to varying degrees of reduction in R_t. Small and large gathering bans lead to a 0.10 unit reduction in R_t, similar to the effect of school closures, which leads to a 0.09 unit reduction in R_t, followed by workplace closures (0.05 unit reduction). We do not find closures of public transport to have a significant effect on R_t.

Table 2: Baseline Results: R_t and Control Measures

Variables	(1)	(2)	(3)	(4)
Change in time at home	−.0176***		−.0204***	−.0211***
	(.0043)		(.0038)	(.0039)
Change in time at home x Household size	5.9e-04		.003***	.0031***
	(.0011)		(9.4e-04)	(9.9e-04)
Small gathering ban		−.175***	−.0975**	−.099***
		(.0377)	(.0372)	(.0372)
Large gathering ban		−.143***	−.0987***	−.0976***
		(.0363)	(.0335)	(.0337)
School closure		−.177***	−.0942***	−.092***
		(.0253)	(.0257)	(.0252)
Workplace closure		−.105***	−.0474*	−.0471*
		(.0261)	(.0256)	(.0254)
Public transport closure		−.0197	−.0105	−.0079
		(.0318)	(.0312)	(.0309)
Mask use		−.0416	−.0535	−.0603*
		(.0347)	(.034)	(.0342)
Mass testing		−.0542*	−.0551**	−.0542**
		(.0297)	(.0267)	(.0261)
Contact tracing		−.146**	−.156***	−.0472
		(.0649)	(.0562)	(.0636)
Early tracing		−.0032**	−.0037***	−.0029***
		(.0015)	(.0013)	(.001)
Tracing x PSL				−.207***
				(.0697)
Time trend		−.0029***	−.0028***	−.0028***
		(5.5e-04)	(5.6e-04)	(5.6e-04)
Max temperature		−.0036*	−.0059**	−.0058**
		(.0021)	(.0024)	(.0024)
Day of the week FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes

continued on next page

[17] For context, average household size is 2.73 in developed countries in our sample, compared to 4.26 in developing countries.

Table 2 *continued*

Variables	(1)	(2)	(3)	(4)
Observations	6,639	6,639	6,639	6,639
No. of countries	75	75	75	75
R-squared	0.204	0.522	0.566	0.572
F statistic	13.500	37.341	33.242	34.866

FE = fixed effects, PSL = paid sick leave.

Notes: Robust standard errors clustered by country in parentheses. *** = p<0.01, ** = p<0.05, * = p<0.1.

Source: Authors' estimates.

Third, we find most coefficients on the remaining NPIs to be negative and significant, and that the interaction term on contact tracing and PSL is the largest among all control measures considered. Specifically, when not controlling for PSL, tracing leads to a 0.16 unit of reduction in R_t, and the coefficient is significant. But when tracing is interacted with PSL, the coefficient on tracing is no longer significant and its level becomes much smaller. On the other hand, the coefficient of the interaction term between tracing and PSL is negative and statistically significant, suggesting that tracing is effective in reducing R_t in countries that provide PSL benefits. In other words, the effect of tracing on R_t arises from the combined effect of contact tracing and providing PSL benefits. On average, economies with PSL and tracing experience a 0.21 unit of reduction in R_t compared to economies only implementing tracing, meaning that one infected individual on average infects 0.21 fewer other people. We also find the coefficient on early tracing to be negative and significant.

Intuitively, offering PSL incentivizes workers who may be infected to report their symptoms and self-isolate. In the absence of PSL benefits, workers may choose to hide their symptoms or illness and continue to report for work and get paid. This is particularly relevant for COVID-19 where a large share of cases have mild symptoms or are asymptomatic, but are still capable of spreading the disease. When a worker with a mild case has to choose between staying at home and losing income or reporting for work and getting paid, the absence of PSL can nudge the worker to choose the latter even it means that they might infect coworkers. Providing PSL can not only reduce such "contagious presenteeism," it is also very likely to make tracing of COVID-19 cases easier and more accurate.

Fourth, comparing the results in Columns (2) and (4) shows that the coefficients on lockdown measures become smaller when we control for changes in time at home, with their magnitude smaller by about a half. For example, the coefficient on workplace closure changes from –0.105 to –0.047. On the other hand, there is little difference in the coefficients of nonlockdown measures, such as a mandate on masks, mass testing, and tracing. This indicates that reduced mobility is an important channel linking lockdown measures to reductions in R_t. The coefficients on control measures in Column (2) can be interpreted as an upper bound of their effects on R_t, while the coefficients on control measures in Column (4) can be interpreted as a lower bound.

Fifth, we have performed the same regression with additional control variables for the presence of major COVID-19 clades, and this reveals that more recent clade 20B appears to increase transmission rates (Table 3). In this specification, most of the other coefficients remain similar, although masks, gathering bans, and mobility reductions have larger effects, whereas testing loses significance. Because clades are not characterized for some countries, the sample is slightly smaller, and we use the specification without this variable in the other analyses presented subsequently. However, we include the result here, as the implication of this result is that newer mutations may be making COVID-19 more infectious and difficult to control. When this is considered along with our significant negative coefficients on temperature, this may imply that large second waves are likely when temperatures cool in countries with many infections later in 2020.

Covid Economics 63, 7 January 2021: 35-72

Table 3: R_t and Control Measures when Genetic Strains are Controlled

Variables	Baseline	Clade
Change in time at home	–.0211***	–.0278***
	(.0039)	(.0032)
Change in time at home x Household size	.0031***	.0052***
	(9.9e-04)	(9.3e-04)
Small gathering ban	–.099***	–.134***
	(.0372)	(.0421)
Large gathering ban	–.0976***	–.117***
	(.0337)	(.0363)
School closure	–.092***	–.0888***
	(.0252)	(.0284)
Workplace closure	–.0471*	.0158
	(.0254)	(.0222)
Public transport closure	–.0079	–.0185
	(.0309)	(.0331)
Mask use	–.0603*	–.0896**
	(.0342)	(.0339)
Mass testing	–.0542**	–.0155
	(.0261)	(.0264)
Contact tracing	–.0472	.0297
	(.0636)	(.0606)
Early tracing	–.0029***	–.0018*
	(.001)	(.001)
Tracing x PSL	–.207***	–.226***
	(.0697)	(.0667)
Time trend	–.0028***	–.0024***
	(5.6e-04)	(5.8e-04)
Max temperature	–.0058**	–.0083***
	(.0024)	(.002)
Clade 19A presence		–.0506
		(.0523)
Clade 19B presence		–.0271
		(.0536)
Clade 20A presence		–.0712
		(.0508)
Clade 20B presence		.0845**
		(.0393)
Clade 20C presence		–.054
		(.0411)
Day of the week dummy	Yes	Yes
Country FE	Yes	Yes
Observations	6,639	5,102
No. of countries	75	56
R-squared	0.572	0.649
F statistic	34.866	58.414

FE = fixed effects, PSL = paid sick leave.

Notes: Robust standard errors clustered by country in parentheses. *** = p<0.01, ** = p<0.05, * = p<0.1.

Source: Authors' estimates.

Covid Economics 63, 7 January 2021: 35-72

B. Robustness Tests

We test the robustness of our baseline results in two ways. We use an alternative and stricter definition of a PSL benefit that is relevant as a COVID-19 control measure. We also restrict our samples to countries with direct Google mobility time at home data. Our results are maintained under both cases.

First, to see if our highly significant result on the interaction of PSL and tracing is spurious due to the construction of the PSL dummy, we test the same specification using a much stricter PSL dummy. In the baseline specification, we constructed our PSL dummy by distinguishing whether a country offers *some* duration of PSL and the program covers *some* self-employed and part-time workers. In this setup, 25 out of 75 countries are considered to offer PSL. As an alternative, we consider a country to offer a COVID-19 relevant PSL only if the scheme offers at least 2 weeks of well-paid sick leave; it starts from the first day of absence from work; and guarantees coverage for both part-time and self-employed workers. In this strict setup, the number of countries offering PSL is down to 9 out of 75. The results, shown in Column (1) of Table 4, are only slightly different in terms of the coefficient compared to the baseline specification, with the significance levels of tracing, early tracing, and interaction term involving tracing and PSL the same as those in the baseline.

Second, we restrict our sample to only those countries with direct time at home data from Google. In our baseline specification, we use predicted time at home for countries without Google data to increase sample size. There are seven countries in our sample using the stringency-proxied time at home.[18] To see if our result is sensitive to the inclusion of projected time at home due to multicollinearity, we restrict our sample to the 68 countries with direct Google data in Column (2) of Table 4. Results are largely similar compared to the baseline results. The signs and significances of coefficients on the independent variables that are prone to the issue of multicollinearity largely stay the same, including change in time at home, household and change in time at home interaction, gathering bans, school closure, public transport closure, contact tracing, early tracing, and tracing and PSL interaction.

Table 4: Robustness Test of R_t and Control Measures

	Strict PSL Definition	Google Mobility Only
Variables	(1)	(2)
Change in time at home	-.0197***	-.0239***
	(.0037)	(.004)
Change in time at home x Household size	.0027***	.0036***
	(9.3e-04)	(.0011)
Small gathering ban	-.1***	-.0929***
	(.0374)	(.0302)
Large gathering ban	-.1***	-.0958***
	(.0346)	(.0307)
School closure	-.0979***	-.0761***
	(.0256)	(.0223)
Workplace closure	-.0449*	-.0214
	(.0253)	(.0254)
Public transport closure	-.0092	-.0088
	(.031)	(.0336)
Mask use	-.0603*	-.0346

continued on next page

[18] These seven countries are: Azerbaijan, Cuba, Guinea, Iran, Palestine, the PRC, and Uzbekistan.

Covid Economics 63, 7 January 2021: 35-72

Table 4 *continued*

Variables	Strict PSL Definition (1)	Google Mobility Only (2)
	(.0341)	(.0297)
Mass testing	-.0511**	-.0229
	(.0256)	(.025)
Contact tracing	-.0813	-.0456
	(.0551)	(.0598)
Early tracing	-.0035***	-.0032***
	(9.9e-04)	(.0012)
Tracing x PSL	-.220***	-.196***
	(.0729)	(.0709)
Time trend	-.0028***	-.0032***
	(5.6e-04)	(4.7e-04)
Max temperature	-.0057**	-.009***
	(.0024)	(.0024)
Day of the week FE	Yes	Yes
Country FE	Yes	Yes
Observations	6,639	5,932
No. of countries	75	68
R-squared	0.572	0.618
F statistic	33.615	36.297

FE = fixed effects, PSL = paid sick leave.

Notes: Robust standard errors clustered by country in parentheses. *** = p<0.01, ** = p<0.05, * = p<0.1.

Source: Authors' estimates.

C. Heterogeneity in Results across Developed and Developing Countries

To see whether there exists heterogeneity in the effects of control measures on R_t across developed and developing countries and phases of the pandemic, we split the sample by development level as defined by the World Bank and by prepeak and postpeak phases as defined by active cases.

Columns (1) and (2) of Table 5 show the results when samples are split by economic development level of countries implementing the measures.[19] There are two differences worth noting. First, the effect of change in time at home, and its interaction with household size are significant in developed countries, but not significant in developing countries. One reason for this is suggested by Figure 4: people in developing countries do not stay at home as much during lockdown. Second, the coefficient of the PSL and contact tracing interaction term in developing countries is a lot larger than that in developed countries. A reason that may underpin both findings could be that workers in developing countries have less ability to cope with income loss, so that contagious presenteeism may be more frequent.

We also split the sample in each country by the first wave peak of the pandemic in each country, as captured within the time frame of our sample. The peak of the pandemic is defined as the date with the largest number of active cases before 17 June 2020. The results (Columns 3 and 4 of Table 4) show that the coefficients on time at home and control measures in the prepeak sample have similar significance levels to those in the baseline, while coefficients in the postpeak sample are not significant.

[19] We categorize high-income countries classified by the World Bank as developed, and the rest as developing.

CEPR PRESS

This indicates that the baseline results are largely driven by the prepeak phase of the pandemic. In other words, the association between R_t and control measures are much weaker in the postpeak phase.

Table 5: Split Sample Heterogeneity of R_t and Control Measures

	Developed	Developing	Prepeak	Postpeak
Variables	(1)	(2)	(3)	(4)
Change in time at home	−.0331***	−.0024	−.0216***	.0037
	(.0053)	(.0063)	(.0045)	(.0059)
Change in time at home x	.0064**	−9.0e-04	.0035***	−6.5e-04
Household size	(.0024)	(.0013)	(.001)	(.0019)
Small gathering ban	−.0985**	−.0929	−.0769*	−.1**
	(.0382)	(.0662)	(.0408)	(.0477)
Large gathering ban	−.0888**	−.0936*	−.0963**	−.0681
	(.0393)	(.0543)	(.0438)	(.0495)
School closure	−.0712**	−.142***	−.101***	−.04
	(.0334)	(.048)	(.0301)	(.0307)
Workplace closure	−.0192	−.0434	−.0653**	−.0038
	(.0322)	(.0337)	(.03)	(.0264)
Public transport closure	.0371	−.0472	−.021	.0167
	(.0528)	(.0349)	(.0405)	(.0394)
Mask use	−.0402	−.0876	−.0045	−.0461*
	(.0386)	(.0528)	(.0343)	(.026)
Mass testing	−.035	−.0834*	−.0686*	.011
	(.0299)	(.0433)	(.0347)	(.0262)
Contact tracing	−.0782	−.0634	−.0068	−.0283
	(.0669)	(.0731)	(.0662)	(.0975)
Early tracing	−.0026**	−.0028	−.0015	−9.4e-04
	(.0012)	(.0017)	(.0012)	(.0018)
Tracing x PSL	−.15*	−.258**	−.229***	0
	(.0764)	(.104)	(.0839)	(.)
Time trend	−.003***	−.0021**	−.0033***	.0034***
	(6.3e-04)	(9.5e-04)	(6.8e-04)	(4.6e-04)
Max temperature	−.0115***	−.0013	−.004	−.0024
	(.0021)	(.0031)	(.0031)	(.002)
Day of the week FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Observations	3,157	3,482	3,875	2,764
No. of countries	34	41	75	58
R-squared	0.680	0.507	0.591	0.316
F statistic	107.936	57.032	26.761	17.078

FE = fixed effects, PSL = paid sick leave.

Notes: Robust standard errors clustered by country in parentheses. *** = p<0.01, ** = p<0.05, * = p<0.1. Column 1 is restricted to the sample of developed economies (i.e., high-income economies), and Column 2 is the sample of developing economies. Column 3 is restricted to the sample before the date with the highest active cases, and Column 4 is the sample after the date with the highest active cases.

Source: Authors' estimates.

Covid Economics 63, 7 January 2021: 35-72

The findings for the samples split by prepeak and postpeak periods are further confirmed by the results of the quantile regressions. Table 6 shows the regression results at 10th/30th/50th/70th/90th percentile of R_t. Several control measures, such as gathering bans, a mandate on masks, and the combination of testing and tracing are associated with larger reductions in R_t when R_t is high. Similar results are found for change in time at home.

Table 6: Quantile Regression of R_t and Control Measures

Variables	(1) R_t=0.8 (10th percentile)	(2) R_t=1.0 (30th percentile)	(3) R_t=1.1 (50th percentile)	(4) R_t=1.2 (70th percentile)	(5) R_t=1.5 (90th percentile)
Change in time at home	–.0063*	–.0111***	–.0111***	–.0206***	–.0395***
	(.0036)	(.0035)	(.0035)	(.0062)	(.0125)
Change in time at home x Household size	.0023**	.0023***	.0023***	.0034*	–.0015
	(9.3e-04)	(8.4e-04)	(8.4e-04)	(.0018)	(.0033)
Small gathering ban	–.0584	–.0816**	–.0816**	–.111**	–.114
	(.0373)	(.0335)	(.0335)	(.0473)	(.0998)
Large gathering ban	–.0574	–.0509*	–.0509*	–.0844**	–.142
	(.0418)	(.0277)	(.0277)	(.0384)	(.0955)
School closure	–.105***	–.038	–.038	.0074	–.0939
	(.0295)	(.0256)	(.0256)	(.0279)	(.0784)
Workplace closure	–.0332	–.025	–.025	–.0494	–.0365
	(.0269)	(.0259)	(.0259)	(.0389)	(.0648)
Public transport closure	–.0249	–.0013	–.0013	–2.0e-04	–.0494
	(.0297)	(.0239)	(.0239)	(.0548)	(.0946)
Mask use	–.0416	–.051*	–.051*	–.0769*	–.142*
	(.0296)	(.0266)	(.0266)	(.0459)	(.0755)
Mass testing	–.0129	.004	.004	–.0257	–.159**
	(.0301)	(.0259)	(.0259)	(.0312)	(.0781)
Contact tracing	–.005	.0557	.0557	.0577	–.208
	(.0375)	(.0445)	(.0445)	(.0488)	(.162)
Early tracing	2.6e-04	–5.1e-04	–5.1e-04	–.0021	–.0095***
	(5.5e-04)	(7.8e-04)	(7.8e-04)	(.0013)	(.0028)
Tracing x PSL	–.0511	–.169***	–.169***	–.275***	–.399
	(.0455)	(.0607)	(.0607)	(.0678)	(.248)
Time trend	8.2e-04*	1.2e-05	1.2e-05	–.0042***	–.0104***
	(4.8e-04)	(4.8e-04)	(4.8e-04)	(6.7e-04)	(.0015)
Max temperature	–.0033*	–.0042**	–.0042**	–.0037	–.0068
	(.0018)	(.0019)	(.0019)	(.0038)	(.0063)
Day of the week FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Observations	6,639	6,639	6,639	6,639	6,639
No. of countries	75	75	75	75	75
R-squared	0.227	0.387	0.387	0.512	0.557
F statistic	2.512	8.280	8.280	36.169	29.619

FE = fixed effects, PSL = paid sick leave.

Notes: Robust standard errors clustered by country in parentheses. *** = p<0.01, ** = p<0.05, * = p<0.1.

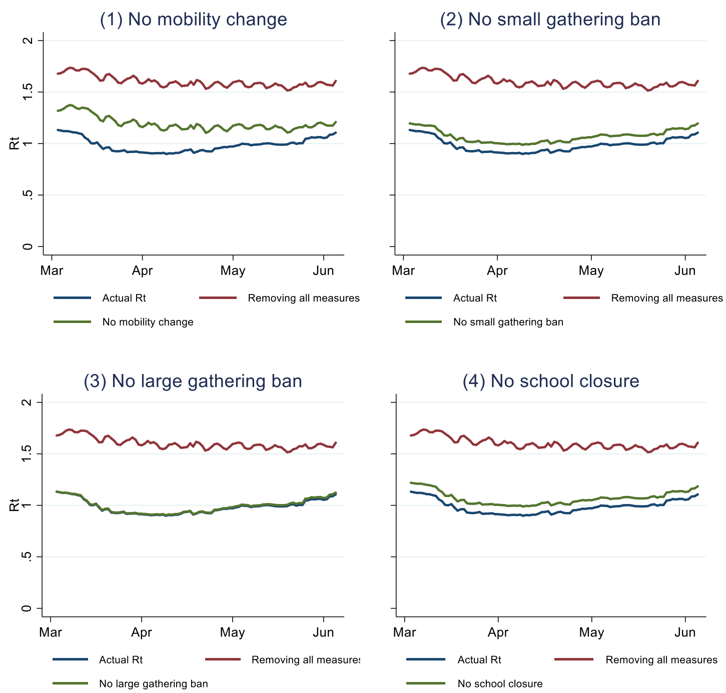
Source: Authors' estimates.

D. Evaluating Counterfactuals of COVID-19 Transmission

We conduct an exercise involving the counterfactual of how R_t would evolve if certain measures were not implemented. Using the baseline regression results, we predict the counterfactual R_t by removing each control measure for a given country at each date. We also predict the R_t in a country if it were to not implement the control measures it did. We then aggregate both sets of counterfactual R_t and actual R_t across countries at each given date and weight these by cases in each country.

Figure 5 shows the aggregated actual R_t and counterfactual R_t for sample countries when removing all control and time at home measures, and the counterfactual R_t when removing one specific measure. A key finding here is that absent explicit control measures, the time-varying reproductive rate is substantially lower than typical initial R_0 estimates of 2 or more. A lower reproductive rate has many important implications, including a lower herd immunity threshold and lower expected share of the population that will be eventually infected absent control measures. The contribution of adopted measures to keeping R_t reduced generally follows the coefficients estimated, but the figures also imply that relaxation of measures will be likely to lead to second waves in many countries, as the R_t will substantially exceed 1.

Figure 5: Actual versus Counterfactual R_ts



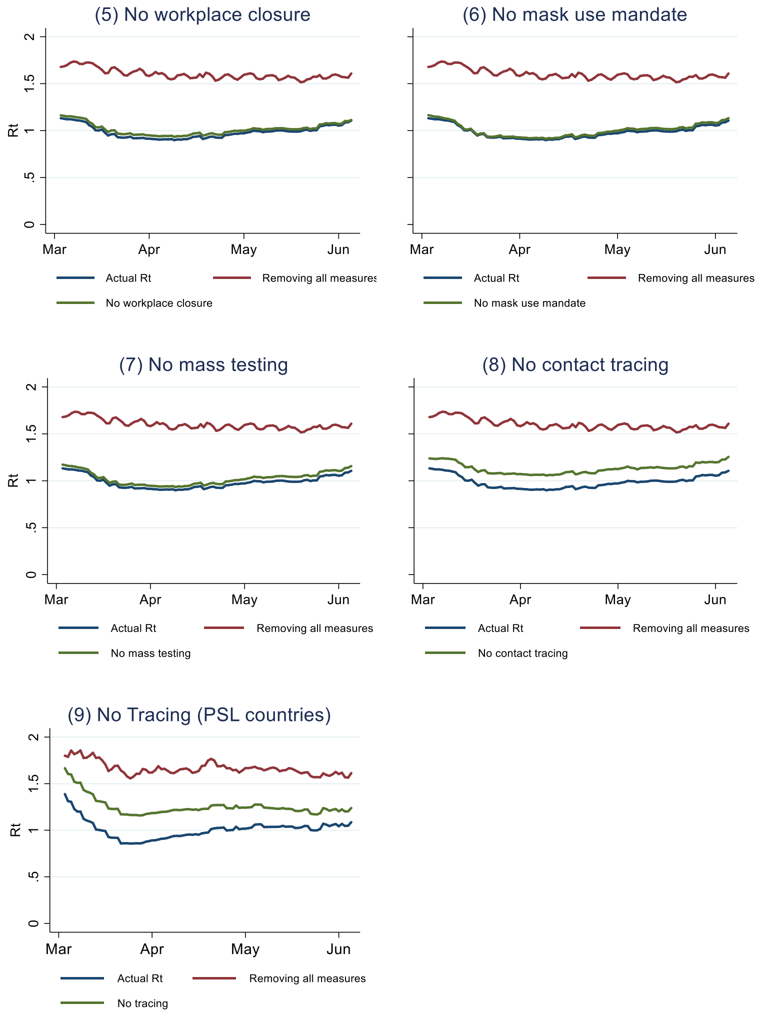
continued on next page

Covid Economics 63, 7 January 2021: 35-72

CEPR PRESS

Covid Economics 63, 7 January 2021: 35-72

Figure 5 *continued*



PSL = paid sick leave.

Notes: (i) "Removing all measures" indicates the counterfactual R_t resulting from an absence of all COVID-19 control measures and no changes in the time spent at home, while a "No" preceding a specific control measure indicates the counterfactual R_t resulting from an absence of that measure while keeping other measures as they actually are. (ii) Removed measures include small and large size gathering bans, school closure, workplace closure, mass testing, mask mandates, contact tracing, and PSL. For the counterfactual involving the changes in time spent at home, we set the change in time at home to 0. (iii) For contact tracing, we additionally perform a counterfactual exercise for the subsample of countries with PSL. (iv) R_t values are weighted by the cumulative case counts in each country.

Source: Authors' estimates based on baseline regression results.

E. Quarterly Gross Domestic Product Growth Rate and Control Measures

We now turn our focus to the economic costs of the various control measures. Table 7 shows the results of regressing quarterly GDP growth rates on key control measures of workplace, school, and transport closures, as well as other interventions. Countries implementing workplace and school closures experienced significant growth contractions as a result. For 1% increase in the duration of workplace and school closures, growth contracts by approximately 0.005 percentage points. On the other hand, the results suggest that other types of control measures, such as contact tracing and testing do not lead to contraction of the economy.

Table 7: Regression Results of Quarterly Gross Domestic Product and Control Measures

Variables	Quarterly GDP Growth
Workplace closure	–0.491**
	(0.204)
School closure	–0.464*
	(0.266)
Public transport closure	–0.194
	(0.390)
Index of other control measures	–0.252
	(0.220)
Days since first case	–1.166**
	(0.532)
GDP in quarter in previous year	–0.481***
	(0.112)
Constant	4.322***
	(0.388)
Observations	511
R-squared	0.816
F statistic	50.991

GDP = gross domestic product.

Notes: Quarter dummies omitted. Standard errors in parentheses. *** = p<0.01, ** = p<0.05, * = p<0.1.

Source: Authors' estimates.

Covid Economics 63, 7 January 2021: 35-72

VI. DISCUSSION

A. Limitations

Our empirical analysis is subject to two main data limitations. The first concerns our dependent variable, R_t, for the regressions of COVID-19 control measure effectiveness. The procedure used to estimate R_t depends on the quality of case reporting, even if it attempts to correct for reporting delays and underreporting. The procedure relies on global corrections and may not be fully able to account for differences among countries, although this is a limitation shared by almost all studies of COVID-19 outcomes. Estimates of R_t are also unstable when cases are low, so that some truncation is needed to cover periods during which the variable is stable.

The second data limitation concerns how widely enforced or applicable the various COVID-19 control measures are across countries and over time. In particular, unlike our measure of mobility (as captured by time at home) which is continuous, the degree to which control measures such as workplace closures or a mandate to use masks are adhered to is an unknown. To the extent that enforcement is not captured by the inclusion of country fixed effects, our coefficients may be estimated with some bias. For example, some measures may be enforced more intensely or more effectively in certain countries and at different phases of the pandemic. Mobility has been measured based on Google, which may have issues of selection bias, in that the data are only captured from populations with smart devices and location tracking enabled. Thus, the variable may only reflect the patterns of part of the population, and the representativeness of that part of the population may differ across countries. Unfortunately, we are not aware of a similar mobility data source without this problem that could substitute for all our sample countries.

Although our approach is able to control for time-invariant factors that differ among countries, it is dependent on the parallel trends assumption that the countries that did not institute a particular measure at a particular time would have had similar trends to those that did absent the measure. This assumption appears to be reasonable, given the similarity of initial reproductive rates across countries, as well as that the regressions are operating off the specific timing of when measures were adopted within the outbreak. The specific timing variations appear to largely be driven by exogenous specificities of decision-making within individual countries.

In terms of isolating the economic effects of containment measures, the analysis is constrained by the infrequency of GDP estimates. This infrequency limits observation sizes and renders multicollinearity a constraint that limits the variables that can be included simultaneously in the regression.

B. Consistency with Other Literature

Despite these limitations, our findings contribute to the body of work that is trying to understand the effectiveness of different measures to control the spread of COVID-19 and their associated costs on the economy. As future waves of the disease emerge, control measures proven to be effective and with lower economic costs should be implemented early and fast. Such measures should also be central features of the "new normal" until herd immunity is achieved.

Covid Economics 63, 7 January 2021: 35-72

In many ways, the results of our work are consistent with other recent analyses of COVID-19 control measures and policies to control similar respiratory communicable diseases. Islam et al. (2020) reached somewhat similar conclusions, with limited effects of transport closure detected, but effects on other measures found. Our analysis adds to this by including control measures omitted from that analysis, such as testing, contact tracing, and PSL, and by using a specification that accounts for interaction and individual measure effects.

Flaxman et al. (2020) find a large effect of lockdown on R_t, although the paper is unable to distinguish this from other interventions, due to timing similarities, which this paper overcomes through the use of data from more countries. The Brauner et al. (2020) paper is similarly able to overcome this limitation by analyzing a larger observation set (41 countries), and finds large effects from closing most nonessential businesses, closing universities and schools, and smaller, but significant effects of mandating wearing masks.

Carraro, Ferrone, and Squarcina (2020) similarly conclude that fewer measures are effective in low-income economies than higher-income ones, and find many of the same measures effective in high-income economies, but find workplace closure as an effective measure in low-income economies. Our paper finds a much smaller effect of business closing in both high- and low-income economies. Part of the latter result is due to the inclusion of a mobility variable that captures an additional behavioral response, but even in the specification lacking the variable, we still find a smaller effect of business closing, due to additional controls included in our regression, such as temperature. Islam et al. (2020) also share our finding of lower effectiveness of measures in low-income economies.

The result that larger household sizes tend to diminish the effectiveness of mobility reductions is a new contribution to the literature from an empirical perspective. At the same time, it is well understood from the perspective of social contact networks that larger household sizes mean that a larger share of total contacts that can contribute to disease spread is within the household, and that reduction of outside home contacts and intensification of within home contacts as mobility is reduced will lower contact rates less than in a smaller household contact setting (Nande et al. 2020).

Our novel finding of the importance of PSL to contact tracing effectiveness, while new for COVID-19, is also not without precedent in the broader literature. The importance of PSL to reduce disease transmission in workplaces and overall disease reproductive rates has been demonstrated for influenza like illnesses (Pichler, Wen, and Ziebarth 2020; Pichler and Ziebarth 2017). Given the particular characteristics of COVID-19—that most workers with mild symptoms face minimal risk from engaging in contagious presenteeism, and that the benefits of accurately disclosing information on exposure and symptoms accrue principally as an externality to other parties—it is logical to expect that payment to help correct incentives will make tracing more effective. The theoretical model in Appendix 1 provides further details.

Our results on additional controls are also consistent with prior literature. Wu et al. (2020) find that higher temperature is associated with lower transmission of COVID-19. There is also suggestive evidence that recent mutations are increasing COVID-19 transmission, in line with the significant coefficient on the presence of one of the newer clades (Korber et al. 2020). Unlike several other papers, our analysis finds a lower effective reproductive rate absent control measures of approximately 1.6, rather than the initial reproductive rate of around 2.5 typically generated from early observations (such as by Wu, Leung, and Leung 2020). At the same time, there are unobserved behavioral responses that are likely conditioning this difference, such as more frequent handwashing and maintenance of physical distance when in public settings. In addition, recent papers suggest that heterogeneity in social contacts and

Covid Economics 63, 7 January 2021: 35-72

susceptibility may make transmission over longer time periods behave as though the reproductive rate is lower than observed in the initial phases of the pandemic (Gomes et al. 2020).

In terms of economic effects, our results confirm the findings of Demirgüç-Kunt, Lokshin, and Torre (2020) that there are substantial effects on economic activity of lockdown measures, especially, business closure, as shown in our results. Unlike their analysis, however we find significant effects of school closure.

Our findings of large consequences of school closure however are consistent with literature that demonstrates how parental labor force participation declines when schools are closed and parents need to devote additional time to childcare, affecting both household income and broader macroeconomic output (e.g., Sadique, Adams, and Edmunds 2008). In essence, suspension of school or remote education requires parents to stay at home, crowds out labor supply and reduces productivity when working from home. For example, Fuchs-Schündeln, Kuhn, and Tertilt (2020) estimate that school and childcare center closure will affect 11% of workers and 8% of working hours. Dingel, Patterson, and Vavra (2020) estimate that 14% of workers under the age of 55 would likely face childcare obstacles to returning to work with schools closed. A second mechanism may be that, school closure, which is often implemented as a very early control measure, draws attention to epidemic risks and prompt a large share of the population to take COVID-19 seriously, thus reducing certain types of consumption, such as going to restaurants or travelling, as part of precautionary behavior.

Covid Economics 63, 7 January 2021: 35-72

VII. CONCLUSION

We have examined how the transmission of COVID-19 as captured by the reproduction number, R_t, is associated with various measures undertaken to control its spread by analyzing daily data from 75 economies for the first half of 2020. There are a number of important findings from a policy perspective.

First, while the reduction of COVID-19 spread is strongly driven by increases in time at home, this relationship is weaker when household size is large and especially so in developing countries. This suggests that lockdown orders that aim to suppress the spread of COVID-19 by restraining the mobility of people are less likely to be effective in communities with large households or where compliance is not compatible with the economic pressures that the population faces.

Second, the largest reductions in R_t are driven by gathering bans and school closures, followed by the use of masks, mass testing, and workplace closure. These effects are largely driven when the measures are put in place in the early phase of the pandemic. More generally, this demonstrates the importance of considering behavioral incentives set by policies to ensure that they have desired effects.

Third, we find that contact tracing, when implemented early and in contexts where PSL benefits tend to cover all types of workers (i.e., including self-employed and temporary workers), is strongly associated with reductions in R_t, especially in developing countries.

Fourth, countries implementing workplace and school closures experienced larger contractions in GDP growth in the first half of 2020, while countries implementing other measures do not show significant contractions in economic growth. This highlights the importance of moving beyond these measures to

CEPR PRESS

more targeted strategies, such as gathering bans, testing, and contact tracing supported by appropriate incentives.

Overall, our results suggest that tools such as workplace closures may be too blunt to deal with the spread of COVID-19, as they also take a huge toll on the economy. Countries would be better off expanding not only their capacity to test, trace, and isolate potential carriers of COVID-19 but also their PSL benefits to discourage the negative externality that potentially sick and infectious workers impose when they report for work and make tracing efforts more effective and accurate. In particular, efforts should be made to cover the self-employed and temporary workers under PSL for the entire duration of the pandemic. Our results also suggest that school closures have high costs and do not contribute much to epidemic control postpeak and when R_t levels are low. They should not be used for protracted periods.

Covid Economics 63, 7 January 2021: 35-72

Covid Economics 63, 7 January 2021: 35-72

APPENDIX 1: PAID SICK LEAVE, THE DECISION TO ISOLATE WHEN SICK, AND DISEASE TRANSMISSION

A. Model Setup

The absence of paid sick leave (PSL) can lead to faster transmission of coronavirus disease (COVID-19). To see why, consider the following simple model of a single firm with $N+1$ workers living in a two-period horizon, period 0 and 1. The time it takes for any worker from being infected to fully recovered is one period. In the case of COVID-19, this period can be interpreted as around 14 days. During the window of infection, the worker can infect other workers if she goes to work and thus interact with coworkers.

In each period, workers choose the number of days working (l) and consume a uniform consumption good (c). Wage and price of consumption goods are normalized to be 1. Assuming there are no initial endowments or intertemporal financing, each worker consumes whatever she earns in each period. Unhealthy workers gain disutility from working, while healthy workers do not. The quasi-linear utility function of worker i can be written as

$$U_i = \sum_{t=0}^{1} \beta^t \{u(c_{it}) - l_{it} \times \mathrm{I}_{it}\} \text{ for } i \in [0, N],$$

where $c_{it} \geq 0$ is consumption and $l_{it} \in [0,1]$ is the fraction of time at work in period t; function u is standard well-behaved utility function with the following properties: $u' > 0, u'' < 0, \lim_{c \to 0} u' = +\infty, and \lim_{c \to \infty} u' = 0$; I_{it} is a health indicator which equals to 1 if the worker is unhealthy and 0 otherwise.

At the beginning of the first period, all $N+1$ workers are healthy and have not gained immunity of COVID-19 yet. In the first period, worker 0 gets infected from external sources. She then chooses the l_{00} duration at work in period 0 and recovers in period 1. For the other N workers, they have an equal $p(l_{00})$ chance of being infected and become unhealthy, which is an increasing function of l_{00}, or $p' > 0$.

B. Regime without Paid Sick Leave

We first consider the regime without PSL. Since each worker consumers their labor income, the individual utility maximization problem for worker 0 can be written as:

$$\max_{\{c_{0t}, l_{0t}\}} U_0 = \sum_{t=0}^{1} \beta^t \{u(c_{0t}) - l_{0t} \times \mathrm{I}_{0t}\}$$

$$s.t.: c_{0t} = l_{0t};$$

$$\mathrm{I}_{00} = 1, and\ \mathrm{I}_{01} = 0.$$

We are most interested in the labor supply of worker 0 in period 0: l_{00}^*. It can be shown that:

$$u'(l_{00}^*) = 1, \tag{A.1}$$

where l_{00}^* is the individual optimal labor supply of worker 0 at period 0. Obviously, the only condition governs l_{00}^* is the marginal utility from consumption goods in period 0 of worker 0. The effect of increased infection probability $p(l_{00})$ is not the concern of worker 0.

When considering the socially optimal case, the choices of each worker need to maximize the sum of all workers' utility:

$$\max_{\{c_{it},l_{it}\}} U_s = \sum_{i=0}^{N}\sum_{t=0}^{1}\beta^t\{u(c_{it}) - l_{it}\times \mathrm{I}_{it}\}$$

$$s.t.: c_{it} = l_{it};$$

$$\mathrm{I}_{00} = 1, \mathrm{I}_{01} = 0;$$

$$\mathrm{I}_{j0} = 0, \mathrm{I}_{j1} = p(l_{00}), \qquad for\ \forall j \neq 0$$

Under optimization conditions, the socially optimal l_{00}^s satisfies:

$$u'(l_{00}^s) = 1 + \beta N p'(l_{00}^s)u'^{-1}\big(p(l_{00}^s)\big). \tag{A.2}$$

Combine equation (A.1) and (A.2) we have

$$u'(l_{00}^s) = u'(l_{00}^*) + \beta N p'(l_{00}^s)u'^{-1}\big(p(l_{00}^s)\big). \tag{A.3}$$

The left-hand side of equation (A.3) is the marginal social benefit of one unit of extra labor supply of worker 0 in period 0. The right-hand side of equation (A.1) is the marginal social cost of one unit of extra labor supply of worker 0 in period 0, which includes the marginal disutility incurred to worker 0 working when contagious in period 0, and marginal disutility incurred to all other N workers working when contagious in period 1.

There are two observations that can be drawn from equation (A.3). First, the individually optimal labor supply l_{00}^* exceeds the socially optimal labor supply l_{00}^s. This is because the likelihood of being infected for the N workers increases as the labor supply of worker 0 in period 0 increases, $p'(l_{00}^s) > 0$, and the properties of quasi-linear utility function make sure that $u'^{-1}\big(p(l_{00}^s)\big) > 0$. Therefore, $u'(l_{00}^s) > u'(l_{00}^*)$, which means $l_{00}^* > l_{00}^s$.

Second, the discrepancy between l_{00}^* and l_{00}^s increases with the number of exposed workers, N. When $N = 0$, $l_{00}^* = l_{00}^s$.

C. Regime with Paid Sick Leave

Suppose unhealthy workers could claim wage replacement ratio $s \in (0,1]$ from the PSL program for every unit of time not going to work, the individual and social planner's utility maximization problems are the same as the case without PSL, except the budget constraint for worker i in period t is now

$$c_{it} = (1 - s)l_{it} + s.$$

We first consider the case where s must be less than 1. The first-order condition of worker 0's individual utility maximization means

$$u'\big((1-s)l_{00}^{**}+s\big)=\frac{1}{1-s}. \tag{A.4}$$

where l_{00}^{**} is the optimal individual labor supply of worker 0 in period 0 when PSL is available. And the first-order conditions of social utility maximization mean

$$u'\big((1-s)l_{00}^{S*}+s\big)=\frac{1}{1-s}+\frac{\beta Np'(l_{00}^{S*})u'^{-1}\left(\frac{p(l_{00}^{S*})}{1-s}-s\right)}{(1-s)^2}, \tag{A.5}$$

where l_{00}^{S*} is the optimal social labor supply of worker 0 in period 0 when PSL is available.

It is easy to show that the two observations in the no PSL case still hold. That is, $l_{00}^{**}>l_{00}^{S*}$ and the difference increases with N.

More importantly, it can be shown that $l_{00}^{**}<l_{00}^{*}$ when $s\neq 1$. Equation (A.1) and (A.4) mean

$$u'\big((1-s)l_{00}^{**}+s\big)>u'(l_{00}^{*}).$$

Since $u'<0$, it follows that

$$l_{00}^{**}<l_{00}^{*}+s(l_{00}^{**}-1)<l_{00}^{*},$$

which means the individually optimal labor supply of worker 0 in period 0 under the PSL regime is less than her labor supply under the no PSL regime. Further, the reduced labor supply $l_{00}^{*}-l_{00}^{**}$ increases with PSL replacement ratio s.

It then follows that the likelihood for the other N workers to get infected is less than the no PSL regime, i.e., $p(l_{00}^{**})<p(l_{00}^{*})$. The reduced likelihood increases with PLS replacement ratio. In other words, a regime with positive PSL replacement ratio is predicted to experience slower transmission of COVID-19 than a regime not implementing any PSL schemes.

In the extreme case where $s=1$, worker 0 does not go to work at period 0, suppressing the case in this period, and zero case happens in period 1.

D. Discussion

To summarize, under the assumptions of usual properties of utility function and contact-duration-dependent infection rate, this model demonstrates that the individually optimal labor supply of a COVID-19 infected individual exceeds her socially optimal labor supply and brings excess likelihood of infection to coworkers. Introducing PSL could reduce or eliminate the discrepancy between individually and socially optimal labor supply of infected workers.

The model is deliberately simple in scope to illustrate the negative externality from the income-transmission trade-off of unhealthy workers. The following assumptions of the model could be generalized to study dynamic and more generalized issues, such as the design of optimal PSL scheme. First, the current model focuses on comparing the labor supply of worker 0 under individually and socially optimal case. It does not discuss the labor supply of the other N workers, nor does it solve for welfare loss due to socially suboptimal choices. Second, the model only considers two periods and is not concerned with future transmissions. To expand the framework into multiple time periods, standard SEIR assumptions could be introduced to track the immune, infected, and exposed workers. Third, the replacement ratio s is not necessarily constant over time. In an optimal design, it should be contingent on the share of infected and exposed workers. It could also introduce new cases from external shocks. Forth, the model assumes perfect information. In implementation, a PSL scheme design should introduce incentive compatibility constraint to curb moral hazard from both healthy and unhealthy workers. Lastly, the model is not concerned with the cost and financing of PSL.

In general, the framework could be extended toward a principal–agent model with infinite time horizon, tracking immunity profile using SEIR assumptions, time-variant replacement ratio, incentive compatibility constraint, and nonzero external infection likelihood. It can then be used to study the dynamics of optimal PSL replacement ratio and welfare gains of such PSL schemes.

Covid Economics 63, 7 January 2021: 35-72

APPENDIX 2: OTHER SUPPLEMENTAL INFORMATION

Table A2.1: Pairwise Correlations of the First Differences of 3-Day Moving Averages of Nonpharmaceutical Intervention

Variables	Change in Time at Home	Small Gathering Ban	Large Gathering Ban	School Closure	Workplace Closure	Public Transport Closure	Mask Use	Mass Testing	Contact Tracing	Maximum Temperature
Change in time at home	1.000									
Small gathering ban	0.121	1.000								
Large gathering ban	–0.004	–0.538	1.000							
School closure	0.100	0.134	–0.020	1.000						
Workplace closure	0.138	0.230	–0.097	0.124	1.000					
Public transport closure	0.114	0.160	–0.052	0.068	0.237	1.000				
Mask use	–0.001	–0.024	0.032	–0.009	–0.065	–0.025	1.000			
Mass testing	0.020	–0.026	0.020	–0.050	–0.040	0.018	0.032	1.000		
Contact tracing	0.035	–0.003	0.049	0.011	0.029	0.017	–0.011	0.059	1.000	
Maximum temperature	–0.094	0.000	–0.003	0.030	0.015	–0.014	–0.002	–0.031	–0.015	1.000

Source: Authors' estimates.

Covid Economics 63, 7 January 2021: 35-72

Table A2.2: List of Economies and Their Corresponding Three-Letter Codes

Economy	Code	Economy	Code
Aruba	ABW	Mongolia	MON
Afghanistan	AFG	Mozambique	MOZ
Andorra	AND	Mauritius	MUS
Argentina	ARG	Myanmar	MYA
Australia	AUS	Nepal	NEP
Austria	AUT	Niger	NER
Azerbaijan	AZE	The Netherlands	NET
Bangladesh	BAN	Nigeria	NGA
Burundi	BDI	Nicaragua	NIC
Belgium	BEL	Norway	NOR
Benin	BEN	New Zealand	NZL
Burkina Faso	BFA	Oman	OMN
Bhutan	BHU	Pakistan	PAK
Bosnia and Herzegovina	BIH	Panama	PAN
Belarus	BLR	Peru	PER
Brunei Darussalam	BRU	Philippines	PHL
Cambodia	CAM	Papua New Guinea	PNG
Canada	CAN	Portugal	POR
Chile	CHL	People's Republic of China	PRC
Colombia	COL	Qatar	QAT
Cuba	CUB	Republic of Korea	ROK
Czechia	CZE	Rwanda	RWA
Denmark	DEN	Saudi Arabia	SAU
Dominican Republic	DOM	Singapore	SIN
Ecuador	ECU	Sierra Leone	SLE
Egypt	EGY	El Salvador	SLV
Finland	FIN	Spain	SPA
Georgia	GEO	Serbia	SRB
Germany	GER	Sri Lanka	SRI
Ghana	GHA	South Sudan	SSD
Guatemala	GTM	Suriname	SUR
Hong Kong, China	HKG	Slovenia	SVN
Haiti	HTI	Sweden	SWE
India	IND	Switzerland	SWI
Indonesia	INO	Tajikistan	TAJ
Ireland	IRE	Taipei,China	TAP
Iraq	IRQ	Togo	TGO
Iceland	ISL	Timor-Leste	TIM
Italy	ITA	Turkey	TUR
Japan	JPN	Tanzania	TZA
Kazakhstan	KAZ	Uganda	UGA
Lao People's Democratic Republic	LAO	United Kingdom	UKG
Libya	LBY	Ukraine	UKR
Lithuania	LTU	United States	USA
Luxembourg	LUX	Uzbekistan	UZB
Latvia	LVA	Viet Nam	VIE
Malaysia	MAL	Yemen	YEM
Moldova	MDA	South Africa	ZAF
Mexico	MEX	Zambia	ZMB

Note: For ADB member-economies, the three-letter codes follow the codes prescribed in the ADB Handbook of Style and Usage 2017 edition. The rest are represented based on the three-letter codes defined in the International Organization for Standardization 3166-1 (ISO Alpha-3).
Source: Authors' compilation.

CEPR PRESS

REFERENCES

Abbott, Sam, Joel Hellewell, Robin Thompson, Katharine Sherratt, Hamish P. Gibbs, Nikos I. Bosse, James D. Munday, Sophie Meakin, Emma L. Doughty, June Young Chun, Yung-Wai Desmond Chan, Flavio Finger, Paul Campbell, Akira Endo, Carl A. B. Pearson, Amy Gimma, Tim Russell, CMMID COVID modelling group, Stefan Flasche, Adam J. Kucharski, Rosalind M. Eggo, and Sebastian Funk. 2020. "Estimating the Time-Varying Reproduction Number of Sars-Cov-2 Using National and Subnational Case Counts." *Wellcome Open Research* 5 (112).

Avery, Christopher, William Bossert, Adam Clark, Glenn Ellison, and Sara Fisher Ellison. 2020. "Policy Implications of Models of the Spread of Coronavirus: Perspectives and Opportunities for Economists." Covid Economics: Vetted and Real-Time Papers, 12, pp.21-68.

Bergman, Nittai K., and Ram Fishman. 2020. "Correlations of Mobility and Covid-19 Transmission in Global Data." *medRxiv*. 10.1101/2020.05.06.20093039.

Brauner, Jan Markus, Sören Mindermann, Mrinank Sharma, David Johnston, John Salvatier, Tomáš Gavenčiak, Anna B. Stephenson, Gavin Leech, George Altman, Vladimir Mikulik, Alexander John Norman, Joshua Teperowski Monrad, Tamay Besiroglu, Hong Ge, Meghan A. Hartwick, Yee Whye Teh, Leonid Chindelevitch, Yarin Gal, Jan Kulveit, 2020. "The Effectiveness of Eight Nonpharmaceutical Interventions against COVID-19 in 41 Countries." *medRxiv*: 2020.05.28.20116129. 10.1101/2020.05.28.20116129.

Brodeur, Abel, David M. Gray, Anik Islam, and Suraiya Jabeen Bhuiyan. 2020. "A Literature Review of the Economics of COVID-19." IZA Discussion Papers 13411.

Carraro, Alessandro, Lucia Ferrone, and Margherita Squarcina. 2020. "Are COVID-19 Containment Measures Equally Effective in Different World Regions?" DISEI Working Papers - Economics 11/2020.

Demirgüç-Kunt, Asli, Michael Lokshin, and Iván Torre. 2020. "The Sooner, the Better: The Early Economic Impact of Non-Pharmaceutical Interventions during the COVID-19 Pandemic." Policy Research Working Paper 9257.

Dingel, Jonathan I., and Brent Neiman. 2020. "How Many Jobs Can Be Done at Home?" *Journal of Public Economics* 189: 104235. https://doi.org/10.1016/j.jpubeco.2020.104235.

Dingel, Jonathan, Christina Patterson, and Joseph S. Vavra. 2020. "Childcare Obligations Will Constrain Many Workers When Reopening the US Economy." BFI Working Paper 2020-46.

Flaxman, Seth, Swapnil Mishra, Axel Gandy, H. Juliette T. Unwin, Thomas A. Mellan, Helen Coupland, Charles Whittaker, Harrison Zhu, Tresnia Berah, Jeffrey W. Eaton, Mélodie Monod, Imperial College COVID-19 Response Team, Azra C. Ghani, Christl A. Donnelly, Steven Riley, Michaela A.C. Vollmer, Neil M. Ferguson, Lucy C. Okell, and Samir Bhatt. 2020. "Estimating the Effects of Non-Pharmaceutical Interventions on COVID-19 in Europe." *Nature 584* (7820): 257-61. 10.1038/s41586-020-2405-7.

Fuchs-Schündeln, Nicola, Moritz Kuhn, and Michèle Tertilt. 2020. "The Short-Run Macro Implications of School and Child-Care Closures." IZA Discussion Papers 13353.

Gomes, M. Gabriela M., Rodrigo M. Corder, Jessica G. King, Kate E. Langwig, Caetano Souto-Maior, Jorge Carneiro, Guilherme Goncalves, Carlos Penha-Goncalves, Marcelo U. Ferreira, and Ricardo Aguas. 2020. "Individual Variation in Susceptibility or Exposure to Sars-Cov-2 Lowers the Herd Immunity Threshold." *medRxiv*: 2020.04.27.20081893. 10.1101/2020.04.27.20081893.

Google. COVID-19 Community Mobility Reports. https://www.google.com/covid19/mobility/ (accessed 30 June 2020).

Hadfield, James, Colin Megill, Sidney M. Bell, John Huddleston, Barney Potter, Charlton Callender, Pavel Sagulenko, Trevor Bedford, and Richard A. Neher. 2018. "Nextstrain: Real-Time Tracking of Pathogen Evolution." *Bioinformatics* 34 (23): 4121-23. 10.1093/bioinformatics/bty407.

Hale, Thomas, Noam Angrist, Emily Cameron-Blake, Laura Hallas, Beatriz Kira, Saptarshi Majumdar, Anna Petherick, Toby Phillips, Helen Tatlow, and Samuel Webster. 2020. Oxford COVID-19 Government Response Tracker, Blavatnik School of Government. https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker (accessed 30 June 2020).

Islam, Nazrul, Stephen J. Sharp, Gerardo Chowell, Sharmin Shabnam, Ichiro Kawachi, Ben Lacey, Joseph M. Massaro, Ralph B. D'Agostino, and Martin White. 2020. "Physical Distancing Interventions and Incidence of Coronavirus Disease 2019: Natural Experiment in 149 Countries." *BMJ 370*: m2743. 10.1136/bmj.m2743.

Kim, Daniel. 2017. "Paid Sick Leave and Risks of All-Cause and Cause-Specific Mortality among Adult Workers in the USA." *Int. J. Environ. Res. Public Health* 14 (10): 1247.

Korber, Bette, Will M. Fischer, Sandrasegaram Gnanakaran, Hyejin Yoon, James Theiler, Werner Abfalterer, Nick Hengartner, Elena E. Giorgi, Tanmoy Bhattacharya, Brian Foley, Kathryn M Hastie, Matthew D. Parker, David G. Partridge, Cariad M. Evans, Timothy M. Freeman, and Thushan I. de Silva on behalf of the Sheffield COVID-19 Genomics Group. 2020. "Tracking Changes in Sars-Cov-2 Spike: Evidence That D614g Increases Infectivity of the COVID-19 Virus." *Cell* 182 (4): 812-27.e19. https://doi.org/10.1016/j.cell.2020.06.043.

#Masks4All. What Countries Require Masks in Public or Recommend Masks? https://masks4all.co/what-countries-require-masks-in-public/ (accessed 30 June 2020).

Nande, Anjalika, Ben Adlam, Justin Sheen, Michael Z. Levy, and Alison L. Hill. 2020. "Dynamics of COVID-19 under Social Distancing Measures Are Driven by Transmission Network Structure." *medRxiv*: 2020.06.04.20121673. 10.1101/2020.06.04.20121673.

National Centers for Environmental Information. Land-Based Station Data. https://www.ncdc.noaa.gov/data-access/land-based-station-data (accessed 30 June 2020).

Pichler, Stefan, Katherine Wen, and Nicolas R. Ziebarth. 2020. "Positive Health Externalities of Mandating Paid Sick Leave." IZA Discussion Papers 13530.

Pichler, Stefan, and Nicolas R. Ziebarth. 2017. "The Pros and Cons of Sick Pay Schemes: Testing for Contagious Presenteeism and Noncontagious Absenteeism Behavior." *Journal of Public Economics* 156: 14-33. https://doi.org/10.1016/j.jpubeco.2017.07.003.

Raitzer, David, Rouselle Lavado, Jomar Rabajante, Liming Chen, Glenita Amoranto, Xylee Javier, Alex Cook, and Ludigil Garces. Forthcoming. “Letting Loose without Letting Up: Costs and Benefits of COVID-19 Control Policies in the Philippines.” ADB Economics Working Paper Series.

Sadique, Md Z., Elisabeth J. Adams, and William J. Edmunds. 2008. “Estimating the Costs of School Closure for Mitigating an Influenza Pandemic.” *BMC Public Health* 8 (1): 135. 10.1186/1471-2458-8-135.

WORLD Policy Analysis Center. Short-term Paid Sick Leave Data. https://www.worldpolicycenter.org/maps-data/data-download/short-term-paid-sick-leave-data (accessed 2 July 2020).

Wu, Joseph T., Kathy Leung, and Gabriel M. Leung. 2020. “Nowcasting and Forecasting the Potential Domestic and International Spread of the 2019-Ncov Outbreak Originating in Wuhan, China: A Modelling Study.” *Lancet* 2020 (395): 689–97.

Wu, Yu, Wenzhan Jing, Jue Liu, Qiuyue Ma, Jie Yuan, Yaping Wang, Min Du, and Min Liu. 2020. “Effects of Temperature and Humidity on the Daily New Cases and New Deaths of COVID-19 in 166 Countries.” *Science of The Total Environment* 729: 139051. https://doi.org/10.1016/j.scitotenv.2020.139051.

Xie, Jingui, and Yongjian Zhu. 2020. “Association between Ambient Temperature and COVID-19 Infection in 122 Cities from China.” *Science of The Total Environment* 724: 138201. https://doi.org/10.1016/j.scitotenv.2020.138201.

CEPR PRESS

Covid Economics **Issue 63, 7 January 2021**

Living with reduced income: An analysis of household financial vulnerability under COVID-19[1]

Catarina Midões[2] and Mateo Seré[3]

Date submitted: 18 December 2020; Date accepted: 4 January 2021

The COVID-19 crisis has led to substantial reductions in earnings. We propose a new measure of financial vulnerability, computable through survey data, to determine whether households can withstand a certain income shock for a defined period of time. Using data from the ECB Household Finance and Consumption Survey (HFCS) we analyse pre-existing financial vulnerability in seven EU countries. We find that income support is essential for many families: 47.2 million individuals, out of the 243 million considered, cannot afford three months of food and housing expenses without privately earned income. Differences across countries are stark, and those born outside of the EU are especially vulnerable. Through a tax-benefit microsimulation exercise, we then derive household net income when employees are laid-off and awarded the COVID-19 employment protection benefits enacted in the different countries. Our findings suggest that the COVID-19 employment protection schemes awarded are extremely effective in reducing the number of vulnerable individuals. The relative importance of rent and mortgage suspensions in alleviating vulnerability is highly country dependent.

Covid Economics 63, 7 January 2021: 73-97

1 We thank the Joint Research Center (JRC), Koen Decancq, Enrico Bergamini, and participants in the internal seminar of the Center for Social Policy at the University of Antwerp for valuable input.

2 Research Analyst, Bruegel.
3 PhD student, Center for Social Policy, University of Antwerp.

CEPR PRESS

Covid Economics 63, 7 January 2021: 73-97

1 Introduction

The COVID-19 outbreak has brought on, alongside a major health crisis, dramatic economic shocks to European countries. Governments around the continent are taking different measures to face the pandemic while preserving jobs and incomes. This paper analyses households' pre-existing vulnerabilities to an income shock and assesses the degree of protection awarded to employees, in different European countries, by COVID-19 employment protection schemes.

Financial vulnerability has received considerable attention lately, and especially after the 2008 crisis. The concept is defined broadly as the likelihood that an economic shock will result in a substantial decline of individual well-being. Risk of or uncertainty about falling into hardship is the key component that differentiates vulnerability from a state of, for example, poverty (Hoddinott and Quisumbing 2010 and Whelan 1993).

To measure financial vulnerability, the literature uses both objective and subjective approaches. Objective measures are independent of the individual's opinion and may be self-reported or obtained from an external source. Examples include possession of financial assets, amounts in savings accounts, access to credit, or having health insurance. Subjective measures instead are based on perception and self-reported, usually through surveys. An example of the latter is Lusardi et al. (2011) who examine US household financial vulnerability by asking how confident individuals are that they could come up with $2,000 in 30 days to face an unexpected need.

In this paper, we use an objective measure. Instead of asking individuals whether they would be able to cope with a hypothetical shock, we assess whether they can cover their usual basic expenditures under a hypothetical shock. In particular, we analyse whether households can afford basic expenditures if deprived of their privately earned income, resorting, instead, to a combination of their savings and publicly provided income such as pensions and public transfers.[1] We firstly consider only food and utilities as basic expenditures and then extend this basket to include mortgages and rents on main residences, for individuals who own no other residence[2].

We build on Midoes (2020), which provides an estimate of the number of households that could not afford basic expenses without privately earned income. The paper simulates a scenario where households can resort to bank savings, public transfers, pensions and 50% of their gross privately earned income to face expenses. This percentage of privately earned income is meant to represent living with a COVID-19 unemployment benefit. Here, instead, we simulate net incomes obtained under the actual COVID-19 unemployment protection schemes enacted by each country, and assess whether individuals can afford basic expenditures.

[1] By privately earned income, we refer to income other than pensions and public transfers. It encompasses salary income, self-employed income, rental income, income from financial assets and regular private transfers.

[2] For food expenses we consider average monthly expenditure on food and beverages at home. Utility expenses comprise average monthly expenditure on utilities, specifically electricity, water, gas, TV and internet.

We analyse 7 countries: Austria, Belgium, Finland, France, Germany, Italy and Portugal. We calculate financial vulnerability using Wave 3 of the ECB Household Finance and Consumption survey (HFCS), conducted in 2017.

We find a high degree of financial vulnerability across the different countries analysed: without their privately earned income, 18.2 million individuals (or 7% of the population considered) would not be able to cover one monthly of expenditures with food and utilities. In a three months horizon, 31.2 million, or 13% of the population of the countries considered, would not be able to cover those expenses. When we add rent and mortgages on the main residence, almost 20% become vulnerable at the 3 month mark.

This highlights the need for income support even for short-term shocks. Pensions and public transfers are a fundamental source of income for households who receive them in several countries, substantially reducing the number of vulnerable individuals. For example, 32.1% of the Finish population would not be able to cover for food and utilities in a three months horizon if they had to resort exclusively to their bank deposits, but, once pensions and public transfers are considered, this percentage is only 9.6%. Belgium and France are similar. On the contrary, in Italy and Portugal, pre-existing pensions and particularly public transfers are not especially effective in reducing vulnerabilities.

We find that individuals born outside the European Union are 1.8 times more at risk of not being able to cover for their expenses under a 100% privately earned income shock. A similar situation can be observed for households with children and with lower educational level: children are 1.4 times more at risk of being vulnerable than the rest of the population, and those with secondary education or less are 1.38 more at risk than those with tertiary education.

Our results highlight the importance of unemployment benefits: 5.9% of individuals in households affected by a loss of employee income, without income support, are unable to cope with food and utilities in a three months horizon. Once all COVID-19 unemployment benefits enacted by the different countries are considered, only 1.1% of individuals affected cannot cover for these expenses. By expanding the basket to include rent and mortgages on the main residence, the numbers are respectively 10.5%, and 2.1% once the COVID-19 unemployment benefits are awarded.

This vulnerability characterization is useful for economic research and public policy, being simple and readily available from survey data covering consumption and savings. It can help identify groups of individuals more vulnerable to income shocks, distinguishing, for instance, between employees and the self-employed. It can also be used to describe by how much households will have to reduce savings to keep basic consumption constant.

The rest of the article is structured as follows. In Section 2 we summarize the literature on financial vulnerability and the rationale for our specific measure. Section 3 describes the data and methodology, giving details on our financial vulnerability measure. Section 4 presents results, firstly describing the vulnerability of the population to a shock to privately earned income, and, secondly, the vulnerability of the population to a shock to employee income, with and without COVID-19 employment protection

Covid Economics 63, 7 January 2021: 73-97

schemes. Section 5 discusses how different policies could further reduce vulnerability. Section 6 concludes.

2 Related literature

The measure of vulnerability used in this paper is based on the idea that when deprived of their labor and capital income, individuals resort to a combination of savings and remaining sources of income (publicly provided) to cover for basic expenses. Yet this is not the only way people can face an economic shock. Arguably, they can adapt their consumption patterns, by, for example, reducing their demand for certain types of goods (Hamermesh 1982) or increasing their home production of goods (Aguiar and Hurst 2007). Although individuals might adapt their consumption when faced with a financial shock, their ability to do so is constrained. Many households have "consumption commitments", for instance, in what pertains to housing, that are costly to adjust, especially in the short-term. Indeed, most homeowners do not move during unemployment spells and have mortgage or rent payments commitments (Chetty and Szeidl 2007).

Another reason why changes to consumption might not come about immediately is that individuals have consumption habits. Models of habit formation state that the instantaneous utility function of individual i, having habit forming preferences $u(c_i, x_i)$, depends not only on current consumption c_i, but also on the habit level x_i. In particular, this type of models assumes that only the component of consumption over and above the habit level, i.e., $c_i - x_i$, contributes to utility (Naik and Moore 1996). Hence, any change in consumption from the habit level is perceived as a gain or a loss (Günther and Maier 2014).

The housing expenses we consider are costly to adjust and so can be basic utilities. These expenses, together with food - excluding restaurants -, might be somewhat adjusted, given intertemporal substitution of consumption, yet the elasticity of substitution is expected to be below one. Thus, individuals whose savings are insufficient to keep past consumption levels are vulnerable in the sense that they are more likely to experience larger decreases in welfare.[3]

To meet ordinary living expenses under income shocks, households might also rely on resources other than bank savings, pensions and public transfers; namely, they might resort to consumer credit. This, however, comes at a cost (interest) and can in itself be taken as a measure of financial vulnerability. And even if some families do take out loans to afford housing expenses (Andersen et al. 2020), Horvath et al. (2020) shows that in the United States, since the onset of COVID-19, new supply of credit to risky borrowers is limited. In the presence of liquidity constrains, another important resource to consider are loans or gifts from family and friends, which can, likewise, ensure minimum levels of consumption. While these loans are typically short-term and in low amounts (Long 2020), they do provide an additional buffer. Such formal and informal credit could be acknowledged explicitly in future research to better

[3]See Browning and Crossley 2009 for further details on how households in temporarily constrained circumstances cut back on expenditures, and how they spend marginal dollars of unemployment benefits.

Covid Economics 63, 7 January 2021: 73-97

assess short-term financial vulnerability.

Precautionary savings in cash are another resource not explicitly considered. Our analysis overall considers only households which have a bank account, as these households are less likely to use cash as an important source of savings (Kendall 2010).

As a sensitivity analysis, we kept only households which have a bank account, but allocated cash to individuals above 18, according to the percentage reported in Esselink and Hernández (2017) as having precautionary cash savings in the country. We added such cash savings to their household available savings. In all the EU countries covered, less than than 40% of the population keeps cash outside of a bank account. In most countries, the percentage is below 36%. Furthermore, according to Esselink and Hernández (2017), those who do keep cash outside of bank accounts keep relatively low amounts: 23% state having less than 100 €, 22% between 100 € and 250 € and 19% between 250 € and 500 €. Our estimates, as a result, remained very similar, and are not shown. Yet, it should be noted that such question is necessarily sensitive, with individuals more likely to omit and underestimate cash holdings.[4]

3 Data and methodology

Our analysis uses the ECB Household Finance and Consumption Survey (HFCS), a cross national survey covering household assets, liabilities, income and consumption.

We use Wave 3, released in March 2020 and carried out in 2017. Income and expenses are uprated to 2020 through inflation. The survey is representative of households residing in 21 EU countries. Weights provided ensure the number of households matches the total number of households in the country. The survey provides information on all individuals within each household sampled.

We determine which households in the sample cannot afford their typical expenses with certain types of resources (e.g., only with their bank deposits), as explained below, and count the number of individuals living in such households. We then extrapolate to the countries' population by weighing each individual within a household by that household's weight.

Data has been multiple imputed by the ECB to correct for non-response. The HFCS data thus consists of 5 implicates - datasets with small differences between them. Following the HFCS methodology, we resort to averages across the 5 implicates. We calculate, on each implicate, the weighted number of individuals living in households which cannot afford expenses, and report the average number across the

[4]We used the cash saving brackets by country provided by Esselink and Hernández (2017) to decide on amounts allocated. Cash savings were allocated randomly among individuals aged 18 or above, in percentage of the countries' cash holders. Individuals randomly selected as storing savings in cash were then randomly assigned to a bracket of precautionary savings in cash, replicating country percentages, and allocated the midpoint of the interval. Individuals assigned to the bracket "above 1000" were assigned 1500 euros.

Covid Economics 63, 7 January 2021: 73-97

five implicates.[5] Table 1 in the annex presents summary statistics of our sample.

3.1 Determining whether households can afford expenses

To determine whether a household can afford expenses, we divide the resources a household has available in m months (pooled resources of all household members) by a basket of expenses in m months (pooled expenses of all household members). If the ratio is below one, we say that the household cannot afford expenses.

We thus construct a dummy variable $vulnerable_h^m$ which, for each household h in an m-month time horizon, is a simple indicator function:

$$vulnerable_h^m = 1\left\{ ratio_h^m = \frac{pooled\_resources_h(m)}{pooled\_expenses_h(m)} < 1 \right\} \tag{1}$$

We will work with several versions of the denominator $pooled\_expenses_h(m)$. A first version aims to capture vulnerability by considering the most basic expenses: those with food at home and with utilities (comprising electricity, water, gas, telephone, internet, and television). A second version includes rents and mortgages on the household main residence. For the latter, we consider loans contracted to purchase, construct, refurbish or renovate the household's main residence. We change the denominator in this way only for households which own no other residential properties. The objective is to capture only the most vulnerable individuals, who would not have an alternative residence in case they were not able to face housing expenses. Some of the individuals we exclude might also have no alternative residence if their properties are for instance rented out, so the exercise is conservative. A scenario where properties beyond the main residence are considered is provided in Section 5.2

The numerator $pooled\_resources_h(m)$ always considers household bank deposits. We change it in an additive way, adding different household resources, while keeping the denominator fixed, and thus identify fewer and fewer households not able to afford expenses. In section 4.1, as household resources, we consider (beyond bank deposits) public pensions, unemployment benefits and other (pre-COVID-19) public transfers, and liquid assets beyond deposits. Separately, in section 4.2, we determine whether households can afford expenses when individuals are deprived of salary income and when they are deprived of salary income but awarded COVID-19 employment protection income.

Given HFCS data only covers gross income, in Section 4.2, we derive net incomes through the EUROMOD microsimulation model. EUROMOD is a static model that calculates country-specific social insurance contributions, income taxation and means-tested cash benefits to obtain market incomes. It simulates cash benefit entitlements and direct tax and social insurance contribution liabilities, on the basis of the tax-benefit rules in place and information available in the underlying datasets (see Suther-

[5] More information on the sampling design, weighting and multiple imputation is available in the ECB HFCS Wave 3 Methodological Report.

Covid Economics 63, 7 January 2021: 73-97

land (2001) and Kuypers et al. (2017)). We build on Boone et al. (2019) to convert HFCS data into a EUROMOD database to obtain disposable income.

4 Results

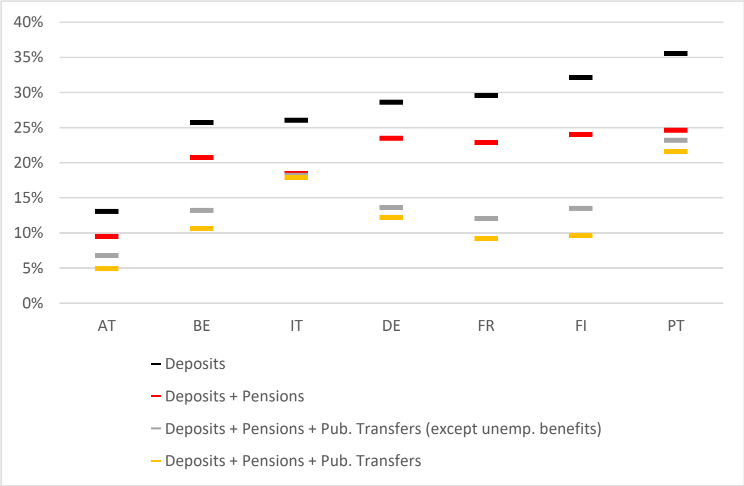
4.1 Vulnerability without unemployment protection schemes

Considering the seven countries of our sample, Austria, Belgium, Finland, France, Germany, Italy and Portugal, we estimate that 31.2 million of individuals - or 12.8% of their population - are financially vulnerable when we consider food and utilities in a three months horizon, meaning that they would not be able to afford those expenses for three months without privately earned income.

In Figure 1 we plot, for each country, the percentage of vulnerable individuals, and how the availability of resources beyond deposits decreases vulnerability.

There are stark country differences. In Portugal and Italy, after considering deposits, pensions and public transfers, 21.5% and 17.8% of the population could not afford food and utilities if they were deprived of their privately earned income. This is more than double the proportion of vulnerable population in Austria, where just 4.9% would fall in that category. The role played by public transfers is also very heterogeneous across countries: while in Finland they seem crucial, reducing the percentage of vulnerable individuals by more than 8 percentage points (from 24.0% when we consider deposits and pensions to 9.6% when we consider all public transfers), in Italy they are not a meaningful buffer for families which currently receive them (the percentage of vulnerable population goes from 18.2% to 17.8%).

Figure 1: Percentage of vulnerable individuals in a three months horizon, considering food and utilities, resorting to deposits and different sources of income

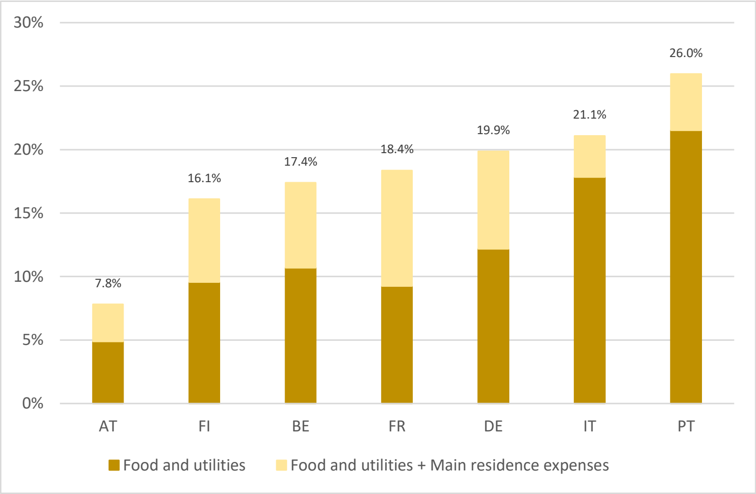


Covid Economics 63, 7 January 2021: 73-97

CEPR PRESS

Figure 2 presents our results when we include housing expenses. Both rent and mortgages expenses substantially increase the number of vulnerable individuals: considering deposits, pensions and public transfers, 47.2 million, or 19.4% of the population analysed, are vulnerable when we add rents and mortgages to the basket of basic expenses. The impact of housing expenses is more severe in some countries such as Germany and France (in the former, the percentage of vulnerable individuals jumps from 12.2% to 19.9% and in the latter it doubles, from 9.2% to 18.4%). As highlighted in Midoes (2020) and discussed in more detail in Section 5, this suggests that rent and mortgage suspension can be an effective policy to alleviate household vulnerability in some countries.

Figure 2: Percentage of vulnerable individuals in a three months horizon when rent and mortgages are added to food and utilities.



4.1.1 Vulnerability by specific groups

In this section we briefly discuss how three subgroups of the population are more likely to be vulnerable: immigrants, individuals with low educational level and households with children. Results are presented in Table 2.

Immigrants: Individuals born outside of their country of residence and particularly outside of Europe are more at risk of not being able to cover for their food, utilities, and housing expenses (columns 1 and 2 in Table 2).

For individuals living in their country of birth, the probability of not being able to cover for such expenses for three months without any privately earned income is 20%, while for those born elsewhere in the EU and outside of Europe, it is 33.2% and 29.8% respectively. That is, individuals born elsewhere in the EU are in average 1.5 times more at risk, while individuals born outside the EU 1.7 times more at

Covid Economics 63, 7 January 2021: 73-97

CEPR PRESS

risk.

The difference is accentuated in some countries: in Italy, those born outside of the EU are 2.6 times more at risk; in Austria, 2.4, and in Belgium, 2.3 times.

Households with children: Children are always more likely to live in vulnerable households, regardless of the country considered. The probability that a child aged 12 or below lives in a household unable to cover for three months of expenses without privately earned income is 30%, a risk 1.5 times larger than for the remaining population. In Italy, children are 1.5 times more at risk and in Germany 1.4 times, followed by Portugal at 1.25 (see column 4 in Table 2). This echoes Lusardi et al. (2011) and Hasler and Lusardi (2011), which find having children is associated with higher self-reported measures of financial fragility by households.

Education: Considering all countries in our sample, individuals living in households where the highest educated individual has only up to secondary education, are more likely to live in vulnerable households. In Italy, individuals with secondary education or lower are 1.4 times more at risk than those with tertiary education. In Germany, they are 1.3 times more at risk and in Portugal, 1.25 times (column 4 of Table 4.1).

4.2 Vulnerability under COVID-19 unemployment benefits

In this section we consider whether households can afford expenses when they are deprived of salary income (only of salary income, instead of all privately earned income as in the preceding section) and when deprived of salary income but awarded COVID-19 support measures as enacted in each country. We restrict our sample to households where at least one individual has been in employment throughout the previous year [6]. We first assess vulnerability through the number of individuals in households unable to afford basic expenses without salaries. We compare this scenario to one in which individuals are receiving COVID-19 unemployment benefits. In both cases, our final income metric is net income, obtained through the microsimulation model EUROMOD.

Besides applying income taxation, in the scenario where individuals are not receiving salaries, they also receive means-tested social benefits to which they would be entitled under reduced income. We awarded COVID-19 benefits to all employees accruing a yearly salary income of at least twelve times the minimum wage, as they are more likely to have been in full employment the previous year and thus entitled to coverage.[7]

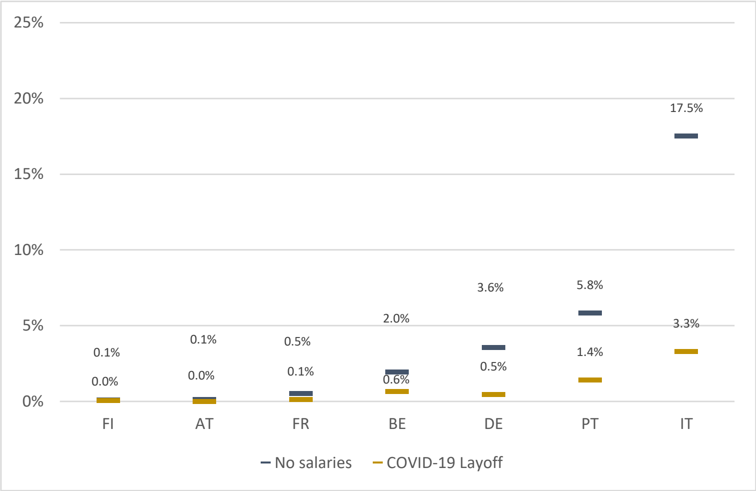
For an affected household, i.e., where someone accrues salary income, household net income differs between the scenario with no salaries and the scenario with no salaries but with COVID-19 employment protection benefits because of two types of individuals: i) individuals who, instead of accruing their normal employee income above the minimum wage, now receive a part of it as defined in the COVID-19 policies

[6] Percentual results are in percentage of individuals living in such households.
[7] Although the specific criteria for eligibility change from country to country.

Covid Economics 63, 7 January 2021: 73-97

Covid Economics 63, 7 January 2021: 73-97

Figure 3: Percentage of vulnerable individuals with and without COVID-19 layoff, in a three months horizon, considering food and utilities



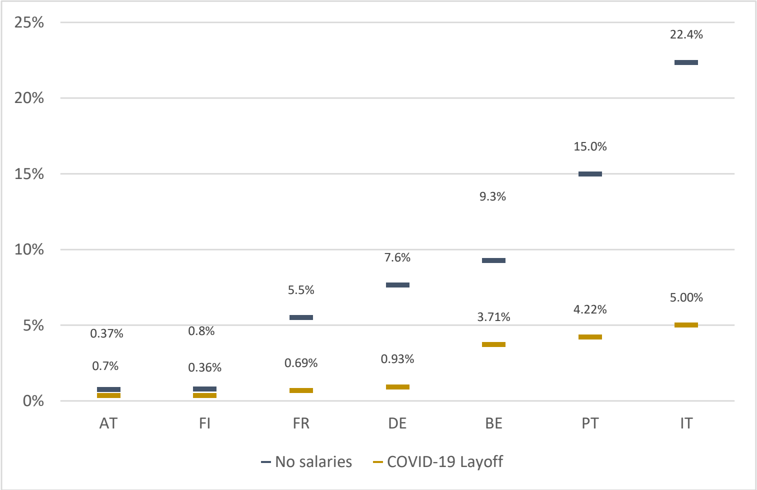
and ii) individuals who reported an employee income below the minimum wage who now receive a zero employee income under our simulations.

We find that, considering food and utilities only, at the three months mark, the situation is not too dire overall: only 5.9% of affected individuals are vulnerable at this point. This number camouflages important country differences, specifically, that in Italy, 17% of affected individuals are vulnerable. Figure 3 shows the percentage of vulnerable individuals when salaries are removed and when COVID-19 unemployment benefits are subsequently added, by country.[8] For all countries the situation improves substantially when we add COVID-19 benefits. In Italy, there is a drastic reduction to only 1.13% of vulnerable individuals. For all the other countries, less than 1% remain vulnerable. While we estimate that 9.6 million people in the countries considered could not afford food and utilities, only 1.7 million would not be able to once COVID-19 unemployment benefits are awarded.

When we consider rents and mortgages as part of basic expenses, the percentage of vulnerable individuals increases to 10.5%. Nonetheless, the COVID-19 employment protection benefits reduce the percentage of vulnerable individuals to 2.1%. As Figure 4 shows, the benefits are again quite effective at reducing vulnerabilities across all countries. In Italy, Portugal and Belgium where vulnerability is highest at baseline, we estimate only 5.0%, 4.2% and 3.7% of those affected are vulnerable at the three month mark. Rent and mortgages suspension, as a complementary policy to the COVID-19 layoff, are analyzed in more detail in Section 5 yet this result already sheds light on the role these expenditures play.

[8] In addition Table 4 contains our results for 1, 3, 6 and 12 months.

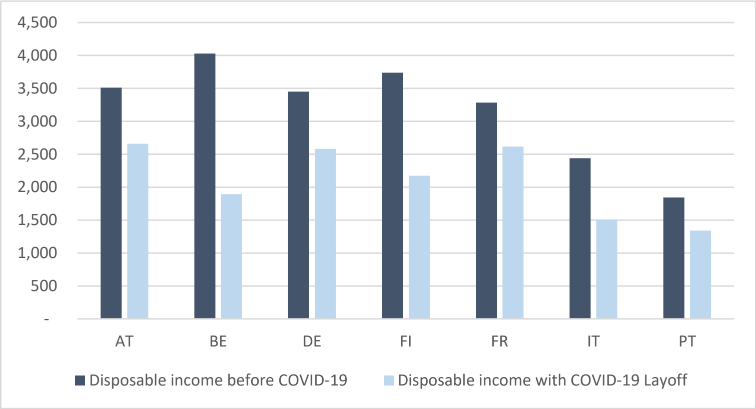
Figure 4: Percentage of vulnerable individuals with and without COVID-19 layoff, in a three months horizon, considering food and utilities and rent and mortgages on the main residence



In a scenario where employees are not receiving their salary, suspending rents and mortgages on main residences would reduce the number of vulnerable people by 8.2 million.

Percentages are informative to make cross-country comparisons, but it is also relevant to assess in absolute numbers where individuals are located. Even if in Italy only 2.5% of the individuals considered are vulnerable under the COVID-19 layoff scenario, it is the country with the highest absolute number of vulnerable individuals: 969 thousand. France, where only 0.85% of those affected are vulnerable, nonetheless follows, with 360 thousand. These vulnerabilities result both from a lack of savings and from reduced income directly. How income, on average, is reduced, can be seen in Figure 5, where we present mean disposable household income before COVID-19 layoff (that means, assuming individuals receive their normal salary) and after we eliminate their usual salary income but award them COVID-19 benefits, for households affected (those who receive employment income). While in countries like France and Portugal average incomes with COVID-19 layoff are only 25% lower, Belgium stands out, with average household income under the COVID-19 layoff scenario being less than half the status quo average household income.

Figure 5: Average household disposable income for households earning salary income, before COVID-19, and with COVID-19 layoff but no other salary income (in €).



4.3 Liquid assets as a buffer

To face expenses in the short-run, households might resort not only to deposits but also to other liquid assets, which can be easily sold. Besides deposits, households can resort to their mutual funds, bonds, non self-employment private businesses (though their liquidity is more conditional on economic circumstances), shares and managed accounts.

The prevalence of these assets across EU countries, though quite variable, is generally low, particularly for lower income and lower wealth individuals. Since we are focusing on individuals who, without deposits, would not be able to cover for the most basic expenses for three months, we are analysing a quite low wealth (in deposits) group, but a low-wealth group generally. In its majority, the group considered holds assets only in the form of deposits and on occasion real estate, a quite illiquid asset.

Thus, when we consider liquid assets beyond deposits as a resource to cover expenses, the percentage of vulnerable individuals decreases only very slightly. In certain countries where these other liquid assets are more prevalent, specifically in Finland, the percentage of individuals unable to cover for 3 months of expenses with liquid assets is 8 p.p lower than when resorting to deposits alone. If Finnish households have available deposits, pensions and public transfers, adding other liquid assets reduces the vulnerable by only 0.7 p.p. Indeed, once we consider households might use not only deposits or all liquid assets, but also pensions and public transfers, using all liquid assets instead of other deposits leads to only residual reduction in the number of vulnerable individuals. After Finland, the reduction ranges from 0.1pp in Austria and Portugal to 0.5pp in Germany.

Covid Economics 63, 7 January 2021: 73-97

5 Policy discussion

To conclude, we discuss the effectiveness of two key policies to protect the most vulnerable: i) The introduction of a more generous COVID-19 unemployment benefit and ii) Rent and loans suspension.

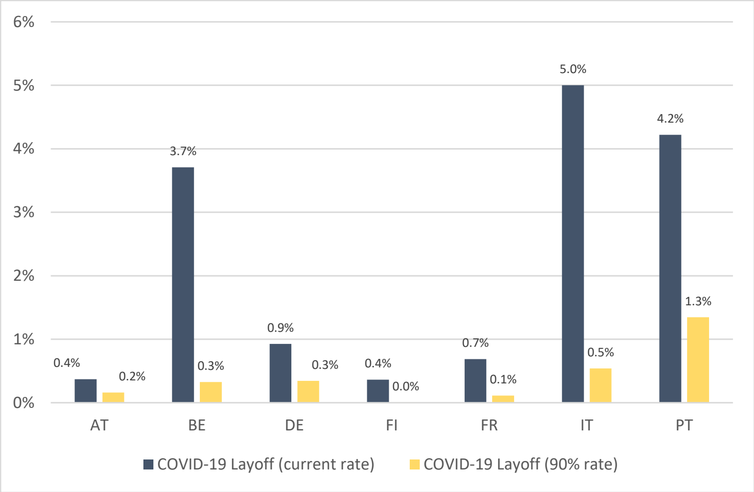
5.1 Effects of a more generous COVID-19 unemployment benefit

With the exception of Finland, - where the unemployment benefit is a daily fix amount-, the unemployment scheme covers a percentage of salaries, varying between 60% (in Portugal) to 90% (in Austria). By allowing for a higher income replacement rate, countries try to protect jobs and mitigate the economic shock by sustaining consumption levels (Schnetzer. et al 2020). In this section we analyse the impact on households' vulnerability if, in all countries, the unemployment scheme covered 90% of salaries. Our main results are presented in Figure 6.

As explored in section 4.2, the percentage of vulnerable individuals is already low when considering country-specific coverage rates. Setting a rate of coverage of 90% of salaries amounts to increasing coverage. This increase has a more noticeable effect in Italy and Portugal, where the percentage of vulnerable was still above 2.5% with current rates. Nonetheless, there are also meaningful reductions in countries with an already extremely low percentage of vulnerable individuals: in France, Finland and Belgium. In our microsimulation exercises, individuals were vulnerable both because the reduced monthly income is not enough for basic expenditures, and because of low savings. For most households, their monthly income becomes insufficient to cover for expenses under the layoff scheme not because they were deemed ineligible to receive it under our exercise, but because the proportion of income ensured, together with savings, is insufficient. In Portugal and Italy, 62% and 58% of individuals vulnerable at the 3-month mark are in households where all individuals were either deemed eligible for the COVID-19 support (accruing more than the minimum wage) or unaffected (because they did not accrue any employee income). In France, 80% of vulnerable individuals are in such households. In Belgium, Germany and Austria, all individuals deemed vulnerable are in this situation. The vulnerable individuals identified in our simulations do not come from gaps in coverage generated by our procedure, but from the coverage itself not being sufficient for expenses. The results we now find, where there is an important reduction of vulnerability under a more generous layoff scheme, are a reflection of this. The results of Section 4 showed Belgium with the lowest percentage of vulnerable individuals after Austria when we considered deposits, pensions and pre-existing public transfers. However, once the COVID-19 layoff is considered, Belgium only performs better than Italy and Portugal. This is because the Belgian COVID-19 income support is amongst the least generous (as detailed in Figure 5 on the previous section).

Covid Economics 63, 7 January 2021: 73-97

Figure 6: Percentage of vulnerable individuals with the current COVID-19 layoff and with a replacement rate of 90% of salaries, in a three months horizon, considering food and utilities and housing expenses



5.2 Effect of rent and loan suspensions

In previous sections we considered mortgages and rents together. In section 5.2.1, we discuss the relative effectiveness of rent and loan suspension policies to protect the most vulnerable, policies enacted in several European countries (Anderson et al. 2020). We consider the effects of these policies on their own, but also in tandem with COVID-19 unemployment benefits. While measures of this type have not been enacted in all the countries and access to these benefits is not straightforward (Anderson et al. 2020), it is worth estimating the percentage of vulnerable individuals once all possible alleviation mechanisms are in place. As we have done so far, we only consider rents and mortgages on main residences, and only for individuals who own no other residences. We did not consider other types of loans, since we were limiting ourselves to a strict definition of "basic expenses". In Section 5.2.2 we instead consider all rents and loan payments (mortgage debt and non-mortgage debt) of households. In that case, we estimate the percentage of individuals who might have to default on their loan payments or suspend non-primary residence loan payments if deprived of salary income or receiving COVID-19 unemployment benefits. Against that baseline, we see whether the suspension of rents and mortgage loans on main residences (the typical typology of COVID-19 payment suspension policies) is enough to meaningfully decrease those vulnerable to default.

Covid Economics 63, 7 January 2021: 73-97

Covid Economics 63, 7 January 2021: 73-97

5.2.1 Effect of a suspension of rent and mortgages on the main household

The upper panel of Figure 7 presents our results when rent and mortgages suspension on the main residence are put in place. In Figure 7 we can see the percentage of vulnerable individuals under the no salaries scenario when we consider expenses in food and utilities, rent and mortgages, at the three-month mark, detailing how much each expense contributes to overall vulnerability. In Germany and Italy, expenses with rent explain a larger part of vulnerability than mortgages. For example, in Italy, the percentage of individuals who would not be able to cover expenses considering food and utilities, rent, and mortgages is 22.3%. This percentage would be reduced by 3.4 p.p. if a rent suspension was enacted. By contrast, it would only be reduced by 1.5 p.p. if instead mortgages were suspended. We observe the opposite in countries such as Belgium and Portugal. In these countries, while rent suspension would only reduce the percentage of vulnerable individuals by 1.6 p.p. and 3.1 p.p., mortgages suspension would reduce it by 6 p.p. and 6.4 p.p. respectively.

When we analyse these policies under a scenario where individuals are receiving the COVID-19 layoff (Figure 7b), in Portugal, rent and mortgage expenditures play a similar role. In Italy, rent remains more relevant and in Belgium, mortgages remain more relevant.

Rent and mortgage suspensions thus can be an effective support for vulnerable households. In most countries, both under a non-salaries scenario and under COVID-19 benefits, mortgages play a more relevant role. Yet, in Italy, rent is more relevant, while in France, they are equally important. This highlights the need to develop country-specific policies for alleviating vulnerability.

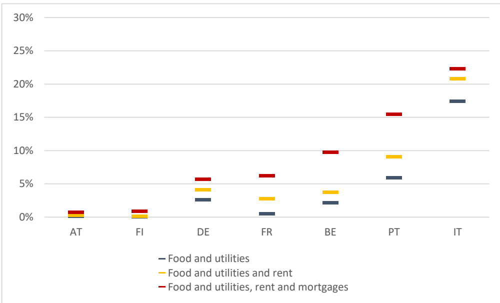
5.2.2 The role played by all rents and loans

The percentage of individuals who, deprived of salary income, would not be able to cover for food, utilities, and all their rent and debt payments, are presented in the lower panel of Figure 7.

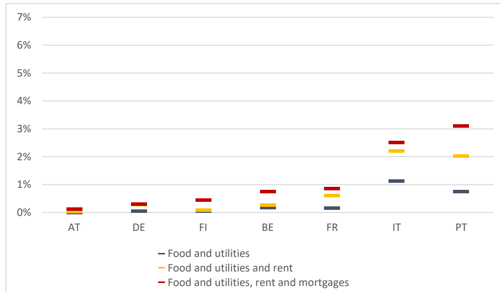
When individuals are deprived of their salaries, considering all rents and loans instead of only those on the main residence, the percentage of vulnerable individuals increases most meaningfully in Portugal (from 15% to 19.2%) and in France (from 5.5% to 9.4%). In Italy and Belgium, the increase is between 1.6 and 2.5 p.p., while in Austria and Germany, it is below 1 p.p..

Covid Economics 63, 7 January 2021: 73-97

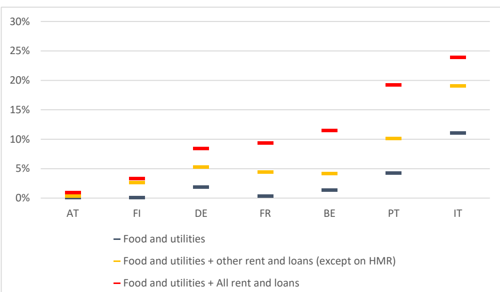
Figure 7: Effect of mortgages and rent suspension



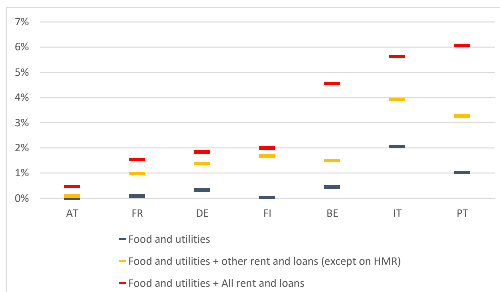
(a) Percentage of vulnerable individuals **without** COVID-19 layoff, in a three months horizon, considering food and utilities and housing expenses (by component)



(b) Percentage of vulnerable individuals **with** COVID-19 layoff, in a three months horizon, considering food and utilities and housing expenses (by component)



(c) Percentage of vulnerable individuals **without** COVID-19 layoff, in a three months horizon, considering food and utilities and all rents and loans



(d) Percentage of vulnerable individuals **with** COVID-19 layoff, in a three months horizon, considering food and utilities and all rents and loans

Once we award individuals COVID-19 unemployment benefits, the percentage of vulnerable individuals with this extended basket of expenses ranges from 0.5% in Austria to 6.1% in Portugal.

In section 4.2, we commented on how household main residence rent and mortgage suspensions substantially decreased the number of individuals unable to face their monthly expenses with food and utilities. Here, we observe that these measures not only allow some families to cover for food and utilities, but could also allow them to repay their other commitments as usual. As Figure 7c shows, when families are deprived of salary income, the suspension of household main residence rent and mortgages would mean 10.1% of affected individuals in Portugal might not be able to cover for food, utilities and all remaining rents and loans, a substantial decrease from the 19.2% unable to cover for a basket including all rents and loans together. In Belgium, there is a reduction of 7.3 p.p. and in France, of 5 p.p.. Overall, the suspension of household main residence rents and loans would mean a reduction of 2.6 p.p. in the individuals who cannot cover for food, utilities and their usual monthly rent and debt payments.

In the scenario where individuals receive COVID-19 unemployment benefits the number of individuals potentially defaulting on their commitments is necessarily lower, but also here, household main residence commitments suspensions are useful (Figure 7d). Indeed, they allow for a reduction of 3.1 p.p. of at risk individuals in Belgium, 2.8p.p. in Portugal and 1.7p.p. in Italy. Overall, the suspension would mean a reduction of 0.8 p.p. of potentially defaulting individuals.

6 Discussion and concluding remarks

While we still do not know how long the economic recession induced by the COVID-19 pandemic will last, this paper intends to provide evidence on how sensitive individuals are to this type of shock and on the effectiveness of the enacted mitigation policies.

Public pensions, a source of income unaffected by COVID-19, are essential to cover basic expenses for many of the households who receive them. The effect of other public transfers is more heterogeneous. They have little effect beyond pensions in reducing the number of vulnerable individuals in some countries, namely Portugal and Italy, but play an important role in France, Belgium and Germany. Even with pensions and public transfers, a large number of individuals depend on household privately earned income to cover for their most basic expenses in the very short term: 18.2 million individuals, or 7%, of the population of the seven European countries analysed, cannot cover for one month of food and utilities by resorting to their deposits, pensions and public transfers. In a three months mark this number increases to 31.2 millions: 13% of the population analyzed.

We find stark differences across countries: in Austria, France and Finland, the percentage is below 9.5%, while in Italy and Portugal it is 17.8% and 21.5% respectively.

In all countries, we observe a significant drop in the number of vulnerable population when we award them COVID-19 unemployment benefits. When we consider net incomes and the dependence on employee income specifically, we find significant differences across countries. Employees in Austria, Finland, Belgium and Germany are less vulnerable to a labour income shock than employees in Italy and Portugal. The employment protection schemes awarded are extremely effective in decreasing these numbers, particularly in Italy. Indeed, considering food and utilities, only 3.3% of those affected remain vulnerable at the 3 month mark when receiving the designed subsidies, implying a reduction of almost 15 percentage points. A sizeable reduction is also observed in Portugal where the vulnerable population decreases from 5.8% to 1.4%.

There are two reasons for the greater effectiveness of the schemes in countries like Austria and France than in, for example, Portugal. The first is that, in the former two countries, only 2.1% and 2.5% receive, under the scheme, an income below basic expenses, while in Portugal, 12.7% do. The difference in the generosity of the support results in a more effective public transfer in the former two countries, just as

Covid Economics 63, 7 January 2021: 73-97

with non-COVID-19 public transfers. The second reason is the pre-existing differential in savings - French and particularly Austrian households can cover for their expenses from deposits alone for a longer period of time.

An important reduction in the percentage of vulnerable individuals can be achieved by providing a more generous layoff scheme. Considering only food and utilities, and setting a rate of coverage of 90% of salaries, implies 187 thousands of individuals falling into vulnerability, which represents around 0.1% of the total population analyzed. This number is considerably smaller than the 1.7 million individuals falling into vulnerability under the current layoffs schemes of each country.

Rent and mortgage suspensions are more effective in some countries than in others. Countries like Portugal, Belgium and France can achieve an important reduction in their vulnerability through these measures, while in Italy, they should be coupled with COVID-19 unemployment benefits to bring about a meaningful reduction. If Italy applies the COVID-19 layoff, it would have the same percentage of vulnerable individuals as Portugal when just rent and mortgages suspension are applied.

Importantly, even when considering the suspension of all loan repayments in tandem with the layoff, there is still a larger percentage of individuals in Italy and Portugal unable to keep the remainder of their usual monthly expenses, than in the rest of the countries without any such measure. Taken jointly, the differential between countries remains. When analysing vulnerability under income support and suspensions, we should bear in mind that these measures are not analogous. A loan repayment suspension is only a suspension, entailing payments in the future. In the short-term, it might serve the same purpose as income support - reducing vulnerability - yet, since it entails repayment in the future, it is comparatively less effective in fueling future consumption, a possible public policy goal.

Countries with wider fiscal space can enact more generous policies. The layoff schemes in Austria or Finland are more generous than the Portuguese. Households in these countries, per our results, are the most robust to overall income shocks, being able to sustain expenses from deposits alone for longest. As a result of differing fiscal space, rather counter intuitively, it is in the countries where individuals least require income support for basic needs that states make available substantially more generous subsidies. As per Eurostat, Finland also experienced some of the lowest dips in industrial production vis-a-vis the same months of 2019. These differentials in suffered impact, household finance, and public finance, underlie the different perceptions of urgency about the crisis and different eagerness for concerted EU-financing of support policies.

Covid Economics 63, 7 January 2021: 73-97

References

Aguiar, Mark and Erik Hurst (2007). "Life-cycle prices and production". In: *American Economic Review* 97.5, pp. 1533–1559.

Andersen, Asger Lau et al. (2020). "Consumer responses to the COVID-19 crisis: Evidence from bank account transaction data". In: *CEPR: COVID Economics - Vetted and Real-Time Papers*. URL: https://cepr.org/sites/default/files/news/CovidEconomics7.pdf.

Anderson, Julia et al. (2020). "The Fiscal Response to the Economic Fallout From the Coronavirus". In: URL: https://www.bruegel.org/publications/datasets/covid-national-dataset/.

Boone, Jonas et al. (2019). *EWIGE 2–Update and extension of the EUROMOD wealth taxation project*. Tech. rep. JRC Working Papers on Taxation and Structural Reforms.

Browning, Martin and Thomas F Crossley (2009). "Shocks, stocks, and socks: Smoothing consumption over a temporary income loss". In: *Journal of the European Economic Association* 7.6, pp. 1169–1192.

Chetty, Raj and Adam Szeidl (2007). "Consumption commitments and risk preferences". In: *The Quarterly Journal of Economics* 122.2, pp. 831–877.

Esselink, Henk and Lola Hernández (2017). "The use of cash by households in the euro area". In: *ECB Occasional Paper* 201.

European Commission (2020). "Policy measures taken against the spread and impact of the coronavirus". In: URL: https://ec.europa.eu/info/sites/info/files/coronovirus_policy_measures_16_november.pdf.

Günther, Isabel and Johannes K Maier (2014). "Poverty, Vulnerability, and Reference-Dependent Utility". In: *Review of Income and Wealth* 60.1, pp. 155–181.

Hamermesh, Daniel S (1982). "Minimum wages and the demand for labor". In: *Economic Inquiry* 20.3, pp. 365–380.

Hasler, Andrea and Annamaria Lusardi (2011). *Financially fragile households: Evidence and implications*. Tech. rep. Global Financial Literacy Excellence Center.

Hoddinott, John and Agnes Quisumbing (2010). "Methods for microeconometric risk and vulnerability assessment". In: *Risk, shocks, and human development*. Springer, pp. 62–100.

Horvath, Akos, Benjamin Kay, and Carlo Wix (2020). "The COVID-19 shock and consumer credit: Evidence from credit card data". In: *CEPR: COVID Economics - Vetted and Real-Time Papers*. URL: https://cepr.org/sites/default/files/news/CovidEconomics36.pdf.

Kendall, Jake (2010). "A Penny Saved: How Do Savings Accounts Help the Poor?" In: *SSRN 1982461 - https://papers.ssrn.com/sol3/papers.cfm?abstract*$_i$*d* = 1982461.

Kuypers, Sarah et al. (2017). *EWIGE-European Wealth data InteGration in EUROMOD*. Tech. rep. JRC Working Papers on Taxation and Structural Reforms.

Long, Melanie G (2020). "Informal Borrowers and Financial Exclusion: The Invisible Unbanked at the Intersections of Race and Gender". In: *The Review of Black Political Economy*, p. 0034644620938620.

Lusardi, Annamaria, Daniel J Schneider, and Peter Tufano (2011). *Financial Fragility among Middle-Income Households: Evidence Beyond Asset Building*. Tech. rep. National Bureau of Economic Research.

Midoes, Catarina (2020). "Who can live without two months of income?" In: *CEPR: COVID Economics - Vetted and Real-Time Papers*. URL: https://cepr.org/sites/default/files/news/CovidEconomics18.pdf.

Naik, Narayan Y and Michael J Moore (1996). "Habit formation and intertemporal substitution in individual food consumption". In: *The Review of Economics and Statistics*, pp. 321–328.

Sutherland, Holly (2001). *EUROMOD: An integrated European benefit-tax model*. Tech. rep. EUROMOD Working Paper.

Whelan, Christopher T (1993). "The role of social support in mediating the psychological consequences of economic stress". In: *Sociology of Health & Illness* 15.1, pp. 86–101.

Covid Economics 63, 7 January 2021: 73-97

Table 1: Summary statistics

	AT	BE	DE	FI	FR	PT	IT
Median monthly gross income (in €)	3,436.2	3,625.2	3,345.0	3,393.7	2,691.7	1,463.5	2,083.4
Median total deposits (in €)	12,724	10,857	7,700	5,000	6,709	3,000	5,000
Median deposits in sight accounts (in €)	1,276.2	1,641.0	1,800.0	3,000.0	1,000.0	1,064.0	1,072.0
Median deposits in savings accounts (in €)	13,380.8	15,185.4	10,000.0	10,000.0	7,000.0	10,000.0	10,000.0
Deposits / (food + utilities) (mean)	45.7	53.2	41.3	42.0	34.0	34.8	20.8
Deposits / (food + utl. + rent + mort.) (mean)	38.1	45.2	33.1	34.4	26.9	32.0	19.6
Deposits / (gross income) (mean)	9.2	11.2	14.5	7.6	12.4	14.7	14.8
Mean disposable income (before covid)	3,109.9	3,214.4	2,578.6	2,949.0	2,785.2	1,396.0	2,091.8
Mean disposable income (with layoff)	2,627.8	2,149.5	2,025.9	2,105.5	2,446.0	1,085.8	1,628.6
Sample (individuals)	6,414	5,370	11,251	24,818	32,799	15,079	19,366
Sample (households)	3,072	2,329	4,942	10,210	13,685	5,924	8,156
Sample (individuals in households with salaries)	4,544	3,346	7,938	18,923	23,052	10,689	10,915

Note: results computed at the household level.

Covid Economics 63, 7 January 2021: 73-97

Table 2: Relative risk by country of birth, educational level, and age.

	Relative risk, born elsewhere in the EU	Relative risk, born outside EU	Relative risk, secondary or lower	Relative risk, 12 or below
AT	2.40	2.43	1.16	1.21
BE	1.33	2.31	1.18	1.08
DE	1.92	1.74	1.29	1.36
FI	1.47	1.43	1.20	1.15
FR	1.25	1.49	1.19	1.21
IT	2.08	2.56	1.44	1.46
PT	0.98	1.60	1.25	1.25

Note: Vulnerability is measured at the three month mark, resorting to deposits, pensions and public transfers. "Relative risk, born elsewhere in the EU" is the ratio between the percentage of vulnerable individuals born elsewhere in the EU and the percentage of vulnerable individuals born in the country. "Relative risk, born outside the EU" is the ratio between the percentage of vulnerable individuals born outside the EU and the percentage of vulnerable individuals born in the country. "Relative risk secondary or lower" is the ratio between the percentage of vulnerable individuals living in households where the highest educated person has at most secondary education, and the percentage of those in household where the highest educated has achieved tertiary education. "Relative risk 12 or below" is the ratio between the percentage of individuals 12 or below who live in vulnerable households and the percentage of those aged 13 or above who do.

Covid Economics 63, 7 January 2021: 73-97

Table 3: Additional details on the COVID-19 unemployment benefits simulated

	Fiscal response
Austria	Percentage of salary coverage ranges from 80% to 90% of previous net monthly earnings, according to their level. If gross monthly earnings of the previous month were above 5,370 €, there is no public compensation.
Belgium	Percentage of salary coverage is 70% of gross salaries, with a minimum of 1,591.72 € (national minimum wage) and a maximum of 2,074.80 €, and subject to income taxation of 15%. An additional 5.32 € per day are awarded to individuals.
Finland	33.66 € per day, gross, are awarded to individuals, plus an additional daily subsidy of up to 10 €, according to the number of children in the household.
France	Percentage of salary coverage is 70% of gross salaries, with a minimum of 1219 € (national minimum wage) and a maximum of 5485.5 €.
Germany	Percentage of salary coverage is, during the first four months, 60% of net income, or 67%, if there are children in the household. For benefit calculation, monthly gross wages are capped at 6,900 €. Between the fourth and seventh month it increases to 70% and after the seventh month to 80%.
Italy	Percentage of coverage is 80% of gross salaries. If salary is below 2,159.48 € contribution is capped at 939.89 €; if it is above, contribution is capped at 1,199.72 €
Portugal	Percentage of coverage is 66% of gross salaries with a minimum of 635 € (national minimum wage) and a maximum of 1,905 €

Sources: Anderson et al. 2020 and European Commission 2020.

Covid Economics 63, 7 January 2021: 73-97

Table 4: Estimated number and percentage of vulnerable individuals in households accruing salary income (at one, three, six and twelve months) when deprived of salaries and when awarded COVID-19 layoff benefits, for a basket of food and utilities, and a basket of food and utilities, rent and mortgages

(a) Austria

	Food and utilities				Food and utilities, rent and mortgages			
	M1	M3	M6	M12	M1	M3	M6	M12
Without salaries	7,838	7,838	7,838	15,281	21,963	44,047	62,888	71,463
With layoff	0	0	0	5,827	7,312	22,073	28,994	35,222
Without salaries	0.1%	0.1%	0.1%	0.3%	0.4%	0.7%	1.1%	1.2%
With layoff	0.0%	0.0%	0.0%	0.1%	0.1%	0.4%	0.5%	0.6%
Observations	4,544	4,544	4,544	4,544	4,544	4,544	4,544	4,544

(b) Belgium

	Food and utilities				Food and utilities, rent and mortgages			
	M1	M3	M6	M12	M1	M3	M6	M12
Without salaries	78,568	150,379	286,917	491,333	235,974	712,135	1,095,138	1,757,590
With layoff	33,068	49,883	230,617	266,963	87,144	285,463	445,014	564,326
Without salaries	1.0%	2.0%	3.7%	6.4%	3.1%	9.3%	14.2%	22.8%
With layoff	0.4%	0.6%	3.0%	3.5%	1.1%	3.7%	5.8%	7.3%
Observations	3,346	3,346	3,346	3,346	3,346	3,346	3,346	3,346

(c) Germany

	Food and utilities				Food and utilities, rent and mortgages			
	M1	M3	M6	M12	M1	M3	M6	M12
Without salaries	928,515	2,113,261	4,142,438	6,707,723	2,405,772	4,532,011	7,707,629	13,269,392
With layoff	133,054	272,374	622,145	802,865	365,147	548,882	1,013,972	1,340,357
Without salaries	1.6%	3.6%	7.0%	11.3%	4.1%	7.6%	13.0%	22.4%
With layoff	0.2%	0.5%	1.0%	1.4%	0.6%	0.9%	1.7%	2.3%
Observations	7,938	7,938	7,938	7,938	7,938	7,938	7,938	7,938

Covid Economics 63, 7 January 2021: 73-97

(a) Finland

	Food and utilities				Food and utilities, rent and mortgages			
	M1	M3	M6	M12	M1	M3	M6	M12
Without salaries	1,827	2,991	3,272	9,416	11,342	29,557	49,917	74,849
With layoff	873	1,828	2,270	2,270	6,167	13,631	25,755	41,534
Without salaries	0.0%	0.1%	0.1%	0.3%	0.3%	0.8%	1.3%	2.0%
With layoff	0.0%	0.0%	0.1%	0.1%	0.2%	0.4%	0.7%	1.1%
Observations	18,923	18,923	18,923	18,923	18,923	18,923	18,923	18,923

(b) France

	Food and utilities				Food and utilities, rent and mortgages			
	M1	M3	M6	M12	M1	M3	M6	M12
Without salaries	104,986	215,637	396,695	729,029	869,591	2,332,955	3,733,395	5,550,351
With layoff	21,866	60,426	76,962	122,124	129,875	291,514	447,911	594,736
Without salaries	0.2%	0.5%	0.9%	1.7%	2.0%	5.5%	8.8%	13.1%
With layoff	0.1%	0.1%	0.2%	0.3%	0.3%	0.7%	1.1%	1.4%
Observations	23,052	23,052	23,052	23,052	23,052	23,052	23,052	23,052

(c) Italy

	Food and utilities				Food and utilities, rent and mortgages			
	M1	M3	M6	M12	M1	M3	M6	M12
Without salaries	4,010,568	6,743,355	9,975,795	14,452,892	5,050,221	8,599,383	12,446,091	16,533,112
With layoff	996,631	1,254,103	1,413,459	1,697,866	1,550,897	1,908,014	2,302,375	2,890,525
Without salaries	10.4%	17.5%	25.9%	37.6%	13.1%	22.4%	32.4%	43.0%
With layoff	2.6%	3.3%	3.7%	4.4%	4.0%	5.0%	6.0%	7.5%
Observations	10,915	10,915	10,915	10,915	10,915	10,915	10,915	10,915

(d) Portugal

	Food and utilities				Food and utilities, rent and mortgages			
	M1	M3	M6	M12	M1	M3	M6	M12
Without salaries	1,827	2,991	3,272	9,416	11,342	29,557	49,917	74,849
With layoff	873	1,828	2,270	2,270	6,167	13,631	25,755	41,534
Without salaries	0.0%	0.1%	0.1%	0.3%	0.3%	0.8%	1.3%	2.0%
With layoff	0.0%	0.0%	0.1%	0.1%	0.2%	0.4%	0.7%	1.1%
Observations	10,689	10,689	10,689	10,689	10,689	10,689	10,689	10,689

Covid Economics 63, 7 January 2021: 73-97

Covid Economics Issue 63, 7 January 2021

The impact of corona populism: Empirical evidence from Austria and theory

Patrick Mellacher[1]

Date submitted: 4 January 2021; Date accepted: 5 January 2021

I study the impact of corona populism – politics aimed at denying or downplaying the danger posed by COVID-19 – on the evolution of the pandemic using regional data from Austria. The right-wing FPÖ made a corona populist turn at the end of the first wave of infections. Using regression analysis, I show that the vote share of the FPÖ at the last national parliamentary elections is a strong predictor for the number of COVID-19 deaths per capita after the FPÖ switched their policy stance, while there is no or even a negative correlation before the policy switch. These results are robust under simple as well as sophisticated specifications of the model controlling for demographic and socioeconomic conditions. Interestingly, I do not find a statistically significant correlation between the FPÖ vote share and the reported number of infections. I hypothesize that this can be traced back to a self-selection bias in testing, which causes a higher dark figure in FPÖ strongholds. To explore this hypothesis, I extend the classical SIRD model to incorporate conditional quarantine, and heterogeneous mixing of two groups of agents who react differently to the pandemic. Such a model can explain the nontrivial empirics: if mixing is sufficiently homophilic, an increase in the share of "corona sceptics" can cause an increase in the number of deaths without increasing the number of reported infections. I finally discuss the implications for both groups.

1 University Assistant, University of Graz, Graz Schumpeter Centre.

Covid Economics 63, 7 January 2021: 98-125

Covid Economics 63, 7 January 2021: 98-125

1 Introduction

Following Acemoglu et al. (2013) and applying it to the case of the corona pandemic, populism can be defined as an anti-elitist view that receives significant support, but ultimately has adverse effects for the majority of the population.[1] Situations in which costs are mainly external and/or difficult to comprehend seem to be particularly susceptible to such populism. This is neither news for scholars who study views on (policies against) climate change, nor for epidemiologists who witness seemingly ever-growing doubt against vaccines, e.g. in the case of the measles.

The Covid-19 pandemic, however, put a spotlight on these views as an imminent danger for society, as health care systems around the world are on the brink of collapse and must rely more or less on voluntary social distancing. Corona populism is, more succinctly, politics aimed at downplaying the threat of COVID-19. If the level of support for such populist views is too high, a democracy has difficulties to implement policies that internalize these externalities effectively – witness the yellow vest protests against the carbon tax in France and e.g. the protests of the "corona rebels" in Germany. Unfortunately, relying on individual responsibility to reduce the level of negative externalities seems to be particularly hopeless in such situations.

We can hypothesize that a) supporters of political parties which adopted corona populism are more likely to underestimate the threat posed by COVID-19, as experimental evidence suggests that voters are more likely to adhere to the policy stance of their own party (Grewenig et al. 2020), and b) that these beliefs translate into behavioral differences between supporters of corona populist parties and the rest of the population, i.e. lower compliance with containment measures and less social distancing as shown by e.g. Allcott et al. (2020). If this is true, the support for corona populist parties in a given community can predict the size of the COVID-19 outbreak.

In this paper, I study whether the policy stance of the Austrian right-wing populist freedom party (FPÖ) had an effect on the evolution of the pandemic in communities in which they can rely on a larger voter base. The FPÖ were the first party to demand that the Austrian

[1] While I find this concise definition to be most useful for my purpose, I do not claim that it is the only correct definition of populism.

government should take drastic measures against COVID-19. By the end of April, however, the FPÖ made a U-turn and demanded to "end the Corona madness" (APA OTS 2020a) by which they meant the containment measures taken by the government. In the end of November 2020, one representative of the party even went so far as to advise people not to participate in a mass testing program announced by the Austrian government to be held before Christmas because testing positive would mean that you would have to spend Christmas home alone (APA OTS 2020b).

Previous research on the effects of political polarization and populism on beliefs, behavior, and public health outcomes during the pandemic have mainly concentrated on the US. Allcott et al. (2020) show using mobile phone data on the county level that democratic counties exercise more social distancing than republican counties (also confirmed by e.g. Baradaran Motie and Biolsi 2020), but also record more cases and deaths per capita. Controlling for a large number of covariates, Gollwitzer et al. (2020) however find that Trump-leaning counties do not only exercise less social distancing, but that this is also linked to higher growth rates in the number of cases and fatalities.

Allcott et al. (2020) also confirm that individual beliefs about the severity Covid-19 are linked to self-reported social distancing using data from an online survey with US participants. Further investigating what drives these differences, Fan et al. (2020) document using data from an online survey that there are partisan differences in social distancing behavior and beliefs, which also depend on differences in news consumption.

Bisbee and Lee (2020) show that Republican-leaning counties were more likely to practice social distancing when Trump voiced emphasized the risks of Covid-19 on his Twitter profile. As seen in their analysis, however, Trump sent at best a mixed message about the severity of Covid-19.

Barbieri and Bonini (2020) show that a higher vote share for the Italian right-wing party Lega is associated with lower social distancing using regional mobility data. Like Trump's course, the Lega's policy was with a zig-zag: first downplaying the pandemic, then agreeing to a lockdown, followed by a call for a fast re-opening. Eberl et al. (2020) show that "populist" attitudes – which they define as being anti-elitist, people-centred and having a "Manichean outlook" – are positively correlated with Covid-19 conspiracy theories in Austria using data

Covid Economics 63, 7 January 2021: 98-125

from a panel survey. They emphasize, however, that such views are scattered around the left-right spectrum and not tied to voters of the FPÖ specifically.

The main contribution of this paper is twofold:

First, I contribute to the literature on the causes and effects of behavioral differences in the pandemic (e.g. Allcott et al. (2020), Fan et al. (2020) and Gollwitzer et al. (2020)). I show that the number of deaths per capita is positively correlated with the vote share of the Austrian FPÖ using district-level data after the FPÖ started to advocate against lockdown measures. This finding holds in both simple and sophisticated specifications of a standard OLS model. The case of the FPÖ is particularly interesting on its own due to the party's long tradition and its clear policy stance subject to a U-turn at the end of the first wave of infections. More importantly, a pattern emerges that is not visible in countries like the US: Although the FPÖ vote share is strongly correlated with the number of deaths, it is not significantly correlated with the number of reported infections after the first wave of infections.

Second, I contribute to the literature on the implications of heterogeneous behavior and heterogeneous mixing on the evolution of the pandemic (e.g. Ellison 2020). I extend the classical SIRD model (Kermack and McKendrick 1927) to explain the distinct Austrian pattern regarding cases and deaths. My model is populated with two types of agents, who behave differently: the corona sceptics and the majority. Corona sceptics practice less social distancing, are less inclined to get tested once they develop symptoms than the majority, and mixing between the two types of agents is more or less homophilic, i.e. corona sceptics are more likely to interact with other corona sceptics than with the majority or not. I show that such a model can explain the Austrian pattern, if mixing is sufficiently homophilic and explore the implications of behavioral differences, group sizes, the degree of homophily on public health outcomes of the two groups, as well as the total population.

The next section discusses the Austrian empirics, i.e. focuses on the first contribution. The third section is devoted to the extended SIRD model and its implications, i.e. the second contribution. The fourth section concludes.

2 Empirics

Data & Method

In order to investigate, whether the policy stance of the FPÖ had an effect on the evolution of the pandemic in Austria, I draw on district-level data on the number of infections and deaths, which are available for a daily basis (BMSGPK 2020). Studying county-level data is a standard approach followed by e.g. Allcott et al. (2020), Fan et al. (2020) and Gollwitzer et al. (2020) to study the impact of polarization on the spread of the virus in the US and districts are the Austrian counterpart for counties.

To get a first graphical intuition of the evolution of the pandemic in communities with a low or a high FPÖ vote share, I split the time series dataset into two groups, one for districts with a FPÖ vote share below or equal to and one above the median share of this party. Figure 1 shows a local regression (loess) of the cumulated number of infections per 1,000 inhabitants and deaths per 100,000 inhabitants over time. This exercise suggests that districts, in which the FPÖ fared relatively well at the last national elections received relatively little damage in the first wave of infections, reporting lower numbers of cases and deaths. In the second infection wave starting in autumn 2020, however, the cumulated death toll in these districts surpasses the total number of deaths in the other districts, indicating that the second wave hit districts with a high FPÖ vote share much harder. We do not observe the same clear trend in the cumulative number of cases per capita, as districts with a low FPÖ vote share continued to have more cumulative cases (see fig. 1).

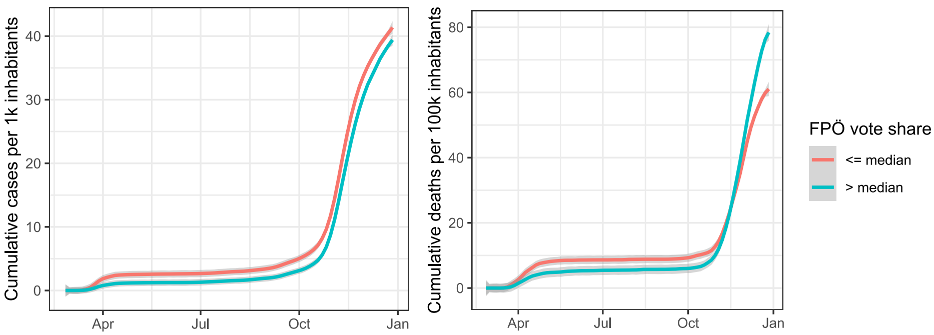


Figure 1: Cumulative cases per 1k inhabitants (left) and cumulative deaths per 100k inhabitants (right).

In order to confirm whether this graphical intuition is also statistically significant when controlling for other district-specific characteristics which may drive this pattern like e.g. the age structure of the population, I then merged the daily data to create two cross-sectional datasets: one covering the number of reported infections and deaths before, and one after the FPÖ-policy switch for each district. When doing so, the time lag between a social interaction causing an infection, the onset of symptoms, the reporting of the test result and eventual death has to be considered. Therefore, the launch of the FPÖ campaign against the containment measures on the 27th of April cannot have had an immediate impact on cases or deaths. I thus chose the 11th of May as a cut-off-date to split the two cross-sectional datasets. However, the main findings are insensitive to reasonable changes in the cutoff-date and thus also hold if we chose e.g. the 27th of April instead. The data analyzed in this paper ranges until 27th of December 2020.

I then merged the cross-sectional dataset with data on the results of the last national elections on the district level as a proxy for the influence of the FPÖ. To control for various other socioeconomic and demographic factors that could influence the evolution of the pandemic, I also merged these datasets with district-level data on population density (Statistik Austria 2020a), age composition and nationality (Statistik Austria 2020b), gross wages, employment status, education and the number of commuters[2] (WKO 2020).

The following two subsections present the results of separate OLS regressions on the number of cases per 1k and deaths per 100k inhabitants on each of the cross-sectional datasets.

Before the policy-switch

Table 1 shows the results of OLS regressions on the number of deaths per 100,000 inhabitants before the policy switch. There is mixed evidence of the effect of support for the FPÖ on the number of deaths per capita before the policy switch, as there is no statistically significant effect in the models with the best fit. The control variables show that districts in which there are more employees and in which employees earned less on average in 2018 had to mourn

[2] The share of commuters did not seem to have any significant impact on the evolution of the pandemic and thus is excluded from any model used in this paper.

more deaths, which points to low-paid employees having more troubles to practice social distancing than the rest of the population.

The share of the population born in Austria also has a significant positive effect, i.e. a higher share of Austrian-born predicts a higher number of deaths. The exact reason for this is unclear, although cultural differences in social distancing, as well as the spread of the disease via networks in which there are few inter-cultural connections can possibly explain this pattern.

Table 1: OLS regressions on deaths per 100,000 before the policy switch

	Dependent variable:						
	deaths per 100,000 inhabitants						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FPÖ vote share in %	-0.576**	-0.306	-0.345	-0.394	-0.661**	-0.410	-0.413
	(0.251)	(0.241)	(0.240)	(0.242)	(0.265)	(0.276)	(0.276)
Share of employees in %		0.903***	1.124***	1.015***	1.052***	0.991***	0.975***
		(0.218)	(0.252)	(0.267)	(0.261)	(0.227)	(0.226)
Share of university graduates in %						0.290	0.329
						(0.246)	(0.242)
Share of population born in Austria in %					0.310**	0.384**	0.372**
					(0.126)	(0.148)	(0.147)
Unemployed in % (January 2020)					0.933		
					(0.817)		
Population density						0.00004	
						(0.00005)	
Mean gross income of employees (2018)				-0.0003	-0.0004	-0.001**	-0.001**
				(0.0003)	(0.0003)	(0.0003)	(0.0003)
Share of population of 85+ years in %			2.619*	1.972			
			(1.545)	(1.632)			
Constant	16.283***	-25.264**	-41.055***	-23.002	-41.898*	-43.855**	-41.623**
	(4.333)	(10.791)	(14.175)	(20.589)	(22.300)	(21.017)	(20.871)
Observations	94	94	94	94	94	94	94
R^2	0.054	0.204	0.229	0.241	0.278	0.290	0.283
Adjusted R^2	0.044	0.187	0.203	0.207	0.238	0.241	0.242
Residual Std. Error	7.502	6.919	6.849	6.831	6.700	6.683	6.679

	(df = 92)	(df = 91)	(df = 90)	(df = 89)	(df = 88)	(df = 87)	(df = 88)
F Statistic	5.259** (df = 1; 92) (p = 0.025)	11.681*** (df = 2; 91) (p = 0.00004)	8.905*** (df = 3; 90) (p = 0.00004)	7.076*** (df = 4; 89) (p = 0.0001)	6.794*** (df = 5; 88) (p = 0.00003)	5.927*** (df = 6; 87) (p = 0.00004)	6.942*** (df = 5; 88) (p = 0.00002)
Note:						*p<0.1; **p<0.05; ***p<0.01	

For the number of cases, however, all models predict a highly significant negative impact of the vote share of the FPÖ, i.e. those districts in which the FPÖ fared better, experienced a lower number of reported infections during the first wave. The models also confirm the relationships observed in Table 1 regarding the share of employees, the share of Austrian-born and the mean gross income . Also, some models predict a statistically significant positive relationship between unemployment in January 2020 and the number of cases, i.e. a higher rate of unemployment predicts more reported cases.[3]

Table 2: OLS regressions on cases per 1,000 before the policy switch

	Dependent variable:						
	cases per 1000 inhabitants						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FPÖ vote share in %	-0.248***	-0.132**	-0.143**	-0.177***	-0.168**	-0.273***	-0.222***
	(0.074)	(0.062)	(0.062)	(0.059)	(0.068)	(0.062)	(0.073)
Share of employees in %		0.388***	0.450***	0.346***	0.406***	0.439***	0.455***
		(0.056)	(0.065)	(0.053)	(0.056)	(0.061)	(0.062)
Share of population of 85+ years in %			0.738*				
			(0.398)				
Share of population which completed an apprenticeship in %					-0.103*		-0.076
					(0.057)		(0.059)
Share of population born in Austria in %					0.125***	0.102***	0.135***
					(0.039)	(0.030)	(0.039)

[3] Unemployed have more leisure time than employees, but on the other hand engage in less economic activities. If infections mainly spread during leisure time, unemployment can thus increase, or at least hold constant the number of infected, as already observed by Mellacher (2020).

Population density					0.00001		
					(0.00001)		
Unemployed in % (January 2020)						0.432**	0.352*
						(0.191)	(0.201)
Mean gross income of employees (2018)				-0.0003***	-0.0003***	-0.0002***	-0.0003***
				(0.0001)	(0.0001)	(0.0001)	(0.0001)
Constant	6.093***	-11.749***	-16.201***	-0.920	-7.954*	-13.831***	-13.024**
	(1.267)	(2.791)	(3.655)	(3.725)	(4.299)	(5.224)	(5.242)
Observations	94	94	94	94	94	94	94
R^2	0.110	0.415	0.436	0.504	0.560	0.565	0.573
Adjusted R^2	0.101	0.402	0.418	0.488	0.529	0.540	0.543
Residual Std. Error	2.194 (df = 92)	1.789 (df = 91)	1.766 (df = 90)	1.656 (df = 90)	1.587 (df = 87)	1.569 (df = 88)	1.564 (df = 87)
F Statistic	11.408*** (df = 1; 92) (p = 0.002)	32.263*** (df = 2; 91) (p = 0.000)	23.229*** (df = 3; 90) (p = 0.000)	30.539*** (df = 3; 90) (p = 0.000)	18.433*** (df = 6; 87) (p = 0.000)	22.835*** (df = 5; 88) (p = 0.000)	19.445*** (df = 6; 87) (p = 0.000)
Note:	*p<0.1; **p<0.05; ***p<0.01						

This analysis suggests that the pro-lockdown policy of the FPÖ during the first wave of infections indeed had a positive effect on public health outcomes in those districts in which they can rely on a large base of support.

After the policy-switch

The analysis of case and deaths after the policy switch shows that the control variables have to be adapted, i.e. the relevant factors at play during the first wave differ partly from the second wave. Importantly, the role of the FPÖ vote share plays a completely opposite role, as the number of deaths per capita increases statistically significantly and strongly with the FPÖ vote share. It is notable that a regression involving solely the FPÖ vote share already explains 21.5% of the variance in observed deaths. Only education and nationality are statistically significant control variables: Deaths are predicted to be higher, if a higher share of the population has completed at most compulsory education, and lower, if a higher share of the population is born in Turkey.

Covid Economics 63, 7 January 2021: 98-125

While we can hypothesize that the first result may to a certain degree also be explained with corona scepticism, the result regarding Turkish-born population may hint to a lower spread of the virus in Turkish communities or to the fact that the Turkish community were able to shield their elders from the virus more efficiently. In any case, it is an unexpected result as Turkish weddings were prominently featured and discussed in the media as superspreader events (e.g. Wiener Zeitung 2020).

Table 3: OLS regressions on deaths per 100,000 after the policy switch

	Dependent variable:						
	deaths per 100,000 inhabitants						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FPÖ vote share in %	4.771***	4.431***	3.763***	3.996***	4.165***	4.129***	4.897***
	(0.951)	(0.981)	(0.998)	(1.012)	(1.038)	(1.008)	(1.109)
Mean gross income of employees (2018)			-0.001				
			(0.001)				
Share of employees in %				0.627			0.074
				(0.895)			(1.062)
Population density					0.004		0.008*
					(0.004)		(0.005)
Unemployed in % (January 2020)						-3.345	-5.237
						(2.660)	(3.375)
Share of population which completed at most compulsory education in %			2.404**	2.737**	2.481**	3.104***	2.794**
			(1.190)	(1.148)	(1.178)	(1.174)	(1.202)
Share of population born in Turkey in %		-3.283	-9.350**	-10.013***	-10.226***	-9.851***	-11.083***
		(2.456)	(3.843)	(3.615)	(3.616)	(3.559)	(3.655)
Share of population of 85+ years in %			-1.398				
			(6.201)				
Constant	-17.765	-8.237	15.363	-63.945	-38.644*	-35.413*	-42.090
	(16.392)	(17.811)	(53.339)	(44.525)	(21.070)	(20.898)	(51.596)
Observations	94	94	94	94	94	94	94
R^2	0.215	0.230	0.287	0.280	0.284	0.289	0.311
Adjusted R^2	0.206	0.213	0.246	0.248	0.252	0.257	0.264

Covid Economics 63, 7 January 2021: 98-125

Residual Std. Error	28.384 (df = 92)	28.263 (df = 91)	27.657 (df = 88)	27.626 (df = 89)	27.553 (df = 89)	27.459 (df = 89)	27.340 (df = 87)
F Statistic	25.164*** (df = 1; 92) (p = 0.00001)	13.583*** (df = 2; 91) (p = 0.00001)	7.080*** (df = 5; 88) (p = 0.00002)	8.671*** (df = 4; 89) (p = 0.00001)	8.836*** (df = 4; 89) (p = 0.00001)	9.048*** (df = 4; 89) (p = 0.00001)	6.547*** (df = 6; 87) (p = 0.00001)
Note:	*p<0.1; **p<0.05; ***p<0.01						

If we look at the number of reported infections (i.e. cases), however, we do not find a statistically significant relationship with the FPÖ vote share (see table 4). Statistically significant control variables are the share of population of 65+ years, which predicts a decrease in reported infections (in line with the expected behavioral response), the share of unemployed and the gross income, which also predict a decrease (both possibly due to enhanced social distancing capabilities). In certain models, the share of the population born in Austria predicts an increase in the number of reported infections.

Table 4: OLS regressions on cases per 1,000 after the policy switch

	Dependent variable:						
	cases per 1000 inhabitants						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FPÖ vote share in %	0.021	0.664*	0.644*	0.380	0.451	0.367	0.275
	(0.375)	(0.388)	(0.381)	(0.394)	(0.364)	(0.373)	(0.378)
Population density		0.001	0.001	0.003	0.001	0.0003	0.002
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Share of population of 85+ years in %		-2.127					
		(2.100)					
Share of population of 65+ years in %			-1.062**	-1.310**	-1.624***	-1.538***	-1.520***
			(0.515)	(0.519)	(0.455)	(0.532)	(0.501)
Unemployed in % (January 2020)		-4.704***	-4.019***	-3.694***	-2.928***	-3.257***	-3.147***
		(1.090)	(1.134)	(1.123)	(1.049)	(1.093)	(1.088)
Share of population which completed at most compulsory education in %		0.853**	0.701**	1.095***		0.584	0.679*
		(0.327)	(0.330)	(0.374)		(0.411)	(0.382)

Covid Economics 63, 7 January 2021: 98-125

Share of population born in Austria in %				0.592**			0.392
				(0.281)			(0.277)
Mean gross income of employees (2018)					-0.001***	-0.001***	-0.001***
					(0.0003)	(0.0004)	(0.0004)
Share of population born in Turkey in %						-1.022	
						(1.312)	
Constant	38.093***	34.545***	50.951***	0.603	118.327***	105.943***	66.351*
	(6.467)	(9.564)	(13.134)	(27.167)	(16.520)	(19.971)	(33.707)
Observations	94	94	94	94	94	94	94
R^2	0.00003	0.263	0.289	0.323	0.365	0.380	0.389
Adjusted R^2	-0.011	0.221	0.248	0.276	0.329	0.329	0.340
Residual Std. Error	11.198 (df = 92)	9.831 (df = 88)	9.658 (df = 88)	9.475 (df = 87)	9.125 (df = 88)	9.124 (df = 86)	9.051 (df = 86)
F Statistic	0.003 (df = 1; 92) (p = 0.956)	6.275*** (df = 5; 88) (p = 0.0001)	7.138*** (df = 5; 88) (p = 0.00002)	6.919*** (df = 6; 87) (p = 0.00001)	10.110*** (df = 5; 88) (p = 0.00000)	7.514*** (df = 7; 86) (p = 0.00000)	7.834*** (df = 7; 86) (p = 0.00000)
Note:							*p<0.1; **p<0.05; ***p<0.01

The fact that the vote share of the FPÖ is strongly correlated with deaths, but not with cases per capita seems at first glance to be paradox and to sow doubt on the hypothesis that the corona populist turn of the FPÖ contributed to the spread of the virus.

However, Covid tests are in Austria usually conducted on individuals who self-report their symptoms or who are named as being close contacts. Thus, they are in one way or another voluntary, which means that there may be a self-selection bias. We can hypothesize that people who underestimate the virus (the "corona sceptics") are less likely to report an infection and to name contacts. In this case, the number of deaths per infection in such communities would be higher.

In order to test this hypothesis, table 5 presents OLS regressions on deaths including the number of reported cases as control variable. It shows that the negative effect of the FPÖ vote share on the number of deaths persist, i.e. communities in which the FPÖ is strong indeed have recorded a higher number of deaths per infection.

Looking at the control variables, we find a statistically significant negative correlation with the share of population born in Turkey. This points to the hypothesis that Turkish communities have indeed been more apt at shielding their elders from the virus. Some models predict a statistically significant positive relationship with the share of population at or above 65 (in line with the expectation that this group has a higher risk of dying) and the share of population which completed at most compulsory education (again, in line with the hypothesis about corona scepticism).

Table 5: OLS regressions on deaths per 100,000 after the policy switch incl cases

	Dependent variable:						
	deaths per 100,000 inhabitants						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FPÖ vote share in %	4.746***	4.189***	4.116***	4.184***	3.765***	3.642***	3.614***
	(0.849)	(0.857)	(0.952)	(0.873)	(0.869)	(0.871)	(0.867)
cases per 1000 inhabitants	1.164***	1.266***	1.427***	1.424***	1.204***	1.274***	1.351***
	(0.236)	(0.233)	(0.264)	(0.254)	(0.232)	(0.237)	(0.249)
Share of population born in Turkey in %		-5.365**			-10.006***	-8.434**	-7.751**
		(2.178)			(3.142)	(3.360)	(3.440)
Share of population born in Austria in %			0.034				
			(0.582)				
Share of population which completed at most compulsory education in %			0.366	0.338	2.053**	1.948*	1.918*
			(0.996)	(0.747)	(1.017)	(1.016)	(1.012)
Share of population of 65+ years in %			3.387**	3.624**			2.112
			(1.325)	(1.480)			(1.362)
Share of employees in %				0.273			
				(0.966)			
Share of population of 85+ years in %						6.967	
						(5.417)	
Constant	-62.118***	-50.408***	-139.510**	-153.090**	-69.381***	-89.859***	-115.857***
	(17.180)	(17.384)	(56.108)	(67.275)	(19.506)	(25.124)	(35.674)
Observations	94	94	94	94	94	94	94
R^2	0.380	0.420	0.429	0.429	0.445	0.455	0.460
Adjusted R^2	0.367	0.400	0.396	0.397	0.420	0.424	0.429

Covid Economics 63, 7 January 2021: 98-125

Residual Std. Error	25.350 (df = 91)	24.672 (df = 90)	24.756 (df = 88)	24.746 (df = 88)	24.261 (df = 89)	24.172 (df = 88)	24.072 (df = 88)
F Statistic	27.943*** (df = 2; 91) (p = 0.000)	21.689*** (df = 3; 90) (p = 0.000)	13.204*** (df = 5; 88) (p = 0.000)	13.231*** (df = 5; 88) (p = 0.000)	17.842*** (df = 4; 89) (p = 0.000)	14.710*** (df = 5; 88) (p = 0.000)	14.980*** (df = 5; 88) (p = 0.000)
Note:							*p<0.1; **p<0.05; ***p<0.01

2 Theory

In order to explore the idea of the self-selection bias and to investigate, whether and under which conditions it can produce the pattern observed in a formal context, I extend the classical SIRD model (Kermack and McKendrick 1927) in a twofold way:

1.) I include a quarantined compartment denoted with Q that includes only detected cases. A certain fraction of infected is assumed to test themself upon infection and is then quarantined, i.e. their social contacts are set to 0. I assume that all critical cases are detected, since they seek medical attention and get tested for showing symptoms of Covid-19. Followingly, only people in the quarantine compartment may die. Holding constant the fraction of infected who will eventually die, the fraction of quarantined who die depends on the fraction of non-critical cases who opt to get tested voluntarily, i.e. on the fraction of critical cases in the quarantine compartment.

2.) I split the compartments governing the susceptible, the infected and the quarantined to incorporate two different groups: a group showing low compliance (the corona sceptics) and one showing high compliance (the majority). I consider differences in a) social distancing, and b) propensity to get tested. I also consider the case of homophilic mixing, i.e. that individuals of a certain group are more likely to get into contact with members of their own group than members of the other group (which is why I need two different compartments for the infected).

Covid Economics 63, 7 January 2021: 98-125

Covid Economics 63, 7 January 2021: 98-125

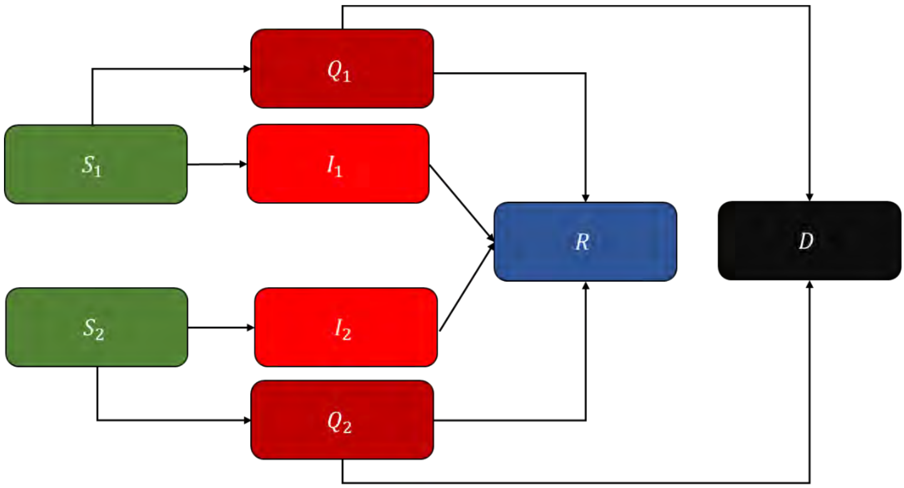


Figure 2: Depiction of the compartments

In setting up the laws of motion between the different compartments, I largely follow the preferred mixing model described by Brauer (2008), which in turn largely follows Nold (1980).[4] In contrast to models such as the homophilic mixing model proposed by Ellison (2020), the model used in my paper is able to replicate the standard homogenous mixing model as a special case if the behavior of the two types of agents is equal (especially the basic reproduction numbers R_{01} and R_{02} respectively). The laws of motion between the different compartments are given as follows, where S_i denotes the susceptibles of group i, I_i the infectious, Q_i the quarantined, N_i the size of group I at period 0, β_{ij} the number of infectious contacts from a member of group j to a member of group i, h the homophily of social contacts, α_i the propensity to get tested, R_{0i} the basic reproduction number of group i, $\frac{1}{\gamma}$ the duration the illness, and μ_i the fraction of detected cases who eventually die:

$$\dot{S}_i(t) = -S_i(t)\beta_i\left(p_{i1}\frac{I_1(t)}{N_1} + p_{i2}\frac{I_2(t)}{N_2}\right)$$

[4] Brauer (2008) considers the fraction that each group *currently* makes up as part of the total population. I refrained from implementing this logic in order to retain the classical SIRD outcome as a special case.

$$\dot{I}_i(t) = (1-\alpha_i)S_i(t)\beta_i\left(p_{i1}\frac{I_1(t)}{N_1} + p_{i2}\frac{I_2(t)}{N_2}\right) - \gamma I_i(t)$$

$$\dot{Q}_i(t) = \alpha_i S_i(t)\beta_i\left(p_{i1}\frac{I_1(t)}{N_1} + p_{i2}\frac{I_2(t)}{N_2}\right) - \gamma Q_i(t)$$

$$\dot{R}(t) = \gamma\big(I_1(t) + I_2(t)\big) + \gamma\big((1-\mu_1)Q_1(t) + (1-\mu_2)Q_2(t)\big)$$

$$\dot{D}(t) = \gamma\big(\mu_1 Q_1(t) + \mu_2 Q_2(t)\big)$$

Where

$$p_{ij} = \begin{cases} h + (1-h)\,p_j & if\ j = i \\ (1-h)\,p_j & if\ j \neq i \end{cases}$$

$$p_i = \frac{(1-h)\gamma R_{0i} N_i}{(1-h)\gamma R_{01} N_1 + (1-h)\gamma R_{02} N_2}$$

$$\beta_i = \gamma R_{0i}$$

In order to better disentangle the effects of behavioral differences of the two groups, I make the following practical assumption: Individuals of both groups are equally likely to die as a result of an infection with a probability of π. We can thus set the probability that a quarantined person dies at $\mu_i = \frac{\pi}{\alpha_i}$ and set a lower boundary for α_i, as I assumed previously that at least all critical cases are tested, i.e. $\alpha_i \geq \pi$.

Homogenous mixing

Let us first consider the case of homogenous mixing, i.e. $h = 0$ and $R_0 = R_{01} = R_{02}$. In this case, we can immediately see that $p_{ij} = p_i = \frac{N_i}{N_1+N_2}$. Thus, if we normalize the population to 1, i.e. $N_1 + N_2 = 1$, the dynamic governing the susceptibles collapses to the dynamic of the classical one-group SIR framework, i.e.:

$$\dot{S}_i(t) = -S_i(t)\gamma R_0(I_1(t) + I_2(t))$$

In such a case, differentiating between two infectious compartments is unnecessary. Nevertheless, we could consider differences in the propensity to get tested (and subsequently

Covid Economics 63, 7 January 2021: 98-125

Covid Economics 63, 7 January 2021: 98-125

get quarantined), i.e. a different evolution of Q_1 and Q_2. From the above formula follows easily that such a difference can only affect both groups equally (relative to their share of total population) in terms of deaths or the sum of infected and quarantined, as the relative share of I_i as part of the total infected does not have an impact on the evolution of S_i.

Setting $S_1 = S_2 = 0.4995$, $I_1 = I_2 = 0.0005$, $R_0 = 2.5$, $\pi = 0.01$ and $\alpha_1 = 0.01$ and varying α_2, we find that the detection rate has a large impact on "flattening the curve", but also on reducing the cumulative number of infected (see figure 2).

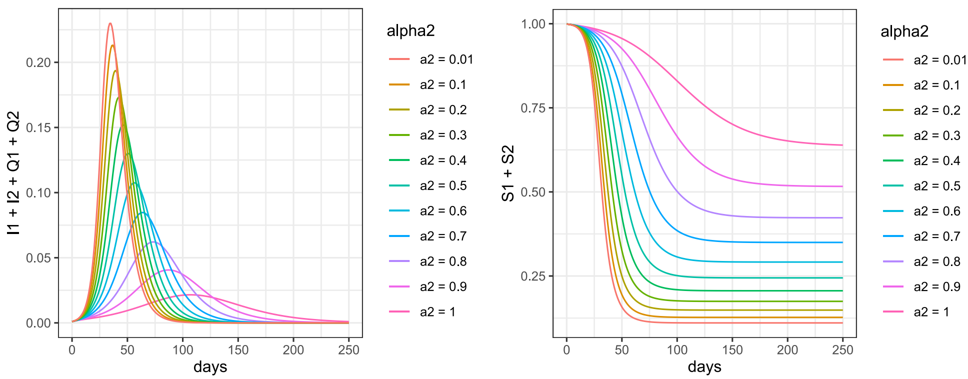


Figure 3: Evolution of total infected including quarantined (left) and total susceptibles (right).

Proportionate mixing

As soon as the two subpopulations engage in different activity patterns, i.e. $R_{01} \neq R_{02}$, homogenous mixing is implausible. If, for instance, group 1 only has one infectious contact per day, whereas group 2 has five, members of group 2 cannot on average have 2.5 infectious contacts with members of group 1, if the two groups are equal-sized. The specification by Brauer (2008), which provides the basis of my model, accounts for this. If activity patterns differ, but mixing is not homophilic, it is proportionate, i.e. members of a specific group meet members of another specific group according to their relative population shares and basic reproduction numbers as specified above. As a result, outcomes for both groups cannot be used interchangeably anymore and can be disaggregated in a meaningful way. Figure 3 shows that an increase in R_{0i} *ceteris paribus* makes both groups worse off. In contrast to a decrease in the detection rate, however, group i is more affected by such an increase than the other group. The simulations are here initialized with $S_1 = S_2 = 0.4995$, $I_1 = I_2 = 0.0005$, $R_{01} = 1$, $\pi = 0.01$ and $\alpha_1 = \alpha_2 = 0.01$, varying R_{02}:

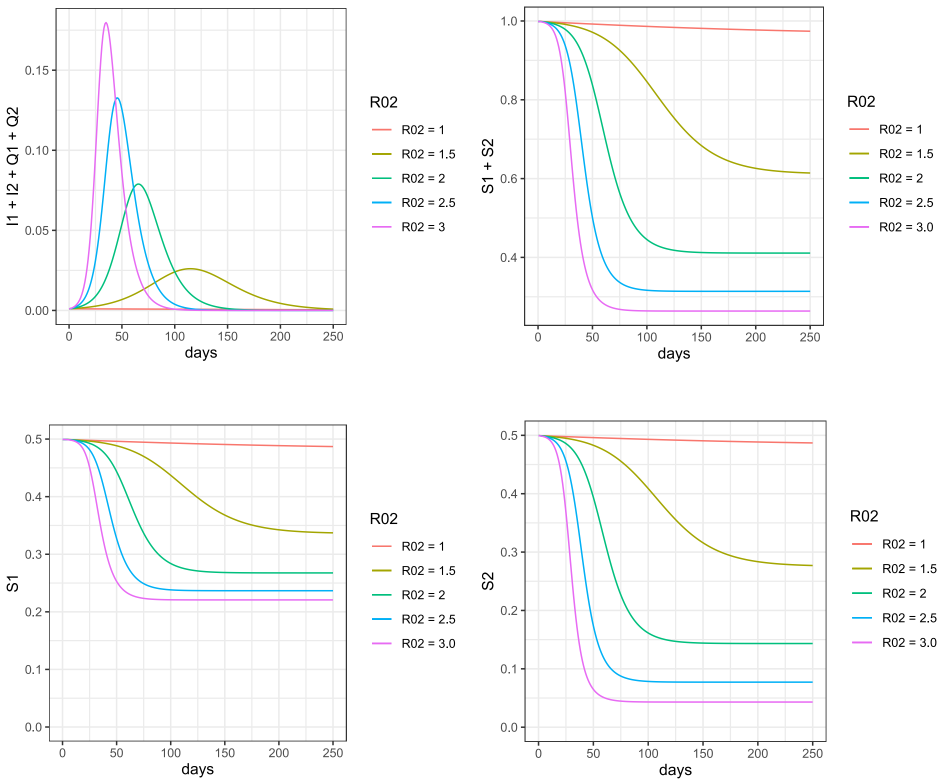


Figure 4: Susceptibles and infected for varying R_{02} under proportionate mixing

Nevertheless, such a setup is also unable to fully explain the Austrian empirics. As fig. 4 shows, a situation in which reported infections are higher in the population that is composed of 20% corona sceptics compared to one with 50% corona sceptics is only possible for a very short period. The relationship regarding the number of reported infections then quickly follows the relationship regarding the number of deaths. These results are produced with the following initialization:

Population 1: ($S_2 = 0.4995, I_2 = 0.0005, S_1 = 0.4995, I_1 = 0.0005$ and population 2: ($S_2 = 0.1998, I = 0.0002,\ S_1 = 0.7992, I_1 = 0.0008$). Both runs are parametrized with $R_{01} = 1$ and $R_{02} = 2$, $\alpha_1 = 0.01$ and $\alpha_2 = 0.5$. In order to highlight the results in the first few days, I only plot the results of the first 50 days. However, the trend remains the same for any period afterwards.

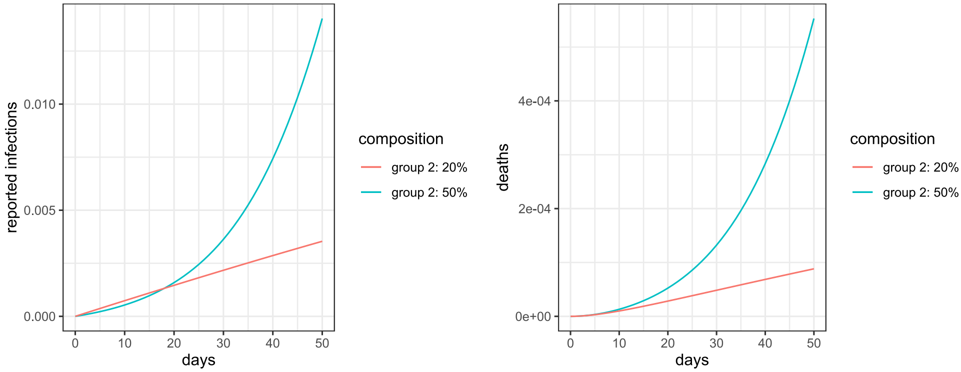


Figure 5: Reported infections and deaths for two differently composed populations under proportionate mixing

Homophilic mixing

Finally, we consider the case of homophilic mixing, i.e. $h > 0$. Again, we compare two populations, in which one is composed of 50% corona sceptics ($S_2 = 0.4995, I = 0.0005$) and one with 20% corona sceptics ($S_2 = 0.1998, I = 0.0002$). Both runs are parametrized with $R_{01} = 1$ and $R_{02} = 2$, $\alpha_1 = 0.01$ and $\alpha_2 = 0.5$:

Figure 5 shows that such a setup can indeed explain the empirics, if mixing is sufficiently homophilic. The higher h, the longer can the reported infections in the population made up of 50% corona sceptics be lower than or equal to the reported infections in the population with a 20% share of corona sceptics. At the same time, however, the number of deaths in the population with more corona sceptics is always equal or higher. If mixing is sufficiently homophilic, a population may permanently have at the same time a lower number of reported infections and a higher number of deaths:

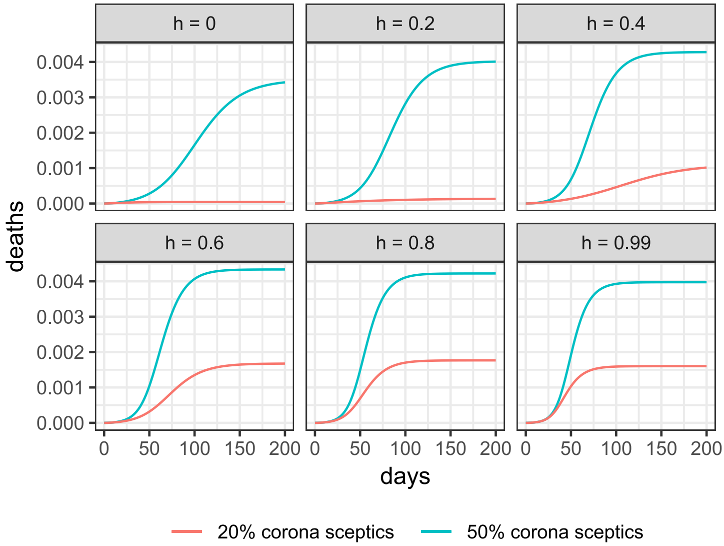


Figure 6: Deaths in two different populations for given $R_{01} = 1$ and $R_{02} = 2$ with varying degrees of homophily.

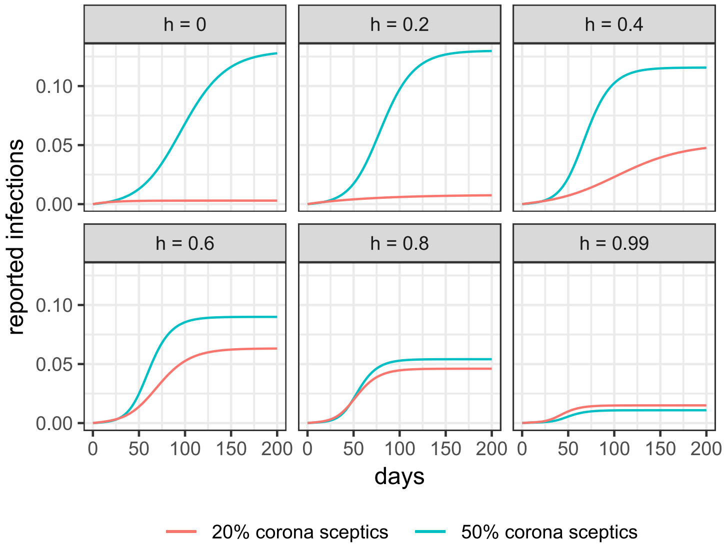


Figure 7: Number of reported infections in two different populations for given $R_{01} = 1$ and $R_{02} = 2$ with varying degrees of homophily.

Covid Economics 63, 7 January 2021: 98-125

CEPR PRESS

The degree of homophily which is necessary to achieve such a pattern crucially depends on R_{01} and R_{02}. More specifically, less homophily in mixing is necessary, if R_{01} is lower and if the gap between R_{01} and R_{02} is larger.[5]

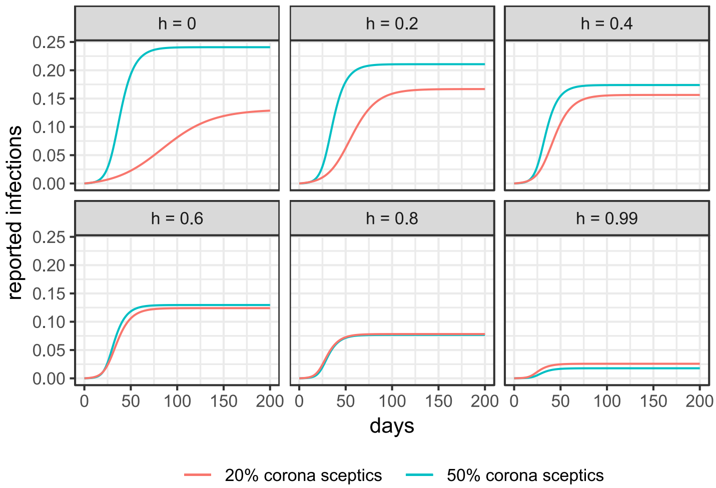


Figure 8: Number of reported infections in two different populations for given $R_{01} = 1$ and $R_{02} = 3$ with varying degrees of homophily.

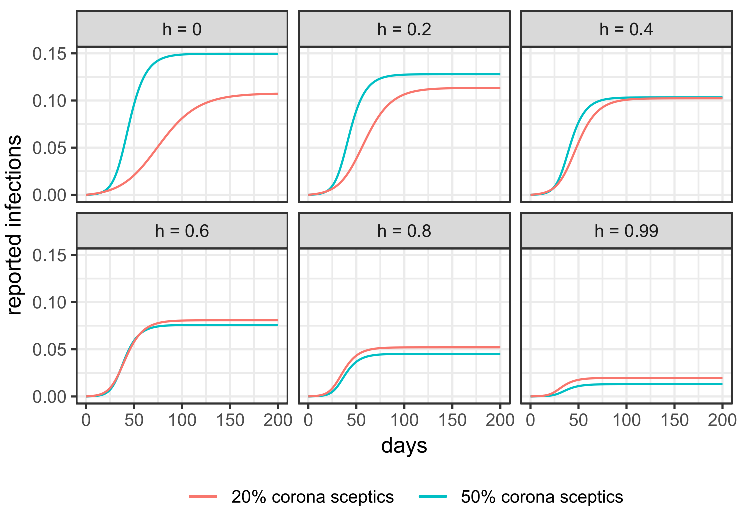


Figure 9: Number of reported infections in two different populations for given $R_{01} = 0.5$ and $R_{02} = 2.5$ with varying degrees of homophily.

[5] It can be seen easily that the *implied* homophily in social contacts is larger for any given $h < 1$ in both cases as the x in the following equation becomes larger: $R_{02} = xR_{01}$.

Covid Economics 63, 7 January 2021: 98-125

Let us finally take a look at public health effects of the prevalence of corona sceptics and the degree of homophily. As deaths in this simple model depend mechanically on the number of true infections, the damage done by corona scepticism can be measured by tracking the evolution of the susceptibles. *Ceteris paribus*, lower homophily translates into better health outcomes for the corona sceptics and worse outcomes for the majority. Figure 9 shows the number of susceptibles for each group for an equal-sized population with $R_{01} = 1, R_{02} = 2$, $\alpha_1 = 0.01$ and $\alpha_2 = 0.5$:

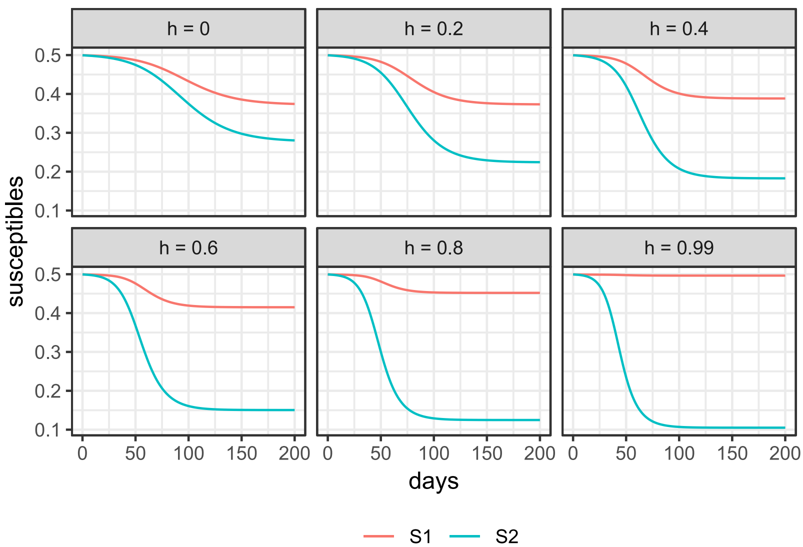


Figure 10: S1 and S2 for a population composed of two equal-sized groups with $R_{01} = 1, R_{02} = 2$.

Figure 5 already intuitively showed that the number of deaths is *ceteris paribus* lower if the share of corona sceptics is smaller. Figure 10 finally shows an intricate interplay between the share of corona sceptics and the degree of homophily. If homophily is low, the marginal public health damage done by corona sceptics increases up to a population size of 50% and then decreases, whereas it is almost constant for high levels of homophily. This means that a well-mixed population can bear a certain fraction of corona sceptics, as long as they are not too numerous. If the corona sceptics are a minority, the total damage is lowest in settings with no or very low homophily, whereas it is lowest with high homophily, if the corona sceptics are the majority. In both cases, however, the damage is highest for intermediate levels of

Covid Economics 63, 7 January 2021: 98-125

homophily, i.e. there is a non-linear relationship between the level of homophily and health outcomes of the total population. There is, however, of course a linear relationship for each group on its own, as shown in fig. 9, i.e. an increase in homophily is always worse for corona sceptics and vice versa.

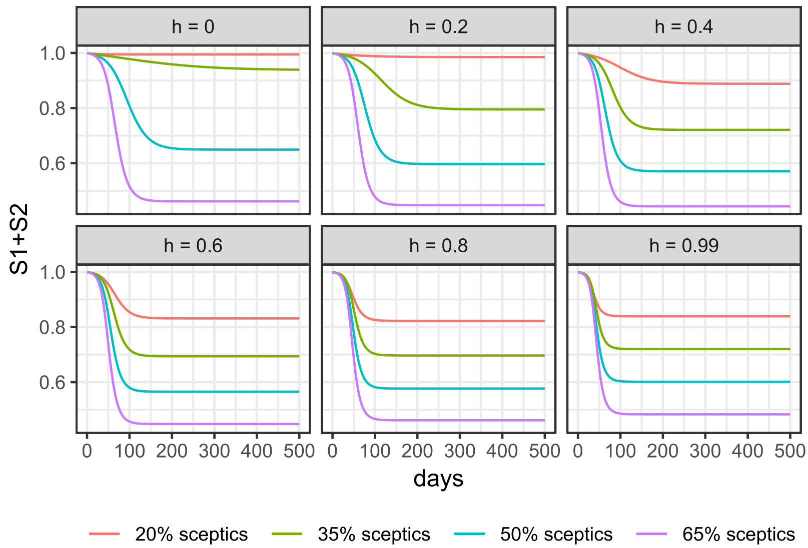


Figure 11: The evolution of total susceptibles under varying degrees of homophily and sizes of the corona sceptics for $R_{01} = 1, R_{02} = 2$.

4 Conclusion

In this paper, I first described corona populism as a political position which is “sceptical” of the danger posed by the virus and the need for containment measures. Following Acemoglu et al. (2013), I characterized this policy stance as populist, since it receives significant public support, although its adoption would at the same time cause adverse effects on the majority of the population.

I then investigated whether the policy stance of the Austrian right-wing freedom party (FPÖ) on the coronavirus crisis had an effect on public health outcomes in communities in which they receive large support. The policy stance of the FPÖ was characterized by a U-turn: until the end of the first wave of infections, the FPÖ followed a strict pro-lockdown course. At the end of April, however, the party switched to demanding “an end of the corona madness”, i.e.

Covid Economics 63, 7 January 2021: 98-125

the containment measures, thereby downplaying the threat posed by the virus and adopting a corona populist attitude.

I merged a time series dataset of daily infections and deaths on the district level into two separate cross-sectional datasets – one before, and one after the policy switch – to study the correlation between support for the FPÖ and public health outcomes in two dimensions: the number of reported infections and the number of deaths. Using the election result of the national elections 2019 as a proxy for support for the FPÖ and controlling for various demographic and socioeconomic variables, I showed that an increased FPÖ election result predicts a) less infections and fatalities for the first wave, and b) more fatalities, but no statistically significant effect on infections, after the policy switch. OLS regressions also showed a significant effect on deaths controlling for (among others) the number of cases, i.e. the case fatality ratio is higher in districts in which the FPÖ is stronger.

While the outcome regarding the first wave of infections supported the hypothesis that the policy stance of the FPÖ has a big impact on the behavior of their voters, the analysis of public health outcomes after the policy switch seemed inconclusive and paradoxical. I hypothesized that they originate from a self-selection bias inherent to the Austrian containment policies: The policy stance of the FPÖ caused their voter base to take the virus less seriously, who then did not only practice less social distancing, but also reported their symptoms less often, which means that they were less likely tested.

In order to explore this hypothesis, I extended the classical SIRD to incorporate quarantine, heterogeneous behavior and heterogeneous mixing. This model is populated with corona sceptics and the majority, and the corona sceptics have a higher basic reproduction number and a lower propensity to get tested. I explored the properties of such a model and showed that it is able to reproduce the Austrian dynamics in a stylized way, if mixing is sufficiently homophilic, i.e. if corona sceptics are much more likely to meet other corona sceptics.

I finally discussed the impact of homophily on health outcomes in both groups. The level of homophily defines the way in which herd immunity is reached. Corona sceptics achieve the best health outcomes, if mixing is not (very) homophilic, whereas the majority is best off, if mixing is almost completely homophilic. Interestingly, for the society as a whole, both low and high levels of homophily lead to better public health outcomes than intermediate homophily.

Covid Economics 63, 7 January 2021: 98-125

The research presented in this paper can be extended in numerous ways. First, it would be interesting to study the cross-national impact of corona populism. Does its effect depend on factors which are constant in Austria, but vary internationally, such as the governmental coalition, the overall success of containment policies during the first wave etc.? Second, it would be interesting to study corona populism and scepticism in a more complex model. Agent-based models such as the COVID-Town model (Mellacher 2020) are capable of modeling the spread of the virus via social networks and explicitly modeled heterogeneous agents, who can follow sophisticated behavioral rules. This level of analysis can be highly useful to better understand the impact of corona scepticism. For instance, it may make a big difference whether a corona sceptic faces many customers or is an introverted unemployed person. However, this method can also help to better understand the emergence and dynamics of corona scepticism, e.g. by modeling heterogeneous risk preferences or even opinion dynamics of corona scepticism or corona populism. I hope to be able to study some of these questions in the future.

Acknowledgements: The tables in this paper were created using the stargazer package for R (Hlavac 2018).

Appendix:

Table A1: Cases and deaths before the 11th of May 2020

Statistic	N	Mean	St. Dev.	Min	Max
cases per 1000 inhabitants	94	1.881	2.314	0.000	21.088
deaths per 100,000 inhabitants	94	6.545	7.667	0	39

Table A2: Cases and deaths after the 11th of May 2020

Statistic	N	Mean	St. Dev.	Min	Max
cases per 1000 inhabitants	94	38.452	11.138	17.759	74.885
deaths per 100,000 inhabitants	94	63.144	31.859	0.000	148.554

Covid Economics 63, 7 January 2021: 98-125

Table A3: (Control) Variables

Statistic	N	Mean	St. Dev.	Min	Max
population	94	94,692.170	194,791.567	1,980	1,911,191
Population density	94	5,373.425	15,821.102	22	104,782
FPÖ vote share in %	94	16.959	3.095	10.572	24.037
Share of population born in Austria in %	94	86.430	7.010	63.287	97.030
Share of population born in Turkey in %	94	1.147	1.236	0.000	6.307
Share of population of 85+ years in %	94	2.837	0.551	2.037	5.202
Share of population of 65+ years in %	94	20.361	2.402	16.061	25.960
Mean gross income of employees (2018)	94	33,012.628	2,822.192	26,529	44,010
Share of population which completed at most compulsory education in %	94	16.500	3.721	9.772	29.888
Share of population which completed an apprenticeship in %	94	38.264	5.977	21.064	47.115
Share of university graduates in %	94	11.662	5.075	5.964	31.582
Share of employees in %	94	40.909	3.420	34.733	54.806
Unemployed in % (January 2020)	94	3.402	1.155	1.066	6.608

References

Acemoglu, D., Egorov, G., & Sonin, K. (2013). A political theory of populism. *The Quarterly Journal of Economics*, 128(2), 771-805.

Allcott, H., Boxell, L., Conway, J., Gentzkow, M., Thaler, M., & Yang, D. Y. (2020). Polarization and public health: Partisan differences in social distancing during the Coronavirus pandemic. NBER Working Paper, (w26946).

APA OTS (2020a). *FPÖ – Kickl und Schnedlitz präsentieren Petition „Jetzt reicht's! - Allianz gegen den Corona-Wahnsinn".* https://www.ots.at/presseaussendung/OTS_20200427_OTS0133/fpoe-kickl-und-schnedlitz-praesentieren-petition-jetzt-reichts-allianz-gegen-den-corona-wahnsinn (download 27.12.2020)

APA OTS (2020b). *FPÖ – Belakowitsch und Fürst kritisieren Corona-Massentests der Bundesregierung*. https://www.ots.at/presseaussendung/OTS_20201125_OTS0143/fpoe-belakowitsch-und-fuerst-kritisieren-corona-massentests-der-bundesregierung (download 27.12.2020)

Baradaran Motie, G., & Biolsi, C. (2020). County-Level Determinants of Social Distancing (or Lack Thereof) during the COVID-19 Pandemic. *Contemporary Economic Policy*.

Barbieri, P., & Bonini, B. (2020). Populism and Political (Mis-) Belief Effect on Individual Adherence to Lockdown during the COVID-19 Pandemic in Italy. *Available at SSRN 3640324*.

Bisbee, J., & Lee, D. (2020). Mobility and Elite Cues: Partisan Responses to Covid-19. *APSA Preprints*. doi: 10.33774/apsa-2020-76tv9.

BMI (2019). *Ergebnis der Nationalratswahl am 29.09.2019 inklusive aller Wahlkartenstimmen*. https://www.data.gv.at/katalog/dataset/8becadda-124e-43f3-900e-f1ab685574e5/resource/3865d49b-9d3c-480a-8d0e-959bebddc81a/download/wahl_20191007_163653.csv (download 23.11.2020)

BMSGPK (2020). *COVID-19: Timeline of data on Covid19 cases per district*, https://www.data.gv.at/katalog/dataset/covid-19-zeitliche-darstellung-von-daten-zu-covid19-fallen-je-bezirk (download 29.12.2020).

Brauer, F. (2008). Epidemic models with heterogeneous mixing and treatment. *Bulletin of mathematical biology*, 70(7), 1869.

Eberl, J., Huber, R. A., & Greussing, E. (2020, October 4). *From Populism to the 'Plandemic': Why populists believe in COVID-19 conspiracies*. https://doi.org/10.31235/osf.io/ejpw7

Fan, Y., Orhun, A. Y., & Turjeman, D. (2020). Heterogeneous Actions, Beliefs, Constraints and Risk Tolerance During the COVID-19 Pandemic, *NBER Working Paper No. 27211*.

Gollwitzer, A., Martel, C., Brady, W. J., Pärnamets, P., Freedman, I. G., Knowles, E. D., & Van Bavel, J. J. (2020). Partisan differences in physical distancing are linked to health outcomes during the COVID-19 pandemic. *Nature human behaviour*, 4(11), 1186-1197.

Grewenig, E., Lergetporer, P., Werner, K., & Woessmann, L. (2020). Do party positions affect the public's policy preferences? Experimental evidence on support for family policies. *Journal of Economic Behavior & Organization*, 179, 523-543.

Hlavac, M. (2018). *stargazer: Well-Formatted Regression and Summary Statistics Tables. R package version 5.2.2*. https://CRAN.R-project.org/package=stargazer

Ellison, G. (2020). Implications of heterogeneous SIR models for analyses of COVID-19. *Covid Economics*, 53, 1-32.

Kermack, W. O., & McKendrick, A. G. (1927). A contribution to the mathematical theory of epidemics. *Proceedings of the royal society of london. Series A, Containing papers of a mathematical and physical character*, 115(772), 700-721.

Mellacher, P. (2020). COVID-Town: An Integrated Economic-Epidemiological Agent-Based Model. *GSC Discussion Paper Series 23*.

Nold, A. (1980). Heterogeneity in disease-transmission modeling. *Mathematical biosciences*, 52(3-4), 227-240.

Statistik Austria (2020a). *Dauersiedlungsraum Abgrenzung 2011, Gebietsstand 1.1.2020*. https://www.statistik.at/wcm/idc/idcplg?IdcService=GET_NATIVE_FILE&RevisionSelectionMethod=LatestReleased&dDocName=076826 (download 23.11.2020)

Wiener Zeitung (2020). *Corona-Cluster nach Hochzeit mit 700 Gästen*. https://www.wienerzeitung.at/nachrichten/chronik/oesterreich/2076044-Corona-Cluster-nach-Hochzeit-mit-700-Gaesten.html (download 29.12.2020).

WKO (2020). *Wirtschaftsdaten auf Bezirksebene*. https://www.wko.at/service/zahlen-daten-fakten/wirtschaftsdaten-bezirksebene.html (download 27.11.2020).

Statistik Austria (2020b). *Paket Bevölkerungsstand - Politischer Bezirk*. https://www.statistik.at/wcm/idc/idcplg?IdcService=GET_NATIVE_FILE&RevisionSelectionMethod=LatestReleased&dDocName=059037

Covid Economics 63, 7 January 2021: 98-125

CEPR PRESS

126

Covid Economics Issue 63, 7 January 2021

Perceptive risk clusters of European citizens and NPI compliance in the face of the Covid-19 pandemic

Jacques Bughin[1], Michele Cincera,[2] Dorota Reykowska,[3] Marcin Zyszkiewicz[4] and Rafal Ohme[5]

Date submitted: 16 December 2020; Date accepted: 18 December 2020

Covid Economics 63, 7 January 2021: 126-158

Despite promising announcements on an effective vaccine, the control of the Covid-19 pandemic is critically dependent on the maximum compliance of citizens to a set of non-pharmaceutical interventions (NPI for short). We use statistical clustering to partition European citizens with regards to their perceptive risks and social attitudes during the first wave of the Covid-19 pandemic and find ten segments to predict, both the extent and mix of protective behaviors adopted. Those segments demonstrate a clear divide in the population, with on one extreme, a segment (representing 8% of the population) that is self-centered and exhibits low self-risk perception as well as low NPI compliance. The other extreme is a segment representing 11% of the population that is more socially oriented, and quite responsive to all protective measures. Since the data is survey-based, we adjusted responses based on information gap (by reaction time measurement) of both worry expression and NPI compliance, to confirm the robustness of our results. Further, we extend the notion of worries to be not only health-related but to include financial risk (like losing a job) as well as psychological worries (e.g., feeling alone, or being unable to meet with family and friends), as they prove to drive different NPI behaviors among the population.

1 Solvay Brussels School of Economics and Management, ECARES and iCite, Université libre de Bruxelles; Machaon Advisory; Fortino Capital and Antler and Portulans Institute.
2 Solvay Brussels School of Economics and Management, ECARES and iCite, Université libre de Bruxelles.
3 Neurohm.
4 Neurohm.
5 Neurohm and WSB University.

1. Introduction

The worldwide pandemic of the Covid-19 virus has entered its second wave recently, with significant morbidity and mortality costs.

By early August, Covid-19 had led officially to more than 700,000 fatalities. This is a figure matching the worse cases of annual flu, and already twice larger than the global pandemic of the H1N1 by 2009 (Bughin, 2020). By mid-October, a new inflection point was visible. Along with the softening of lockdown in many parts of the world, the pandemic has made a come-back. By early December, the number of worldwide fatalities has reached 1.5 million individuals or a doubling of death cases in a few months. The number of seriously ill active cases worldwide, which has been stabilized, at roughly 60-65 thousand daily cases in Q2-Q3, has been regrowing, close to reaching 100,000 cases a day, by end of November.[1]

While there have been significant announcements of effective vaccine recovery, e.g. from corporations like Moderna, or Pfizer with BioNtech, controlling the pandemic at the current stage must continue to rely on compliance with a set of non-pharmaceutical interventions (NPI, for short). This is even more important to date, as the full blanket lockdown put in place by many governments in the first wave of the pandemic is difficult to re-impose as it has entailed a major drop in economic activities up to 5 to 10% impact on an annual basis for worldwide GDP (Coibion et al., 2020). It also has led to a significant amount of 200 million job losses among others, according to the ILO.[2]

In the absence of hard lockdown, regaining control of the pandemic must be based on quarantine of (the closely exposed to) the contaminated, as well as the general compliance to a set of NPIs, like social distancing, and hygiene habits like wearing masks, or cleaning hands and objects. But for the quarantine to be effective, one needs to have the tracing tools to spot contaminated (which has appeared complex in practice), while NPIs to be extensively practiced by the population, require good communication and (dis-)incentives.

The merit of integrating economic behavior into a pandemic model is to show that diffusion paths are endogenous to behaviors, but also that under certain parameters, behaviors themselves may lead to an acceleration of the disease. It also puts rationale as to why the combination of strong negative health externalities in a covid economy with a large concentration of incidence and severity, leads to poor NPI compliance at the start of the Covid-19 pandemic, except when too late, hence requiring stringent policy interventions such as quarantines.

[1] https://www.worldometers.info/coronavirus/worldwide
[2] https://news.un.org/en/story/2020/04/1061322

Covid Economics 63, 7 January 2021: 126-158

Casual information suggests that NPIs are more or less being applied, sometimes because it is imposed strictly, sometimes because of large penalties leading to major dis-incentives. In general, the economics of pandemics also hint at different NPI compliance segments, with the simplification that, NPIs will be mostly practiced *by the susceptible* to the extent that the contact benefit is smaller than the health risk of being infected (Bethune and Korineck, 2020). This entails in practice that protective behavior is correlated with age, and with co-morbidity risks, as both drive a large part of the severity of the incidence of Covid-19 (Riou et al., 2020). In contrast, the segment of the infected is likely not to follow NPIs, as the segment is no longer to be infected, at least soon.

Nevertheless, the segmentation used in those models may be both too schematic for policy setting, and even inaccurate. Consider the susceptible segment. It is well known that people may have a hard time estimating their own health risk and thus may suffer cognition bias in their trade-off between social benefits and the risk of being contaminated (Niepel et al., 2020).[3] Second, if health risk has been often recognized as one of the most stable predictors of health-protective behavior (Harper et al., 2020), other risks are clearly being expressed by citizens (like the risk of losing their employment), that can cause them to adapt their behavior.

Finally, the risk to self-contamination is possibly a too narrow view of stimulus to behavioral change during major shocks like the Covid-19. In many cases of natural disasters, a large portion of individuals shows a sign of care for others. Even, before risk materializes, exposure may make people very socially aware (see Bollier, 2020 among others). For example, healthcare professionals' worries at pandemic times are typically altruistic. For instance, in the case of the Covid-19 outbreak in the Wuhan region, major worries quoted by healthcare professionals were first, infection of colleagues (more than 7 out of 10) and second (for 2/3 of healthcare workers) risk of contamination of family (Dai, 2020[4]).

Now assume a covid economy where, instead of the traditional socio-economic assumptions, citizens are very altruistic about others' health, incorporate not only health but financial risks increasing with contaminations, and/or suffer cognitive bias of over-estimating the morbidity risks of the disease. Such an economy will possibly be able to stop the virus dynamics early in its diffusion. Consider another covid economy, where risk is understated despite rapid health

[3] In that study made in the early months of the disease, many US adult residents had severely underestimated their fatality risk compared to what is induced by the Covid-19 epidemiological figures.

[4] The same is visible for the population in general. The data used in this paper have been collected in the first wave of the disease spread, and the official part of the population infected was less than one percent in the European countries we focused on. But focusing on those, the anecdotal evidence is that infected people were more worried about the health risk linked to their kids (55% of them) and elderlies (80% of them) than their *own health* risks. This is in contradiction to the characterization of the contaminated segment in the socio-economic model of pandemics.

Covid Economics 63, 7 January 2021: 126-158

penalty, and recovered cases engaged in even more socialization as an overshoot reaction to the number of social interactions lost during their infection, this economy is of course bound to become largely infected.

1.1. Article scope and fit with the literature

This paper develops a detailed segmentation of citizens' risk perception to self and others, as a further driver of NPI differentiated compliance.

We believe that the originality of this article is many-fold. First, if many studies are looking at *health* risk perception of a pandemic, this paper develops a detailed segmentation of how citizens perceive a broader set of risk archetypes, e.g. health, financial, social risks, that are congruent to the pandemic. Second, those risk perception studies are often country-specific, e.g. Harper (2020) for the UK, Wise et al. (2020) for the US, Faasse and Newby (2020) for Australia, or Zickfeld et al. (2020) for Norway, Bughin et al. (2020) for France among others. This research relies on a sample of more than 5,000 European citizens, above 18 years old, out of France, Germany, Italy, Spain, and Sweden, so that one can assess the generality of country-specific behavior. Countries were indeed chosen to reflect a spectrum of lockdown policies and health systems. Also, we cover 5 of the largest countries that make the core of Euro-27.

Third, on purpose, we look at risk perception to self *and others*, as this drives key externalities, but also because it may well be that those risk perceptions are not Covid-19 related but can arise as critical social traits. Do et al. (2017) have argued that risk-taking and prosocial tendencies are two inherently intertwined personality dimensions and that high risk-taking behavior and low social tendency may lead to negate all social protective behaviors. We find evidence of this in the segmentation results, in line with other recent surveys (Howard, 2020).

Fourth, the study uses cluster analysis as a powerful way to assess where the population can be represented by some cohesive attitudinal segments, as highlighted for early epidemic outbreaks such as SARS or H1N1 (see Vaughan, 2011; Leppin and Aro, 2009). Regarding Covid-19, Massaad and Cherfan (2020) leverage tweets to demonstrate the prevalence of clusters linked to the extent of perception of morbidity risk of the Covid-19 disease. Bodrud-Doza et al. (2020) use a survey in Bangladesh to assess the type of risk perception linked to covid and find four cluster groups that are linked to mortality risks and food scarcity, socio-economic issues, or mental health issues. Those early studies confirm that the prevalence of cohesive risk profiles clusters around the Covid-19 pandemics, while our study further informs on how social orientation, and experience of infections/quarantines, may also be important segmentation

Covid Economics 63, 7 January 2021: 126-158

factors, that furthermore are critical drivers of externalities in the economics of pandemics. Also, Bodrud-Doza et al. (2020), based on a relatively small sample of 400 individuals in Bangladesh, does not link worry segmentation to NPI compliance, as we perform in our current research.

Fifth, when it comes to NPIs, a part of the literature has been looking at the effectiveness of interventions on controlling the pandemics (e.g., Haug et al., 2020; Ferguson et al., 2020). Another part has attempted to understand drivers of compliance (Gialama et al., 2020). Webster et al. (2020) confirm that adherence to quarantine is linked to the intensity of knowledge about the disease outbreak, risk of disease, or social norms, during the Covid-19 pandemics. The results corroborate early studies looking at quarantine compliance during the SARS outbreak (Cava et al., 2005). Our study in contrast first clusters risk attitudes and then successfully looks at how they predict some of the variances in NPI compliance.

But we also find that attitude segments also build up different segments of NPIs, e.g. one segment is especially reluctant to hygiene measure, two other segments are broadly averse to any NPIs, with one slightly less reluctant to quarantine.

Last, but not least, our analysis uses an online survey which makes us at the mercy of the validity of the answers provided. We leverage a powerful data collection technique based on the neuroeconomics field to both filter the non-credible answers and assess the information strength of the answers received (Ohme et al., 2020). Neuro-economics suggests among others that people's speed of answers guides the reliability of the information responses. Our analysis uses an algorithm (Ohme et al., 2020) that both measures the explicit answer as well as the speed of answering making it possible to identify the confidence of attitudes. Additionally, too quick or much too long response times also suggest non-reliable answers as people either escape questions or struggle to answer.

Also, the response time uncovers new insights. For instance, segments that are claiming to be the most worried tend to have *faster* response times than average, reinforcing the idea that they are worried. This contrasts with the segment that claims to be less self-worried, and least NPI compliant, which has produced a longer response time, in virtually all questions than the average respondent.

1.2. High-level findings

Taking all our findings together, the following picture emerges:

Covid Economics 63, 7 January 2021: 126-158

1. 10 Covid-19 risk/NPI segments prevail into the continental European population, a larger set of segments than what has been found so far in the literature using a more restrictive set of attitudes, e.g. Massaad and Cherfan (2020).
2. Dimensions that clearly profile the segmentation are the type and intensity of worry, self versus others orientation, in line with Do et al. (2017). Exposure to the virus and socio-demographics also play a mediating role.
3. Health is the most expressed worry but is far from being exclusive. Among others, financial or job preservation risks are of extensive worry; in particular, a segment (10% of the population) is more worried about financial risk than health risk.
4. Regarding social orientation, about 40% of the population expresses worries towards their children/family or is acknowledging the crucial role of workers in essential jobs, among other health workers.
5. Three attitudinal segments, concentrating about 30% of the population, are less inclined to NPIs and are clearly a valuable target to policy actions.
6. The information gap analysis has proven that the tendency to distort the given answers differs by question type.[5] The highest distortion between declarations and confidence is observed for compliance and the lowest for expressing worries. In the face of the pandemic, people feel authorized to express worries but obliged to confirm compliance. Thus, it is easy to overestimate the usage of the NPI measures by relying on the pure statement made by respondents.

Covid Economics 63, 7 January 2021: 126-158

The rest of the paper reads as follows. The next section discusses the data method and collection and high-level statistics from the research. Section 3 presents the clustering analysis, as well as the links to NPI attitudes. The final sections discuss implications of findings and layout conclusions, including proposed avenues beyond this research.

2. METHODS AND DATA

2.1. Scope

The research is a part of an extensive multinational Covid-19 Fever project aimed at understanding people's attitudes, emotions, and behaviors connected with the pandemic. Based

[5] Information gap is a measure of the proportion of explicit answers given without confidence (see Section 2.3).

on the experience that attitudes/opinions and risk perceptions are critical drivers of protective actions during a health crisis (Harper et al. 2020), 50 questions were selected (see Appendix 1). The list of questions includes among others (see Tables 2a, b, c, and d) the most often raised questions in the burgeoning literature on the Covid-19 regarding concerns (such as worries to get infected) (Lee et al., 2020; Mertens et al., 2020) and behavioral change (such as practicing social distancing) (Asmundson and Taylor, 2020; Banerjee et al., 2020; Harper et al., 2020; Lunn et al., 2020; Oostertoff, 2020; Wise et al., 2020).

For the purpose of this paper, we focus on data from the continental European Union. Five countries are being analyzed: France, Germany, Italy, Spain, and Sweden. Those countries are among the largest of the EU and/or are representative of different socio-economic models (Esping-Andersen, 1999), as well as have chosen different policy responses in the first wave of the Covid-19, by March to June 2020 (notably Sweden and Germany have chosen no, or lighter lockdown than other countries). By pooling the countries together, we are then looking at attitude segmentation that is robust to country idiosyncrasies.

2.2. Data Collection

The data collection was performed online[6], based on country representative samples for age (above 18 years old) and gender, and recruited via a panel agency in April 2020 (See Table 1). The total sample amounts to about 5,000 answers or a minimum of 1,000 per country.[7]

Table 1. Number of respondents and demographic split per country

	Total	Gender		Age		
	N	Females	Males	18-35	36-49	50+
FRANCE	1,024	51%	49%	29%	28%	43%
GERMANY	1,017	49%	51%	27%	24%	50%
ITALY	1,021	51%	49%	26%	30%	44%
SPAIN	1,019	50%	50%	32%	32%	36%
SWEDEN	1,006	51%	49%	30%	20%	49%

Respondents received email invites and the samples were gathered within the first day from the start of the study. Respondents were also informed that the study tests opinions about the pandemic and that it is anonymous.

[6] We would like to thank Neurohm and Syno for collecting the data in all six countries.
[7] Full descriptive statistics on the data are available here.

The task of the respondents was to evaluate if they agree with the statements presented on the screen.[8] To avoid people being « forced » to respond, or respond with answers that are not reflective of actual behavior, each question was structured to respond, on a 3 point scale (yes, hard to tell, no) with "hard to tell" allowing not to force an answer.

A common issue linked to surveys is however that what people report does not always overlap with actions making it hard to predict behavior based solely on explicit answers. In the case in hand, declarations on the compliance with some of the NPI measures can be especially susceptible to distortions due to auto-presentation needs, post-conscious rationalization, or simply for some respondents to hide ill-perceived behaviors.

To avoid this, we have applied response time measurement. As shown by Fazio et al. (1989) correlations between attitudes and behaviors are higher among people with fast reaction time when expressing their opinions. iCode Smart test was used to collect the data (Ohme et al., 2020), with response time (RT) being measured for each answer, making it possible to derive a measure of the reliability of attitudes. In this respect, responses given too fast suggest speeding through the test without giving meaningful answers, or responses given too slow, suggest a person got distracted from the test (Greenwald et al., 2003). For each variable, RT given with a latency lower than 500 milliseconds (ms) (suspected to be given randomly) or higher than 10,000 ms (suspected to have been given after distraction) were replaced by the average of each variable. In total, this amounts to only 0.48% of dubious responses.[9] The latency values were also divided by 10,000 to obtain re-scaled values between 0 and 1.

2.3. High-level statistics

To account for individual differences in reaction speed, we have standardized reaction time data measured in ms, with STD-RT being the z-score of log(RT), with mean = 0 and standard deviation = 1.

The next step was to create a combined measure, taking into account both the explicit answer as well as the reaction time (RT) needed to produce the answer. The RTC index takes values between $-2 < RTC < 2$ and is defined as the difference between a measure of strong Yes, given

[8] Again, see Appendix 1.

[9] Furthermore, to ensure high quality of data and eliminate test biases a calibration phase and control screen have been added. Calibration preceded the test phase and consisted of 3 steps:

a. Familiarization with the scale. The task of the respondents was to press certain answer options – this task made sure respondents are aware of the position of the buttons on the screen.
b. Familiarization with the purpose of the task. A few statements were presented describing the test and the task. After each screen respondents had to press a button. This part served as a motoric warm up.
c. Increasing the focus on the task. During the study, a screen appeared asking to indicate the statement that was presented last. This task aimed to make sure respondents focus their attention on the presented statements. Such a screen was presented twice. The control screen was introduced to eliminate the effect of the position of the mouse on the screen. It was presented before each statement, forcing a standardized position of the mouse (the distance to the yes and no answers was always the same).

by RTC(Y) = 1 – (STD-RT/2) and a measure of strong No, RTC(N), as given by (STDRT/2) – 1.[10] Hard to tell answers are marked as 0 value. From this, we build a re-scaled RTC' index 0 < RTC' < 1, where RTC' = (RTC+2)/4.

We note that (STDRT/2) (= GAP, for short) can be seen as an information gap, as GAP grows with the rate of explicit answers given without confidence. At the extreme, the highest bound of 2 standard deviations leads to an information gap of 100%, that is the answer given, even though not reported as an "I don't know" answer, has so much uncertainty that we recalibrate it to an "I don't know" answer.

Tables 2a, b, c, and d provide the RTC' and GAP statistics computed for the most common questions and statements analyzed in the emerging literature on Covid-19 pandemics and assembled in four categories. The first table 2a looks at the statement regarding the category of Covid-19 health hazard.

Table 2a. The health hazard of Covid-19

Worries Type	Statement	RTC'	S.D.	Information GAP
Dangerousness	Covid-19 is dangerous for my health	71%	0.25	11%
Occurrence	My chances are high to get infected	46%	0.20	14%
Treatment	If infected, I will have the appropriate health treatment	62%	0.15	21%
Vaccine	I will take the opportunity of a vaccine	62%	0.14	19%

For any indicator, RTC' > 50%, except for occurrence, just below, but close to 50%. One might expect this, as the infection rate during the first wave remains below 5%, but epidemiologists have made clear that, without restrictive behavior and/or vaccine, the reproduction rate (R_0) of the virus may affect a dominant portion of the population.

Still, we find in our sample that RTC' = 71%, equivalent to a general « yes » when it comes to the alignment to the question of *whether Covid-19 may be dangerous to the health of the population*. We also find regarding the will to be vaccinated against the Covid-19 that RTC' = 62%. This is a majority of yes, but far from a complete total of the European population. This level of RTC' is in line with other studies, e.g. in France, roughly 7 out of 10 people, have reported accepting vaccination to covid during the first wave (Detoc et al., 2020).[11]

We finally notice that, for the information gap, this measure varies between 11-19%, or an average of 16%, concerning health hazard statements. Otherwise stated, statements have been

[10] STD-RT values above 2 and below -2 were truncated and given the value 2 or -2 respectively (this accounts for around 3% of data).
[11] Uncorrected RTC is more like 74% in our sample, see below.

discounted by 16%, to reflect the uncertainty as measured by response time. This is a rather large factor, as the uncorrected trust statement in healthcare would be 62% x (1+21%) = 75%. This discrepancy between declarations and confident answers naturally happens when respondents recognize some external contingencies (e.g. healthcare system, and the quality of a vaccine if found).

Table 2b first looks at expressed worries, as worries are typically seen as a catalyzer of behavioral change. Regarding worries, the largest worry expression concerns health, with an RTC' range between 50-70%, for the susceptible continental European population. This is consistent with other literature findings, e.g. Dryhurst et al. (2020).[12]

What is interesting is that health worries towards third parties are high especially with regards to the close family circle. It concerns not only kids but especially older family members' health, in line with higher mortality for the older population. Dryhurst et al. (2020) have demonstrated that social orientation is the largest contributor to risk perception.

Worries are also by far, not exclusively around health. The second worry is linked to job preservation, and household and country finance. The country's ability to navigate through the crisis is a worry that is as acute as its health. We hypothesize that this worry emerges from the fact that a large part of the countries we cover has forced full blanket lockdown to re-gain control of the pandemic evolution, with large pressure of economic activity and high volatility of stock market returns (Coibion et al., 2020). Social risks are also important, especially towards friends and family, while worries related to social unrest (such as thefts and breakage) are also made clear. In general, thus, it is rather important to map the type and breadth of risks as possible catalyzers to NPIs.

Table 2b. Worries taxonomy around the Covid-19

Worries Type	Statement	RTC'	S.D.	Information GAP
Health	I am worried about my health	62%	0.33	4%
Job	I am worried about my job situation	49%	0.32	4%
Finance	I am worried that our country will run out of money	63%	0.21	12%

The GAP value associated with the categories of worries is the lowest out of all 4 categories (see Tables 2b, versus 2a, 2c, and 2d), suggesting that in the face of the pandemic people feel rather safe and clear in expressing their worries.

[12] Dryhurst et al. (2020) have assessed in April 2020 health worries around the world to be just below 5 on a Likert scale of 0 (not at all worried) to 7 (extremely worried).

Covid Economics 63, 7 January 2021: 126-158

Table 2c looks at the interface of actors and their actions being implemented around the Covid-19. Public authorities must be trusted in general and in particular for their way of managing the crisis so that citizens adopt recommended protective actions (Li et al., 2018). However, governments have built some, but limited legitimacy, in the eyes of European citizens. Those actors have the least support (see the low RTC') among all groups analyzed in the survey. This is also where the statements have the lowest information gap for all categories so that those statements are the closest reflective of the true perception of respondents.

Table 2c. Perceptions around actors and their actions around Covid-19

Actors	Statement	RTC'	S.D.	Information GAP
Health carers	I am grateful to healthcare professionals	78%	0.16	18%
Workers	I am grateful to our essential workers	70%	0.18	20%
Media	Media provide reliable information about the pandemic	55%	0.21	8%
Health institutions	I am satisfied with how our healthcare system is handling this crisis	62%	0.22	15%
Governments	I am satisfied with how my government is handling this crisis	55%	0.28	3%
	The government is doing a good job dealing with Covid-19	55%	0.22	3%

Table 2d reports on three types of NPI actions. Bo et al. (2020) found that NPIs have been able to contain the Covid-19 pandemic in the first wave around the world. Avoidance elements such as social distancing, then quarantines, then preventive hygienic factors are to be adopted as extensively as possible by the population as those measures seem to have the largest impact on reducing the reproduction rate of the Covid-19. Especially their combination was large enough to push the reproduction rate below unity and break the build-up of the contagion. As a counterfactual, Cho (2020) shows that had Sweden used stricter lockdown interventions, it could have reduced its fatality rate due to Covid-19, by a material amount (up to 75%). Like in other countries where lockdown was rather strict, our data suggest that many people are starting to be complying with avoidance behavior, such as social distancing and staying at home. They also, and as expected to a lesser extent, practice hygienic factors, such as washing hands. This matches results found in multiple studies, e.g. Zickfeld et al. (2020). Still, the reach of compliance stands in the range of 75%, in our data, leaving a place for still broader adoption of NPIs. This category especially proves the importance of reaching to reaction time measurement when it comes to understanding attitudes and behavior in sensitive categories (such as expressing compliance to socially expected behavior). On the declarative level, 80% to 90% of

Covid Economics 63, 7 January 2021: 126-158

respondents expressed compliance with staying at home, social distancing, and washing hands. At the same time these are the statements with one of the highest values of information GAP, suggesting that people give socially acceptable answers, but they do not necessarily believe in them (there is still a significant group not fully confident, thus not complying, only declaring).

Table 2d. NPI compliance

Behavior Type	Statement	RTC,	S.D.	Information GAP
Distancing	I comply with the recommendations for physical distancing	76%	0.16	18%
Quarantine	I comply with the restrictions to stay home	76%	0.23	13%
Cleaning	I wash hands for 20 seconds when necessary	74%	0.19	18%
Extra caution	I disinfect groceries before putting them away	48%	0.28	13%
Extra caution	I disinfect mail and deliveries before opening them	44%	0.25	22%

3. Segmentation analysis

We have so far discussed averages of metrics from Tables 2a, b, c, and d. These tables however demonstrate widespread variance in most metrics, with 2 standard deviations being on average, more than 50%, or flipping between a yes and a no. This strongly suggests that attitudes and behaviors during Covid-19 are not homogenous.

We can easily hypothesize that behaviors might be clustered. For instance, the old population must be more worried about their health given the virus incidence and health hazards are increasing exponentially with age. Further health risk should be more prevalent than job loss risk as old-timers may be often, already retired. As another example, healthcare workers are typically more exposed to the viral charge and are often reported to be rather worried about infecting their family, as the family indeed did not necessarily adhere to the same healthcare vocation (see Dai, 2020).

Using segmentation techniques, Bodrud-Doza et al. (2020) find that on top of socio-demographics, risk perceptions are better clustered into four homogenous groups linked to risk attitudes towards Covid-19 in Bangladesh - that is, as a mix of mortality risks and food scarcity, socio-economic issues, or mental health problems. In another study, Kamenidou et al. (2020) find cohesive segments in the Greek population in their compliance with NPIs. Here, we use as well clustering techniques, but we include not only diverse forms of risk perception, but also,

Covid Economics 63, 7 January 2021: 126-158

CEPR PRESS

social orientations, in consistency with the neuroscience literature of people traits (Do et al., 2017, and Howard 2020).

3.1. Method

We resort to K-means clustering to partition the population into cohesive and stable segments. We base our clustering analysis on all socio-demographic (i.e. gender, age, education, number of children, location density, occupation, incomes, political orientation) and risk perceptions variables less the 6 NPI variables (i.e. the 6 first variables of Table in Appendix 1).

The K-means technique minimizes the sum of square distances within each possible cluster to its centroid. Following the literature, we draw upon the statistical gap technique to infer the appropriate number of clusters before implementing K-means.

From an initial number of random centroids (2,500), the final number of segments using the statistical gap, leads to k = 24, with convergence achieved after 500 Monte-Carlo bootstrapping iterations, meaning that the partition obtained is stable (see Figure 1). We observe however that additional gains in terms of the total within intra-cluster variation decrease significantly from k = 11 onwards. Therefore, we decided to retain a clustering with k = 10.[13]

As can be seen from Table 3, segments' size varies from 8.1% of the population for the smallest, to 12.6% for the largest one. The between sum of squares/total sum of squares achieved by the K-mean clustering is 22.8%, implying that clusters are relatively close to each other, but still, sufficient difference prevails between each other.

3.2. Clusters discussion

Appendix 2 synthesizes the clustering outcome with the associated RTC', GAP and latency mean values of the key distinctive statements linked to worries, and opinions, as well as key socio-demographics compared to the overall sample mean. Table 4a (sociodemographic features) and Table 4b (RTC' and GAP values) further summarize a high-level archetype of those segments from Appendix 2.

[13] We also tested different values of k ranging from 6 to 12 and the segments obtained brought out the same risk profiles (with more granularity as k increased). We have chosen the value of k = 10, which turned out to bring out these different risk profiles the best.

Covid Economics 63, 7 January 2021: 126-158

Covid Economics 63, 7 January 2021: 126-158

Figure 1. Optimal number of clusters (K = 10) of European citizens' attitudes towards Covid-19 pandemic - Gap statistic method

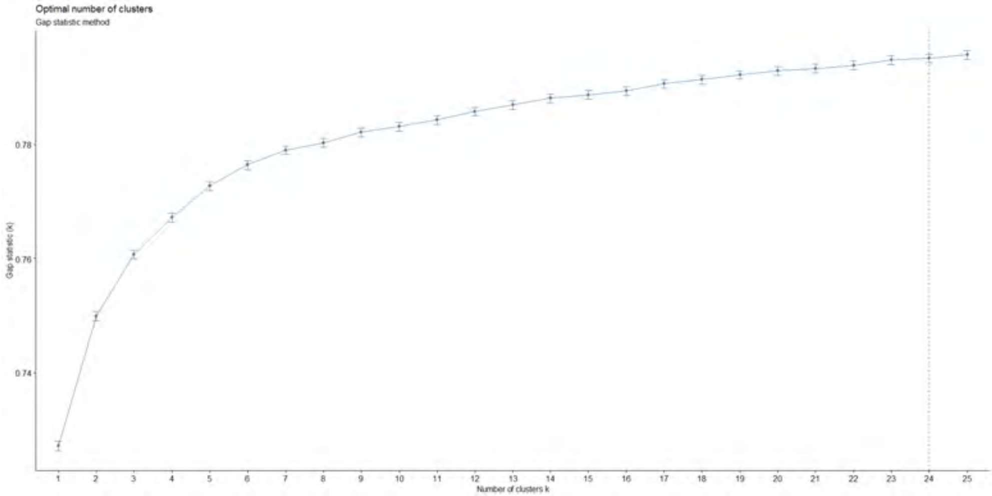


Table 3. K-means (k = 10) clustering of European citizens' attitudes towards Covid-19 pandemic

Cluster #	sum of squares by cluster	Cluster size	%
1	17,443.2	577	11.3
2	19,011.6	639	12.6
3	14,477.9	412	8.1
4	15,238.9	449	8.8
5	17,344.2	525	10.3
6	19,093.8	586	11.5
7	14,432.2	428	8.4
8	12,174.0	429	8.4
9	16,816.9	455	8.9
10	18,297.1	587	11.5
Total sample		5,087	100

Tables 4a and 4b provide key statistically relevant factors emerging out of the segment and already help witness a few important drivers of segmentation. First (Table 4a), work status, age, income, family status, and education drive part of the segmentation, and still, to a lower extent, gender, political orientation, and location density. While socio-economic drivers are well known to impact attitudes, e.g. Papageorge et al. (2020), Table 4a also shows that differences in sociodemographic factors never explain all 10 segments, but at maximum correlated with segment inclusion for a maximum 4 out of the 10 segments. Work status exhibits the broadest correlations, with 6 segments out of 10. This is to be expected as we also look at risks such as finance and job preservation on top of health. Work status also plays a role in health risk because workers (versus non-workers) face the additional challenge of social interactions at work, at least for essential jobs.

Second (Table 4b), exposure to the disease, in the form of close knowledge of people being infected, or being quarantined, is another driver of behavioral change, as also found in Dryhurst et al. (2020). Third, social orientation and self-risk profile are clearly important in defining segments, with some segments clearly being low risk, low social orientation, like the 3rd or 9th segments, up to high risk, self-centered, like the 4th segment or still high social orientation such as the 10th segment, in line with the social trait theory of Do et al. (2017). Note also how different is the 3rd and 9th segment. The latter is biased towards the older, retired population, that feels safe; the former is more of the type of limited risk perception across all categories and among its family peers.

Finally, it is rather informative to look at the information gap by segment as reported in Table 4b. Among the three less NPI compliant segments, the 6th segment exhibits some latency, when it concerns its compliance to NPI. Further, it is likely not as so sure as stated that covid is dangerous, but it looks like more affecting the older part of the family than themselves.

The 8th segment has significant latency of answers on the moral hazard of the Covid-19, as well as their NPI compliance. This segment looks rather unstable.

The claim by the 5th segment that the state does a good job in handling the Covid-19 is slightly undermined by a higher latency in the way they answer the question as well as for their will to be vaccinated.

Covid Economics 63, 7 January 2021: 126-158

Table 4a. High-level sociodemographic features by segment of European citizens' attitudes towards Covid-19 pandemic

Segment	Underestimate the dangers of Covid-19	Highly worried (family oriented)	Neglecters	Health worried (self-centered)	Fake worried (Antigovernment)	Carefree (Government supporters)	All others	Social instability (non-self centric)	Remote safe	Health care protected (compliant and grateful)
Cluster	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
% of obs.	**11.3**	**12.6**	**8.1**	**8.8**	**10.3**	**11.5**	**8.4**	**8.4**	**8.9**	**11.5**
Infected		NO	YES		NO					
Quarantine	YES									
Age					18-25			50-64	>64	26-49
Gender			Female							
Education	High school	Primary school			Bachelor or higher	High school				
Income				High		Low	High			
Political orientation	Right		Left			No right				
Work status				Not employed	Students	unemployed		Not employed	Retired	Employed/ entrepreneur
# of Kids	0			1-3						
Location							Small town			

Covid Economics 63, 7 January 2021: 126-158

Table 4b. High-level sociodemographic features and information GAP by segment of European citizens' attitudes towards Covid-19 pandemic

Cluster	1	2	3	4	5	6	7	8	9	10
	Underestimate the dangers of Covid-19	Highly worried (family oriented)	Neglecters	Health worried (self-centered)	Fake worried	Carefree (Government supporters)	All others	Social instability (non-self centric)	Remote safe	Health care protected (compliant and grateful)
Health hazard perception										
Dangerousness				**Y / +**					**N / -**	
Occurrence								**Y / =**		
Treatment								**Y / +**	**N / -**	
Vaccine									**N / -**	**Y / +**
Worries taxonomy around the Covid-19										
Health			**N / -**	**Y / =**						
Job		**Y / +**	**N / -**							
Finance		**Y / +**				**N / -**				
Social		**Y / +**	**N / -**					**Y / +**		
Perceptions around actors and their actions										
Health carers									**N / =**	**Y / =**
Workers					**Y / =**				**N / -**	
Media	**N / -**	**Y / +**	**N / -**					**Y / +**		
Health institutions						**Y / +**			**N / -**	
Governments					**N / -**	**Y / +**				
NPI compliance										
Distancing								**Y / +**	**N / =**	**Y / =**
Quarantine		**Y / =**								
Cleaning		**Y / +**				**N / +**			**N / -**	
Extra caution						**N / +**		**Y / +**		

Notes:
RTC': Y = High YES; N = high NO; GAP information: + means low confidence, – means high confidence and = means average confidence.
Dangerousness: Covid-19 is dangerous for my health; Occurrence: My chances are high to get infected; Treatment: If infected, I will have the appropriate health treatment; Vaccine: I will take the opportunity of a vaccine; Health: I am worried about my own health; Job: I am worried about my job situation; Finance: I am worried that our country will run out of money; Social: I am worried about not being able to meet with my family and Living in isolation negatively impacts my wellbeing and I am anxious about not being able to meet with friends; Health carers: grateful to healthcare professionals; Workers: I am grateful to our essential workers; Media: Media provide reliable information about the pandemic; Health institutions: I am satisfied with how our healthcare system is handling this crisis; Governments: I am satisfied with how my government is handling this crisis and The government is doing a good job dealing with Covid-19; Distancing: I comply with the recommendations for physical distancing; Quarantine: I comply with the restrictions to stay home; Cleaning: I wash hands for 20 seconds when necessary; Extra caution: I disinfect groceries before putting them away and I disinfect mail and deliveries before opening them.

3.3. Segments as drivers of NPIs

Given the segments found, and the importance of risk and social profiling, we now analyze whether those segments may explain differences in NPIs compliance, extending some of the findings by e.g. Howard (2020).

Table 5 reports the regression results of linking individual RTC' value to the 10 segments for the three most important actions reported to significantly reduce the reproduction rate of the Covid-19 pandemics, that is: social distancing, quarantine, and hygiene (see Bo et al., 2020). Regressions also include country fixed effects, to account for differences in the types of measures taken by the various countries during the pandemic. Further, we also have experimented with re-including as control, the socio-demographic features of each citizen, and found the results of Table 5 to hold, with no significant change in the differentiated effect by segment, confirming that key primary drivers of NPI are attitudinal perceptions.

Note first that all regressions have Large F-values, with the Probability > F always below 1%, implying we cannot reject the existence of a systematic relationship between NPI compliance and segments. Second, segments have a large marginal impact on positive compliance to NPIs, e.g., based on Table 5, the average practice of social distancing / stay at home and clean hands for segment 3 are on average practiced by 5 points less than the baseline[14]; this is a material difference in compliance of 20% (= 70-50/75-50, where 50% is the spit between yes and no).

Third, from the hypothesis that (mostly health) worries should drive more health protection, we should expect that segments with limited health worries - such as segments 3, 6, and 9 should have a much lower propensity to NPI compliance. This is exactly what we find in the three regressions.

Fourth, each of those three lower NPI compliant segments, have *also different* NPI profiles, otherwise stated, attitude segmentation guides NPI segmentation. As an example, the 3rd segment is reluctant to all three NPIs; the 6th segment is more reluctant to homestay and the 9th segment is the least compliant on both keeping social distancing as well as hands cleaning. Segments 4 and 5 have lower NPI compliance across the board, but with higher compliance than the 3rd segment.

Segments 5 and 7 have lower compliance on social distancing, while the 10th segment initiates relatively more social distancing and hygiene behavior, relative to baseline.

All this fits with the results on NPI compliance in a recent study on the Greek population by Kamenidou et al. (2000), which also uncovers segments based on the intensity of NPI used,

[14] RTC' is 76% for social distancing or an RTC value of 1.04. Using Table 5, RTC for segment 3 is 1.04-0.1 = 0.94, or an RTC' of 73%.

Covid Economics 63, 7 January 2021: 126-158

with roughly 50% of the population close to being following all NPI measures, 35% in between and about 15% rather unconcerned. In our case, segments 1, 2, and 10 combined account for 30% of the total European population and are the most NPI compliant. In contrast, segments 3, 6, and 9 stand for 35% of the European population and are the least compliant, with a performance gap at the margin (see above) of more than 25% compared with the best compliant citizens.

Using as a benchmark the study by Bo et al. (2020), which shows a decline of 45% of the 5 days Covid-19 reproduction rate, Rt, by using a combination of quarantines and social distancing (versus non-use), our figures implies a reduction of the 5 days' Rt of about 3.5% for the total population.[15] Using Rt estimates as computed in rteu.live for the countries of our sample, the cumulative effect of infection from May ended to 30th of October (5 months), would amount to be between *20% to 30%* of total infections lower by now, as a result of the compound effect. Spain, as one of the most affected countries in our sample, has for example added 1 million infected cases in those 5 months, according to Worldometer. Roughly 250,000 deaths could have been likely avoided if the three segments would have been at the same level of compliance as the rest of the population.

[15] The three segments have on average 26% lower use than the frontier - for 30% of the population - or a 7.8% use gap. At 45% impact of the use, we have a marginal effect on the reproduction rate of 3.5%.

Covid Economics 63, 7 January 2021: 126-158

Table 5. Attitude segments as NPI predictor for European citizens, based on RTC value

	Social distancing			Stay at home			Clean hands		
Segment	Coeff.	s.e.	P-val	Coeff.	s.e.	P-val	Coeff.	s.e.	P-val
2	-0.01	0.008	0.270	-0.01	0.010	0.262	0.01	0.009	0.467
3	-0.10	0.012	0.000	-0.18	0.016	0.000	-0.13	0.014	0.000
4	-0.03	0.010	0.002	-0.04	0.013	0.004	-0.03	0.012	0.007
5	-0.03	0.009	0.002	-0.02	0.012	0.042	-0.02	0.010	0.047
6	-0.04	0.009	0.000	-0.09	0.013	0.000	-0.06	0.011	0.000
7	-0.02	0.010	0.014	-0.03	0.013	0.014	-0.02	0.012	0.095
8	-0.04	0.009	0.000	-0.06	0.011	0.000	-0.04	0.010	0.000
9	-0.09	0.011	0.000	-0.13	0.014	0.000	-0.12	0.013	0.000
10	0.00	0.008	0.612	0.00	0.012	0.714	-0.03	0.011	0.006
Country effects									
ES	0.02	0.008	0.062	0.16	0.012	0.000	-0.05	0.009	0.000
FR	-0.06	0.009	0.000	0.13	0.013	0.000	-0.03	0.010	0.001
IT	-0.05	0.008	0.000	0.18	0.012	0.000	-0.05	0.010	0.000
SE	0.01	0.008	0.313	0.11	0.012	0.000	-0.01	0.009	0.410
Constant	0.79	0.058	0.000	0.68	0.059	0.000	-0.05	0.009	0.000
# of observations	5,087			5,087			5,087		
F-stat (45, 5041)	15.87		0.000	17.61		0.000			0.000
R^2	0.1166			0.1647			0.0732		

Notes:
s.e. = robust standard errors; dependent variable is RTC' values;
Country fixed effects and socio-economic characteristics included;
Segment 1 and Germany are the reference groups.

4. DISCUSSION AND CONCLUSIONS

This study has demonstrated the prevalence of consistent clusters of risk and social orientation attitudes, which themselves are good predictors of different clusters of NPI compliance among continental European citizens. Further, it clearly shows that three segments, standing for a material portion (30%) of citizens, are less compliant than average regarding key non-pharmaceutical interventions that have been proved to be effective in controlling the Covid-19 pandemic.

Those segments have proven to be solid, prevailing in each of the countries we have analyzed, and with the same impact on the way, people perform NPI and their mix.

Given the power-law nature of a pandemic, this non-compliance may quickly build up a large amount of contamination, which calls for identifying those citizens. The exact tactics to communicate, induce or enforce those segments to expand their NPI are beyond the scope of the paper but it is clearly important to have a more targeted approach, exploiting the fact that those segments tend to have different work status profile, different age structure, or political affinity. The common theme is, however, their social orientation profile, requiring trying to stimulate how they relate to family, friends, and colleagues. The fact that they may be more risk-taker may need to build disincentive too, e.g. penalties that are a function of repeated non-compliance, and pandemic development. In all cases, given the compound nature of the pandemic, actions must be taken early.

One final element of our work is that we have adjusted our data to reflect the solidity of answers as measures by reaction time. While this is becoming a natural procedure in neuro-economics, it is especially important to also use such procedures when one looks at critical behaviors – such as in this case, behavioral adjustments like a pandemic. Even if the survey provides the escape route of not answering the question ("hard to tell"), we find that RT is an important metric to compute. In general, we find an information gap of between 4% to 21% depending on questions asked. The information gap naturally evolves based on the respondent's sense of control over the action asked. Interestingly, people tend to respond fast when it comes to their worries, reflecting that those are real; while there is a tendency of over-estimating compliance, especially for the segments much less inclined to follow them.

As for the next steps, it would be interesting to see how stable these segments are and how they change in time with the development of and waves of the pandemic. Second, strict lockdown, in a situation of the first wave, has possibly made people follow new rules. But there are clearly signs of fatigue by the population in respecting those NPIs. Finally, it would also be beneficial to look at more distant cultures – Asia or Arabic countries. Are the segments culturally universal, or are there differences in the perception, attitudes, and behavior connected with the pandemic?

In general, we believe that in line with Do et al. (2017), that segments are likely the result of stable personality treats and will possibly be expressed along the way the pandemic evolves and in reaction to the types of policy made by multiple governments. The fact that NPI compliance may be only a bit weaker for a relatively large group of the population has a large consequence for how the pandemic can be stopped and there is thus a need for deeper analysis within those segments with less compliance, to prevent negative externalities within the covid economy.

Covid Economics 63, 7 January 2021: 126-158

REFERENCES

Asmundson, G., S. Taylor (2020). How health anxiety influences responses to viral outbreaks like COVID-19: What all decision-makers, health authorities, and health care professionals need to know. Journal of anxiety disorders, 71: 102211. https://doi.org/10.1016/j.janxdis.2020.102211

Banerjee D., M. Rai (2020). Social isolation in Covid-19: The impact of loneliness. Int J Soc Psychiatry, 66(6):525-527. doi:10.1177/0020764020922269

Bethune, Z.A., A. Korinek (2020). Covid-19 infection externalities: Trading off lives vs. livelihoods (No. w27009). National Bureau of Economic Research).

Bo, Y., C. Guo, C. Lin, Y. Zeng, H.B. Li, Y.S. Zhang, S.Y. Wong (2020). Effectiveness of non-pharmaceutical interventions on COVID-19 transmission in 190 countries from 23 January to 13 April

Bodrud-Doza, M., M. Shammi, L. Bahlman, A.R.M. Islam, M. Rahman (2020). Psychosocial and socio-economic crisis in Bangladesh due to COVID-19 pandemic: a perception-based assessment. International Journal of Infectious Diseases, Frontiers in public health, 8, 341.

Bollier D. (2020) Commoning as a pandemic survival strategy. Free, fair and alive: the insurgent power of the commons. https://www.freefairandalive.org/commoning-as-a-pandemic-survival-strategy/.

Bughin, J. (2020), Ten (uncomfortable) moments of truth in the Covid-19, *To appear in Policy Punchline, Princeton*

Bughin, J., M. Cincera, R. Ohme, D. Reykowska, M. Żyszkiewicz (2020). The Worried, the Reckless and the Carefree at Covid time: A cluster analysis of socio-economic and risks perception factors in France, iCite WP2020 - 038. Université libre de Bruxelles.

Cava, M.A., K.E. Fay, H.J. Beanlands. (2005). Risk perception and compliance with quarantine during the SARS outbreak. Journal of Nursing Scholarship, 37(4): 343–347. doi:10.1111/j.1547- 5069.2005.00059.x

Cho, S.W. (2020). Quantifying the impact of nonpharmaceutical interventions during the COVID-19 outbreak: The case of Sweden. The Econometrics Journal, 23(3): 323–344

Coibion, O., Y. Gorodnichenko, M. Weber (2020).

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

Dai (2020). Psychological impact of coronavirus disease outbreak on heatlhcare in China, MedRix.

Detoc, M., S. Bruel, P. Frappe, B. Tardy, E. Botelho-Nevers, A. Gagneux-Brunon (2020). Intention to participate in a COVID-19 vaccine clinical trial and to get vaccinated against COVID-19 in France during the pandemic. Vaccine, 38(45), 7002-7006.

Do, K.T., J.F.G. Moreira, E.H. Telzer (2017). But is helping you worth the risk? Defining prosocial risk taking in adolescence. Developmental cognitive neuroscience, *25*, 260-271.

Dryhurst, S., C.R. Schneider, J. Kerr, A. Freeman, G. Recchia, A.M. Van Der Bles, D. Spiegelhalter, S. van der Linden (2020). Risk perceptions of COVID-19 around the world. Journal of Risk Research (2020): 1-13.

Covid Economics 63, 7 January 2021: 126-158

Esping-Andersen, G. (1999). Social foundations of postindustrial economies, Oxford University Press.

Faasse, K., J.M. Newby (2020). Public perceptions of COVID-19 in Australia: perceived risk, knowledge, health-protective behaviours, and vaccine intentions. medRxiv.

Fazio, R.H., M.C. Powell, C.J. Williams (1989). The role of attitude accessibility in the attitudeto-behavior process. The Journal of Consumer Research, 16(3), 280–288.

Ferguson N.M., D. Laydon, G. Nedjati-Gilani, N. Imai, K. Ainslie, M. Baguelin (2020). *Impact of Non-Pharmaceutical Interventions (NPIs) to Reduce COVID-19 Mortality and Healthcare Demand.* London: Imperial College.

Gialama, M., P. Papaloukas, S. McGilloway (2020). Non-pharmacological interventions for Covid-19: How to improve adherence. Health Psychology Update, Volume 29 Special Issue, Autumn.

Greenwald, A.G., B.A. Nosek, M.R. Banaji (2003). Understanding and using the implicit association test: I. An improved scoring algorithm. Journal of Personality and Social Psychology, 85(2), 197–216.

Harper C.A., L. Satchell, D. Fido, R. Latzman (2020). Functional fear predicts public health compliance in the COVID-19 pandemic. Int. J. Ment. Health Addict. 27 1–14. 10.1017/dmp.2020.338

Haug, N., L. Geyrhofer, A. Londei, E. Dervic, A. Desvars-Larrive, V. Loreto, P. Klimek (2020). Ranking the effectiveness of worldwide COVID-19 government interventions. MedRxiv.

Howard, M.C. (2020). Who wants to reopen the economy during the COVID-19 pandemic? The daring and uncaring. *Personality and Individual Differences*, *168*, 110335.

Kamenidou, I., A. Stavrianea, Ch. Liava (2020). Achieving Covid-19 Free Country: Citizens Preventive Measures and Communication Pathways International Journal of Environetal Res and Public Health2020 Jun 27;17(13):4633.

Lee, S.A., A.A. Mathis, M.C. Jobe, E.A. Pappalardo (2020). Clinically significant fear and anxiety of COVID-19: A psychometric examination of the Coronavirus Anxiety Scale. Psychiatry Research, 113112,

Leppin, A., A.R. Aro (2009). Risk perceptions related to SARS and avian influenza: theoretical foundations of current empirical research. International journal of behavioral medicine, 16(1), 7-29

Li, Y.L., W.Z. Wang, J. Wang (2018). Government intervention behavior and optimization strategy of major epidemic control: Based on game theory and China's H7N9 prevention and control practice in 2013. J. Hunan Agri. Uni. (Soc. Sci.), 19, 61–66.

Lunn, P.D., S. Timmons, M. Barjaková, C.A. Belton, H. Julienne, C. Lavin (2020). Motivating Social Distancing During the Covid-19 Pandemic: An Online Experiment. PsyArXiv, https://doi.org/10.31234/osf.io/x4agb

Massaad, E., P. Cherfan (2020). Social Media Data Analytics on Telehealth During the COVID-19 Pandemic. Cureus, 12(4)

Mertens, G., L. Gerritsen, S. Duijndam, E. Salemink, I.M. Engelhard (2020). Fear of the coronavirus (COVID-19): Predictors in an online study conducted in March 2020. Journal of Anxiety Disorders, 102258.)

Niepel, C., D. Kranz, F. Borgonovi, V. Emslander, S. Greiff (2020). The coronavirus (COVID-19) fatality risk perception of US adult residents in March and April 2020. British Journal of Health Psychology.

Covid Economics 63, 7 January 2021: 126-158

Ohme, R., M. Matukin, P. Wicher (2020). Merging Explicit Declarations With Implicit Response Time to Better Predict Behavior. In Chkoniya, V., Madsen, A. O., & Bukhrashvili, P. (Ed.), Anthropological Approaches to Understanding Consumption Patterns and Consumer Behavior (pp. 427-448). IGI Global.

Oosterhoff, B., Palmer, C. A., Wilson, J., & Shook, N. (2020, April 6). Adolescents' Motivations to Engage in Social Distancing during the COVID-19 Pandemic: Associations with Mental and Social Health. https://doi.org/10.31234/osf.io/jd2kq

Papageorge, N.M., M. Zahn, E. Belot, S. van den Broek-Altenburg, J. Choi, J. Jamison, E. Tripodi (2020). Socio-demographic factors associated with self-protecting behavior during the Covid-19 pandemic, Covid Economics, 40, July.

Riou J., A. Hauser, M.J. Counotte, C.L. Althaus (2020). Adjusted age specific case fatality ration during the COVID-19 epidemic at Hubei, China, Janauary and February 2020; MedrXiv

Vaughan, E. (2011). Contemporary perspectives on risk perceptions, health-protective behaviors, and control of emerging infectious diseases. International journal of behavioral medicine, 18(2), 83.

Webster, R.K., S.K. Brooks, L.E. Smith (2020). How to improve adherence with quarantine: Rapid review of the evidence. Public Health, 182, 163

Wise T., T.D. Zbozinek, G. Michelini, C.C., D. Mobbs (2020). Changes in risk perception and protective behavior during the first week of the COVID-19 pandemic in the United States. PsyarXiv [Preprint], 10.31234/osf.io/dz428

Zarikas, V., S.G. Poulopoulos, Z. Gareiou, E. Zervas (2020). Clustering analysis of countries using the COVID-19 cases dataset. Data in Brief, 105787

Zickfeld, J. H., T.W. Schubert, A.K. Herting, J. Grahe, K. Faasse (2020). Correlates of health-protective behavior during the initial days of the COVID-19 outbreak in Norway. Frontiers in psychology, 11.

Covid Economics 63, 7 January 2021: 126-158

APPENDIX 1 Tested statements

BEHAVIOR
1. I actively encourage others to follow the restrictions and guidelines
2. I comply with the recommendations for physical distancing
3. I comply with the restrictions to stay home
4. I disinfect groceries before putting them away
5. I disinfect mail and deliveries before opening them
6. I wash hands for 20 seconds when necessary
7. I would like to help people who are more vulnerable to COVID-19
8. Since COVID-19 I eat healthier
9. Since COVID-19 I eat unhealthier
10. Since COVID-19 I exercise less
11. Since COVID-19 I exercise at home more
12. When a COVID-19 vaccine is available, I'd like to be vaccinated
EMOTIONS
13. I'm worried about my financial situation
14. I'm worried about my job situation
15. I'm worried that our country will run out of money
16. I'm worried that there will not be enough basic necessities in the stores
17. I am worried about my health
18. I am worried about the health of my children
19. I am worried about the health of my older family members
20. I am worried about the health of people in my country
21. I worry that there will be an increase in break-ins and thefts
22. I'm worried about my children's education
23. I am anxious about not being able to meet with friends
24. I am worried about not being able to meet with my family
25. I worry how living in isolation will affect me
26. Living in isolation negatively impacts my wellbeing
OPINIONS
27. The COVID-19 outbreak will make society more unequal
28. Being together all the time increases family tensions
29. COVID-19 increases domestic violence

Covid Economics 63, 7 January 2021: 126-158

30. COVID-19 will increase divorce rates
31. COVID-19 will bring countries closer
32. I am grateful to our essential workers
33. I am grateful to our healthcare professionals
34. My chance of getting COVID-19 is high
35. Slowing the spread of COVID-19 is more important than the economy
36. Coronavirus is dangerous for my health
37. Media exaggerate the situation with COVID-19
38. Media provide reliable information about the pandemic
39. [The President] is doing a good job dealing with COVID-19
40. I am satisfied with how my government is handling this crisis
41. The government is doing a good job dealing with COVID-19
42. I am satisfied with how our healthcare system is handling this crisis
43. In the case of coronavirus infection, I will get appropriate medical help
44. The government discloses real numbers of coronavirus infections and deaths
45. COVID-19 reveals the best in people
46. COVID-19 reveals the worse in people
47. I believe we will beat COVID-19 soon
48. People will stop following the restrictions soon
49. The restrictions caused by COVID-19 will continue at least until the fall
50. The restrictions caused by COVID-19 will continue for about a month

Covid Economics 63, 7 January 2021: 126-158

Appendix 2. Characterization of the K-Mean clustering (k=10)

Cluster 1	577 respondents	cluster	full sample	cluster	full sample	cluster	full sample
		RTC'		LATENCY		GAP	
Quarantine2	Quarantine no	0.81	0.87				
Kids1	0 children	0.56	0.31				
Edu4	High school	0.28	0.37				
Politics2	Right	0.24	0.15				
Politics1	Left	0.24	0.35				
Kids2	1 child	0.21	0.36				
Quarantine1	Quarantine yes	0.09	0.06				
infected3	Infected don't know	0.06	0.05				
Kids4	3 children	0.04	0.07				
RTC.n37	Media exaggerate the situation with COVID-19	0.40	0.30	0.48	0.48	0.85	0.24

Notes:

maximum and minimum average of variables for each cluster
socio-economic characteristics
risk's perceptions (Yes)
risk's perceptions (I don't know)
risk's perceptions (No)
latency
averages in red represent values below the sample's average

Cluster 2	639 respondents	cluster	full sample	cluster	full sample	cluster	full sample
		RTC'		LATENCY		GAP	
Age4	36-49	0.27	0.38				
Country	DE	0.20	0.05				
Country	ES	0.20	0.43				
Country	SE	0.20	0.07				
Edu1	Primary schools	0.03	0.02				
infected2	Infected no	0.69	0.61				
Kids3	2 children	0.18	0.26				
Politics4	Don't associate with politics	0.22	0.35				
Quarantine3	Quarantine don't know	0.10	0.13				
RTC.n18	I am worried about the health of my children	0.84	0.58	0.33	0.37	0.11	0.02
RTC.n12	I am worried about my financial situation	0.83	0.57	0.33	0.36	0.11	0.04
RTC.n03	I comply with the restrictions to stay home	0.81	0.75	0.34	0.36	0.15	0.13
RTC.n19	I am worried about the health of my older family members	0.81	0.70	0.37	0.41	0.18	0.16
RTC.n22	I am worried about my children s education	0.77	0.48	0.36	0.39	0.11	0.09
RTC.n27	I am worried about not being able to meet with my family	0.77	0.61	0.39	0.43	0.18	0.12
RTC.n13	I am worried about my job situation	0.76	0.49	0.35	0.37	0.09	0.04
RTC.n06	I wash hands for 20 seconds when necessary	0.76	0.73	0.39	0.40	0.20	0.18
RTC.n14	I am worried that our country will run out of money	0.75	0.62	0.41	0.44	0.21	0.13
RTC.n44	The government discloses real numbers of coronavirus infections and deaths	0.40	0.52	0.48	0.48	0.54	0.05

Covid Economics 63, 7 January 2021: 126-158

Appendix 2. Characterization of the K-Mean clustering (k=10)

Cluster 3	412 respondents	cluster	full sample	cluster	full sample	cluster	full sample
		RTC'		LATENCY		GAP	
infected1	Infected yes	0.24	0.13				
infected2	Infected no	0.69	0.79				
Politics1	Left	0.24	0.12				
Politics3	Other	0.22	0.29				
Sex1	Female	0.50	0.38				
Sex2	Male	0.49	0.60				
RTC.n03	I comply with the restrictions to stay home	0.60	0.75	0.39	0.36	0.05	0.13
RTC.n24	COVID-19 increases domestic violence	0.56	0.63	0.42	0.42	0.09	0.14
RTC.n50	The restrictions caused by COVID-19 will continue for about a month	0.53	0.59	0.53	0.51	0.12	0.19
RTC.n01	I actively encourage others to follow the restrictions and guidelines	0.52	0.64	0.50	0.47	0.03	0.22
RTC.n07	I would like to help people who are more vulnerable to COVID-19	0.51	0.62	0.52	0.48	0.07	0.22
RTC.n19	I am worried about the health of my older family members	0.50	0.70	0.45	0.41	0.02	0.16
RTC.n23	Being together all the time increases family tensions	0.46	0.54	0.49	0.49	0.11	0.06
RTC.n11	Since COVID-19 I exercise at home more	0.42	0.54	0.44	0.43	0.24	0.01
RTC.n45	COVID-19 reveals the best in people	0.42	0.53	0.46	0.45	0.24	0.03
RTC.n38	Media provide reliable information about the pandemic	0.41	0.55	0.46	0.45	0.27	0.08
RTC.n27	I am worried about not being able to meet with my family	0.40	0.61	0.45	0.43	0.27	0.12
RTC.n29	Living in isolation negatively impacts my wellbeing	0.39	0.55	0.47	0.47	0.48	0.06
RTC.n26	I am anxious about not being able to meet with friends	0.38	0.58	0.44	0.44	0.34	0.09
RTC.n08	Since COVID-19 I eat more healthy	0.37	0.52	0.42	0.43	0.35	0.03
RTC.n30	COVID-19 will bring countries closer	0.36	0.48	0.45	0.45	0.62	0.10
RTC.n33	My chance of getting COVID-19 is high	0.36	0.46	0.46	0.46	0.77	0.13
RTC.n28	I worry how living in isolation will affect me	0.35	0.54	0.48	0.47	1.51	0.01
RTC.n10	Since COVID-19 I exercise less	0.35	0.48	0.43	0.43	0.52	0.06
RTC.n22	I am worried about my children s education	0.23	0.48	0.38	0.39	1.67	0.09
RTC.n17	I am worried about my own health	0.23	0.62	0.36	0.35	0.78	0.04
RTC.n13	I am worried about my job situation	0.20	0.49	0.37	0.37	2.28	0.04
nla43	In case of a coronavirus infection I will get appropriate medical help	0.56	0.61	0.52	0.48		

Cluster 4	449 respondents	cluster	full sample	cluster	full sample	cluster	full sample
		RTC'		LATENCY		GAP	
Income2	>20000€	0.54	0.37				
Kids1	0 children	0.56	0.88				
Kids2	1 child	0.21	0.06				
Kids3	2 children	0.18	0.03				
Kids4	3 children	0.04	0.02				
Occ4	Unemployed	0.16	0.25				
Politics5	Don't want to answer	0.08	0.12				
Quarantine2	Quarantine no	0.81	0.77				
RTC.n17	I am worried about my own health	0.85	0.62	0.34	0.35	0.10	0.04
RTC.n36	Coronavirus is dangerous for my health	0.82	0.71	0.35	0.37	0.13	0.12
RTC.n47	I believe we will beat COVID-19 soon	0.42	0.53	0.43	0.42	0.23	0.00

Cluster 5	525 respondents	cluster	full sample	cluster	full sample	cluster	full sample
		RTC'		LATENCY		GAP	
Age2	18-25	0.11	0.04				
Country	FR	0.20	0.43				
Country	IT	0.20	0.11				
Edu2	Middle school	0.11	0.14				
Edu5	Bachelor or higher	0.30	0.22				
Income3	don't want to asnwer	0.11	0.07				
infected1	Infected yes	0.24	0.33				
Occ1	Student	0.06	0.01				
Quarantine4	Quarantine don't want to answer	0.00	0.00				
Town1	<100000 inhab.	0.59	0.68				
Town2	>100000 inhab.	0.41	0.32				
RTC.n31	I am grateful to our essential workers	0.75	0.70	0.43	0.43	0.20	0.20
RTC.n39	[PRESIDENT] is doing a good job dealing with COVID-19	0.40	0.53	0.45	0.45	0.22	0.05
RTC.n41	The government is doing a good job dealing with COVID-19	0.31	0.55	0.43	0.39	0.61	0.04
RTC.n40	I am satisfied with how my government is handling this crisis	0.31	0.55	0.43	0.39	0.83	0.03
nla35	When a COVID-19 vaccine is available I d like to be vaccinated	0.62	0.61	0.50	0.47		
nla42	I am satisfied with how our healthcare system is handling this crisis	0.54	0.62	0.49	0.43		

CEPR PRESS

Covid Economics 63, 7 January 2021: 126-158

Appendix 2. Characterization of the K-Mean clustering (k=10)

Cluster 6	586 respondents	cluster	full sample	cluster	full sample	cluster	full sample
		RTC'		LATENCY		GAP	
Country	ES	0.20	0.03				
Country	SE	0.20	0.40				
Edu3	Vocational	0.28	0.35				
Edu4	High school	0.28	0.19				
Income1	<20000€	0.35	0.26				
Kids5	>3 children	0.01	0.00				
Occ4	Unemployed	0.16	0.09				
Politics2	Right	0.24	0.31				
Politics5	Don't want to answer	0.08	0.06				
RTC.n40	I am satisfied with how my government is handling this crisis	0.81	0.55	0.38	0.39	0.15	0.03
RTC.n41	The government is doing a good job dealing with COVID-19	0.79	0.55	0.39	0.39	0.16	0.04
RTC.n42	I am satisfied with how our healthcare system is handling this crisis	0.77	0.62	0.42	0.43	0.20	0.15
RTC.n16	The COVID-19 outbreak will make society more unequal	0.56	0.62	0.53	0.48	0.15	0.21
RTC.n48	People will stop following the restrictions soon	0.55	0.61	0.50	0.46	0.10	0.16
RTC.n25	COVID-19 will increase divorce rates	0.53	0.59	0.47	0.44	0.05	0.11
RTC.n46	COVID-19 reveals the worse in people	0.46	0.54	0.47	0.45	0.16	0.01
RTC.n14	I am worried that our country will run out of money	0.43	0.62	0.48	0.44	0.31	0.13
RTC.n21	I worry that there will be an increase in break-ins and thefts	0.37	0.52	0.47	0.45	0.64	0.02
RTC.n15	I am worried that there will not be enough basic necessities in the stores	0.33	0.46	0.48	0.47	3.07	0.23
RTC.n04	I disinfect groceries before putting them away	0.33	0.48	0.44	0.41	0.95	0.13
RTC.n05	I disinfect mail and deliveries before opening them	0.30	0.44	0.45	0.44	1.55	0.22
RTC.n18	I am worried about the health of my children	0.29	0.58	0.41	0.37	0.58	0.02
RTC.n09	Since COVID-19 I eat more unhealthy	0.27	0.37	0.44	0.43	2.18	0.54
RTC.n12	I am worried about my financial situation	0.24	0.57	0.39	0.36	0.69	0.04
nla16	The COVID-19 outbreak will make society more unequal	0.56	0.62	0.53	0.48		
nla01	I actively encourage others to follow the restrictions and guidelines	0.63	0.64	0.51	0.47		
nla19	I am worried about the health of my older family members	0.59	0.70	0.45	0.41		
nla36	Coronavirus is dangerous for my health	0.58	0.71	0.43	0.37		
nla02	I comply with the recommendations for physical distancing	0.76	0.76	0.43	0.40		
nla03	I comply with the restrictions to stay home	0.69	0.75	0.40	0.36		

Cluster 7	428 respondents	cluster	full sample
Age2	18-25	0.11	0.18
Country	FR	0.20	0.11
Country	IT	0.20	0.33
Edu2	Middle school	0.11	0.06
Edu3	Vocational	0.28	0.20
Edu5	Bachelor or higher	0.30	0.44
Income1	<20000€	0.35	0.51
infected3	Infected don't know	0.06	0.08
infected4	Infected don't want to answer	0.01	0.00
Occ1	Student	0.06	0.13
Occ3	Entrepreneur	0.07	0.12
Quarantine4	Quarantine don't want to answer	0.00	0.00
Sex1	Female	0.50	0.58
Sex2	Male	0.49	0.41
Town1	<100000 inhab.	0.59	0.50
Town2	>100000 inhab.	0.41	0.50

Cluster 9	455 respondents	cluster	full sample	cluster	full sample	cluster	full sample
		RTC'		LATENCY		GAP	
Age6	>64	0.12	0.02				
Income3		0.11	0.17				
infected4	Infected don't want to answer	0.01	0.02				
Kids5	>3 children	0.01	0.02				
Occ5	Retired	0.17	0.05				
Quarantine4	Quarantine don't want to answer	0.00	0.02				
RTC.n02	I comply with the recommendations for physical distancing	0.69	0.76	0.38	0.40	0.19	0.19
RTC.n32	I am grateful to our healthcare professionals	0.68	0.78	0.38	0.38	0.17	0.18
RTC.n06	I wash hands for 20 seconds when necessary	0.65	0.73	0.39	0.40	0.14	0.18
RTC.n31	I am grateful to our essential workers	0.63	0.70	0.41	0.43	0.17	0.20
RTC.n43	In case of a coronavirus infection I will get appropriate medical help	0.55	0.61	0.45	0.48	0.15	0.22
RTC.n49	The restrictions caused by COVID-19 will continue at least until the fall	0.52	0.58	0.48	0.51	0.10	0.19
RTC.n34	Slowing the spread of COVID-19 is more important than the economy	0.52	0.59	0.50	0.53	0.05	0.25
RTC.n35	When a COVID-19 vaccine is available I d like to be vaccinated	0.48	0.61	0.45	0.47	0.02	0.20
RTC.n42	I am satisfied with how our healthcare system is handling this crisis	0.46	0.62	0.40	0.43	0.00	0.15
RTC.n36	Coronavirus is dangerous for my health	0.43	0.71	0.37	0.37	0.04	0.12

Appendix 2. Characterization of the K-Mean clustering (k=10)

Cluster 8	429 respondents	cluster	full sample	cluster	full sample	cluster	full sample
		RTC'		LATENCY		GAP	
Age3	26-35	0.18	0.29				
Age5	50-64	0.32	0.20				
Edu1	Primary schools	0.03	0.05				
Occ2	Employed	0.55	0.71				
Quarantine 1	Quarantine yes	0.09	0.13				
Quarantine 3	Quarantine don't know	0.10	0.07				
RTC.n47	I believe we will beat COVID-19 soon	0.73	0.53	0.29	0.42	0.15	0.00
RTC.n38	Media provide reliable information about the pandemic	0.71	0.55	0.30	0.45	0.18	0.08
RTC.n28	I worry how living in isolation will affect me	0.71	0.54	0.32	0.47	0.21	0.01
RTC.n45	COVID-19 reveals the best in people	0.71	0.53	0.31	0.45	0.18	0.03
RTC.n50	The restrictions caused by COVID-19 will continue for about a month	0.70	0.59	0.33	0.51	0.22	0.19
RTC.n43	In case of a coronavirus infection I will get appropriate medical help	0.70	0.61	0.33	0.48	0.24	0.22
RTC.n49	The restrictions caused by COVID-19 will continue at least until the fall	0.70	0.58	0.33	0.51	0.20	0.19
RTC.n07	I would like to help people who are more vulnerable to COVID-19	0.70	0.62	0.33	0.48	0.25	0.22
RTC.n26	I am anxious about not being able to meet with friends	0.70	0.58	0.32	0.44	0.20	0.09
RTC.n39	[PRESIDENT] is doing a good job dealing with COVID-19	0.70	0.53	0.31	0.45	0.15	0.05
RTC.n01	I actively encourage others to follow the restrictions and guidelines	0.69	0.64	0.34	0.47	0.26	0.22
RTC.n25	COVID-19 will increase divorce rates	0.69	0.59	0.31	0.44	0.18	0.11
RTC.n46	COVID-19 reveals the worse in people	0.69	0.54	0.31	0.45	0.15	0.01
RTC.n23	Being together all the time increases family tensions	0.68	0.54	0.33	0.49	0.23	0.06
RTC.n21	I worry that there will be an increase in break-ins and thefts	0.68	0.52	0.33	0.45	0.18	0.02
RTC.n44	The government discloses real numbers of coronavirus infections and deaths	0.68	0.52	0.33	0.48	0.20	0.05
RTC.n48	People will stop following the restrictions soon	0.68	0.61	0.32	0.46	0.19	0.16
RTC.n16	The COVID-19 outbreak will make society more unequal	0.68	0.62	0.34	0.48	0.24	0.21
RTC.n24	COVID-19 increases domestic violence	0.67	0.63	0.32	0.42	0.19	0.14
RTC.n08	Since COVID-19 I eat more healthy	0.67	0.52	0.32	0.43	0.17	0.03
RTC.n30	COVID-19 will bring countries closer	0.67	0.48	0.32	0.45	0.17	0.10
RTC.n29	Living in isolation negatively impacts my wellbeing	0.67	0.55	0.34	0.47	0.22	0.06
RTC.n04	I disinfect groceries before putting them away	0.67	0.48	0.32	0.41	0.14	0.13
RTC.n15	I am worried that there will not be enough basic necessities in the stores	0.66	0.46	0.33	0.47	0.19	0.23
RTC.n34	Slowing the spread of COVID-19 is more important than the economy	0.66	0.59	0.38	0.53	0.25	0.25
RTC.n11	Since COVID-19 I exercise at home more	0.66	0.54	0.33	0.43	0.15	0.01
RTC.n37	Media exaggerate the situation with COVID-19	0.65	0.40	0.30	0.41	0.08	0.24
RTC.n33	My chance of getting COVID-19 is high	0.64	0.46	0.35	0.46	0.14	0.13
RTC.n10	Since COVID-19 I exercise less	0.63	0.48	0.33	0.43	0.13	0.06
RTC.n05	I disinfect mail and deliveries before opening them	0.62	0.44	0.34	0.44	0.14	0.22
RTC.n09	Since COVID-19 I eat more unhealthy	0.60	0.37	0.34	0.43	0.06	0.54

Appendix 2. Characterization of the K-Mean clustering (k=10) (continued)

Cluster 8	429 respondents	cluster	full sample	cluster	full sample	cluster	full sample
		RTC'		LATENCY		GAP	
nla34	Slowing the spread of COVID-19 is more important than the economy	0.66	0.59	0.38	0.53		
nla35	When a COVID-19 vaccine is available I d like to be vaccinated	0.67	0.61	0.35	0.47		
nla33	My chance of getting COVID-19 is high	0.64	0.46	0.35	0.46		
nla09	Since COVID-19 I eat more unhealthy	0.60	0.37	0.34	0.43		
nla05	I disinfect mail and deliveries before opening them	0.62	0.44	0.34	0.44		
nla01	I actively encourage others to follow the restrictions and guidelines	0.69	0.64	0.34	0.47		
nla16	The COVID-19 outbreak will make society more unequal	0.68	0.62	0.34	0.48		
nla29	Living in isolation negatively impacts my wellbeing	0.67	0.55	0.34	0.47		
nla23	Being together all the time increases family tensions	0.68	0.54	0.33	0.49		
nla43	In case of a coronavirus infection I will get appropriate medical help	0.70	0.61	0.33	0.48		
nla11	Since COVID-19 I exercise at home more	0.66	0.54	0.33	0.43		
nla10	Since COVID-19 I exercise less	0.63	0.48	0.33	0.43		
nla15	I am worried that there will not be enough basic necessities in the stores	0.66	0.46	0.33	0.47		
nla07	I would like to help people who are more vulnerable to COVID-19	0.70	0.62	0.33	0.48		
nla50	The restrictions caused by COVID-19 will continue for about a month	0.70	0.59	0.33	0.51		
nla44	The government discloses real numbers of coronavirus infections and deaths	0.68	0.52	0.33	0.48		
nla49	The restrictions caused by COVID-19 will continue at least until the fall	0.70	0.58	0.33	0.51		
nla21	I worry that there will be an increase in break-ins and thefts	0.68	0.52	0.33	0.45		
nla48	People will stop following the restrictions soon	0.68	0.61	0.32	0.46		
nla30	COVID-19 will bring countries closer	0.67	0.48	0.32	0.45		
nla24	COVID-19 increases domestic violence	0.67	0.63	0.32	0.42		
nla14	I am worried that our country will run out of money	0.69	0.62	0.32	0.44		
nla08	Since COVID-19 I eat more healthy	0.67	0.52	0.32	0.43		
nla26	I am anxious about not being able to meet with friends	0.70	0.58	0.32	0.44		
nla28	I worry how living in isolation will affect me	0.71	0.54	0.32	0.47		
nla04	I disinfect groceries before putting them away	0.67	0.48	0.32	0.41		
nla27	I am worried about not being able to meet with my family	0.70	0.61	0.31	0.43		
nla25	COVID-19 will increase divorce rates	0.69	0.59	0.31	0.44		
nla06	I wash hands for 20 seconds when necessary	0.72	0.73	0.31	0.40		
nla45	COVID-19 reveals the best in people	0.71	0.53	0.31	0.45		
nla39	[PRESIDENT] is doing a good job dealing with COVID-19	0.70	0.53	0.31	0.45		
nla46	COVID-19 reveals the worse in people	0.69	0.54	0.31	0.45		
nla31	I am grateful to our essential workers	0.73	0.70	0.30	0.43		
nla22	I am worried about my children s education	0.70	0.48	0.30	0.39		
nla38	Media provide reliable information about the pandemic	0.71	0.55	0.30	0.45		
nla37	Media exaggerate the situation with COVID-19	0.65	0.40	0.30	0.41		
nla19	I am worried about the health of my older family members	0.74	0.70	0.30	0.41		
nla02	I comply with the recommendations for physical distancing	0.73	0.76	0.29	0.40		
nla03	I comply with the restrictions to stay home	0.74	0.75	0.29	0.36		
nla32	I am grateful to our healthcare professionals	0.74	0.78	0.29	0.38		
nla13	I am worried about my job situation	0.70	0.49	0.29	0.37		
nla41	The government is doing a good job dealing with COVID-19	0.72	0.55	0.29	0.39		
nla18	I am worried about the health of my children	0.73	0.58	0.29	0.37		
nla42	I am satisfied with how our healthcare system is handling this crisis	0.73	0.62	0.29	0.43		
nla47	I believe we will beat COVID-19 soon	0.73	0.53	0.29	0.42		
nla40	I am satisfied with how my government is handling this crisis	0.74	0.55	0.28	0.39		
nla12	I am worried about my financial situation	0.73	0.57	0.27	0.36		
nla36	Coronavirus is dangerous for my health	0.75	0.71	0.27	0.37		
nla17	I am worried about my own health	0.76	0.62	0.26	0.35		

Covid Economics 63, 7 January 2021: 126-158

Appendix 2. Characterization of the K-Mean clustering (k=10)

Cluster 10	587 respondents	cluster	full sample	cluster	full sample	cluster	full sample
		RTC'		LATENCY		GAP	
Age3	26-35	0.18	0.09				
Age4	36-49	0.27	0.10				
Age5	50-64	0.32	0.41				
Age6	>64	0.12	0.33				
Country	DE	0.20	0.33				
Income2	>20000€	0.54	0.63				
Occ2	Employed	0.55	0.40				
Occ3	Entrepreneur	0.07	0.02				
Occ5	Retired	0.17	0.43				
Politics3	Other	0.22	0.17				
Politics4	Don't associate with politics	0.22	0.12				
RTC.n32	I am grateful to our healthcare professionals	0.81	0.78	0.41	0.38	0.17	0.18
RTC.n02	I comply with the recommendations for physical distancing	0.81	0.76	0.41	0.40	0.17	0.19
RTC.n35	When a COVID-19 vaccine is available I d like to be vaccinated	0.68	0.61	0.50	0.47	0.24	0.20
nla34	Slowing the spread of COVID-19 is more important than the economy	0.61	0.59	0.59	0.53		
nla50	The restrictions caused by COVID-19 will continue for about a month	0.60	0.59	0.55	0.51		
nla49	The restrictions caused by COVID-19 will continue at least until the fall	0.58	0.58	0.55	0.51		
nla28	I worry how living in isolation will affect me	0.50	0.54	0.54	0.47		
nla23	Being together all the time increases family tensions	0.52	0.54	0.54	0.49		
nla07	I would like to help people who are more vulnerable to COVID-19	0.62	0.62	0.53	0.48		
nla15	I am worried that there will not be enough basic necessities in the stores	0.40	0.46	0.53	0.47		
nla44	The government discloses real numbers of coronavirus infections and deaths	0.60	0.52	0.53	0.48		
nla48	People will stop following the restrictions soon	0.57	0.61	0.52	0.46		
nla33	My chance of getting COVID-19 is high	0.50	0.46	0.52	0.46		
nla29	Living in isolation negatively impacts my wellbeing	0.54	0.55	0.51	0.47		
nla46	COVID-19 reveals the worse in people	0.52	0.54	0.51	0.45		
nla14	I am worried that our country will run out of money	0.57	0.62	0.51	0.44		
nla30	COVID-19 will bring countries closer	0.51	0.48	0.50	0.45		
nla45	COVID-19 reveals the best in people	0.57	0.53	0.50	0.45		
nla21	I worry that there will be an increase in break-ins and thefts	0.49	0.52	0.50	0.45		
nla39	[PRESIDENT] is doing a good job dealing with COVID-19	0.64	0.53	0.50	0.45		
nla38	Media provide reliable information about the pandemic	0.63	0.55	0.50	0.45		
nla10	Since COVID-19 I exercise less	0.46	0.48	0.49	0.43		
nla05	I disinfect mail and deliveries before opening them	0.40	0.44	0.49	0.44		
nla25	COVID-19 will increase divorce rates	0.57	0.59	0.48	0.44		
nla27	I am worried about not being able to meet with my family	0.65	0.61	0.48	0.43		
nla31	I am grateful to our essential workers	0.71	0.70	0.48	0.43		
nla26	I am anxious about not being able to meet with friends	0.64	0.58	0.48	0.44		
nla11	Since COVID-19 I exercise at home more	0.55	0.54	0.48	0.43		
nla08	Since COVID-19 I eat more healthy	0.55	0.52	0.47	0.43		
nla09	Since COVID-19 I eat more unhealthy	0.31	0.37	0.47	0.43		
nla47	I believe we will beat COVID-19 soon	0.54	0.53	0.47	0.42		
nla24	COVID-19 increases domestic violence	0.65	0.63	0.46	0.42		
nla04	I disinfect groceries before putting them away	0.45	0.48	0.46	0.41		
nla22	I am worried about my children s education	0.40	0.48	0.46	0.39		
nla37	Media exaggerate the situation with COVID-19	0.31	0.40	0.44	0.41		
nla41	The government is doing a good job dealing with COVID-19	0.76	0.55	0.43	0.39		
nla06	I wash hands for 20 seconds when necessary	0.76	0.73	0.43	0.40		
nla40	I am satisfied with how my government is handling this crisis	0.77	0.55	0.43	0.39		
nla12	I am worried about my financial situation	0.33	0.57	0.43	0.36		
nla13	I am worried about my job situation	0.21	0.49	0.42	0.37		
nla32	I am grateful to our healthcare professionals	0.81	0.78	0.41	0.38		
nla18	I am worried about the health of my children	0.72	0.58	0.41	0.37		
nla17	I am worried about my own health	0.77	0.62	0.39	0.35		

Covid Economics 63, 7 January 2021: 126-158

Firms and households during the pandemic: What do we learn from their electricity consumption?[1]

Olympia Bover,[2] Natalia Fabra,[3] Sandra García-Uribe,[4] Aitor Lacuesta[5] and Roberto Ramos[6]

Date submitted: 17 December 2020; Date accepted: 18 December 2020

We analyze the impact of the COVID-19 pandemic on electricity consumption patterns in Spain. We highlight the importance of decomposing total electricity consumption into consumption by firms and by households to better understand the economic and social impacts of the crisis. While electricity demand by firms has fallen substantially, the demand by households has gone up. In particular, during the total lockdown, these effects reached -29% and +10% respectively, controlling for temperature and seasonality. While the electricity demand reductions during the second wave were milder, the demand by firms remained 5% below its normal levels. We also document a change in people's daily routines in response to the stringency of the lockdown measures, as reflected in their hourly electricity consumption patterns.

Covid Economics 63, 7 January 2021: 159-185

1 We thank Red Eléctrica de España, and Félix Martínez and Ana Abril in particular, for kindly providing some of the electricity consumption data used in the paper. Natalia Fabra acknowledges financial support from Bank of Spain and from the European Research Council (ERC) under the European Union Horizon 2020 Research and Innovation Program (Grant Agreement No 772331). Mateus Souza provided excellent research assistance. All views and errors are our own.

2 Economist, Bank of Spain.
3 Professor, Universidad Carlos III de Madrid and CEPR.
4 Economist, Bank of Spain.
5 Economist, Bank of Spain.
6 Economist, Bank of Spain.

1 Introduction

In this paper we investigate how electricity consumption patterns have changed during the COVID-19 pandemic. Since electricity consumption has a strong correlation with economic growth, it has traditionally been used as an indicator of economic activity (Kraft and Kraft, 1978; Henderson, Storeygard and Weil, 2012; Stern, 2018). However, as we show in this paper, changes in work and life habits triggered by the lockdown measures have implied a structural break in the relationship between electricity consumption and economic activity. In particular, we provide detailed evidence of a strong reduction in the amount of electricity consumed by firms, which was partly offset by an increase in the amount of electricity consumed by households. Therefore, to the extent that economic activity is better captured by firms' electricity consumption, using total electricity consumption would under-estimate the severity of the economic impacts of the pandemic.

We focus on the Spanish economy, which has been one of the hardest hit by the COVID-19 crisis (IMF, 2020; Banco de España, 2020).[1] Nevertheless, the changes in the electricity consumption patterns that we document should also be illustrative of the effects in other countries that have implemented similar lockdown measures, including travel restrictions, social distancing and shutdowns of non-essential businesses, schools and public offices. Indeed, the electricity demand reductions in other developed countries are similar in scale with those reported in this paper.[2]

Understanding the link between electricity consumption and economic activity has proven to be particularly relevant during the pandemic; for instance, to keep track of the state of the economy in real-time, to assess the trade-offs between health and economic issues when designing the lockdown and deescalation measures, or to assess the need to provide public support to firms and businesses to avoid closures and layoffs. However, there are good reasons to suspect that the link between electricity consumption and economic activity might now be weaker than previously thought. The link between the two had already become weaker before the pandemic - arguably, due to an improvement in energy efficiency and an increased weight of the service sector in the economy (Hirsh and Koomey, 2015; Buera and Kaboski, 2012; Metcalf, 2008) - but the pandemic might have weakened it more by changing the patterns of electricity consumption by firms and households. In the future, the likely increase in remote work (Dingel and Neiman,

[1]The IMF (2020) expects the Spanish economy to decline 12.8% in 2020, only comparable to Italy. Banco de España (2020) expects only a milder reduction, 12.6%.

[2]For instance, see Cicala (2020*a*) and Fezzi and Fanghella (2020) for Italy, Benatia (2020*b*) for France, or Leach, Rivers and Shaffer (2020) for Canada. McWilliams and Zachmann (2020) provide a tracker of electricity consumption at various countries in 2020 relative to 2019.

Covid Economics 63, 7 January 2021: 159-185

CEPR PRESS

Covid Economics 63, 7 January 2021: 159-185

2020), the deployment of on-site rooftop solar installations and electric vehicles, or the improvement in energy efficiency (Davis, 2017; Stern, 2018) might further confound the link between metered electricity consumption and economic activity. These trends do not cast doubt on the usefulness of electricity data to measure economic activity, but rather call for revisiting the link between the two.

In this paper we argue that a key step to do so is to decompose electricity consumption by firms and by households. Whereas the former is mostly unambiguously correlated with economic activity, the latter might be either negatively or positively correlated with economic activity. For example, households' consumption might increase due to unemployment (at least in the short-run) or due to an increase in remote work. However, the data needed to decompose total electricity consumption across consumer types is typically not available close to real time, which is when the use of electricity data as a proxy for economic activity is more valuable relative to other indicators.

We exploit one institutional feature of the Spanish electricity market in order to decompose total electricity consumption into consumption by firms and by households. In particular, different consumers, depending on their peak consumption and voltage, face different choices of types of electricity tariffs. For instance, only households have the right to be supplied at last resort rates, while only firms have the right to access the wholesale electricity market directly. In this study, we use publicly available information provided by the Spanish System Operator on hourly electricity consumed under the various tariffs, allowing us to estimate the consumption by firms and households.[3] To check the validity of our proposed decomposition, we compute the correlation of our estimated series with other data sources that should correlate positively with firms' and households' actual electricity consumption data. In particular, we show that our series for households' consumption data has a strong correlation with TV News audience and with Google's Residential Community Mobility Index, which measures the time people spend at home (Google, 2020). Moreover, we show that quarterly GDP year on year growth rates (INE, 2020) are strongly correlated with our series for firms' consumption (and not so with households' consumption), particularly so during the pandemic.

This study measures the effects of the pandemic on electricity consumption patterns. For that, our empirical analysis captures the departure of (daily or hourly) electricity consumption from what one would predict using previous years' data, while controlling for temperature and seasonality. The daily analysis allows to highlighting the diverging trends of firms' and households' electricity consumption during the pandemic. In turn,

[3]There is not a one-to-one mapping between users and tariffs given that a vast amount of consumers are supplied under a tariff that is available to both firms and households.

the hourly analysis allows to uncovering changes in electricity consumption patterns of firms and households across the day and across the week, depending on the stringency of the lockdown measures.

We find that total electricity consumption fell substantially during the first wave of the pandemic, reaching declines of 18.2% under the total lockdown. Yet, the reduction in firms' demand was much stronger, 29.1% below its normal levels, which was partly offset by the increase in households' electricity demand, 9.6% above its normal levels. During the second wave, the reductions in electricity demand have been milder, which is explained by the less stringent lockdown measures in place. Yet, the 3% reduction in total electricity consumption masks a 4.8% decline in firms' electricity consumption, given that households' electricity consumption was still 2.4% above its normal level. It is unclear whether this is due to a slower rate of economic activity and/or due to an increase in remote work. Nevertheless, this asymmetry is reflective of the change in electricity consumption patterns during the pandemic.

In the Spanish case, the evidence shows a strong correlation between the growth rate of firms' electricity consumption and quarterly GDP. However, in general it is not possible to perfectly map the change in electricity consumption by firms with the decline in economic activity. The reason is that some of the economic activity that used to take place at the workplace has now shifted to the household. Hence, our proposed demand decomposition can be seen as providing bounds to the fall in economic activity: the decline in firms' demand provides an upper bound (as if no activities had shifted to the households) and the decline in total electricity consumption provides a lower bound (as if all the increase in households' demand were due to remote work). Nevertheless, it is important to point out that not all activities that can move into remote work are equally energy intensive. Furthermore, the amount of energy consumed at the workplace and at home for the same amount of work need not be the same. Hence, it is unlikely to find a one-to-one correspondence between the reduction in firms' consumption and the increase in households' consumption.

We also provide evidence of substantial changes in the hourly patterns of electricity consumption, which again differ across firms and households. In particular, we observe large declines in electricity consumption by firms during working times, which are paralleled by simultaneous increases in households' electricity consumption. We also find a morning and a late evening effect in households' demand patterns, i.e., a decline from 8am-9am and an increase from 9pm-10pm, seemingly indicating that people shifted to getting up and going to bed later than usual. Through the lens of households' electricity consumption, we can further assess how the stringency of the lockdown measures in

Covid Economics 63, 7 January 2021: 159-185

place affected people's routines. For instance, the morning effect is no longer present when schools re-opened even if a vast majority of people were still under remote work. We also find that the pandemic affected people's holidays, as they seem to spend more time at home during the summer months than in previous years, an effect that is not explained by remote work. A similar effect can also be seen on Sundays during the total lockdown period.

Related Literature The impact of the pandemic on the power sector has attracted the attention of several institutions and scholars worldwide (Benatia, 2020*a*,*b*; Cheshmehzangi, 2020; Cicala, 2020*a*; Fabra, Lacuesta and Souza, 2020; Fezzi and Fanghella, 2020; Leach, Rivers and Shaffer, 2020; Ghiani et al., 2020; Ruan et al., 2020). These studies focus on measuring the declines of electricity consumption and the consequences for the performance of electricity markets in various countries. However, they all look at aggregate consumption figures without decomposing demand by firms and households.

We are aware of only two other papers focusing on the impacts of the pandemic on households' electricity consumption. Cheshmehzangi (2020) conducted a survey among 352 Chinese households to understand their energy use during the pandemic. Results suggest strong impacts on cooking and entertainment, heating/cooling and lighting, which translated in increased household electricity demand. More closely to related to our work, Cicala (2020*b*) analyzes the distinct impacts of COVID on households' and firms' electricity consumption. Our work mainly differs from his in the time frame, data type and coverage: whereas we use nation-wide publicly available hourly data from Spain for the period Q1 2015 to Q3 2020 (with a focus on Q1-Q3 2020 to assess the impacts of the pandemic), he uses proprietary data from Texas. For households, he uses smart meter hourly data for a subset of customers from Q1 2019 to Q2 2020 (with a focus on April-May 2020 to assess the impacts of the pandemic); for firms, he uses monthly billing data dating back to 2016. Like us, he also reports an increase in households' consumption paralleled by a reduction in firms' consumption. Interestingly, his monthly analysis of utility bills shows that these effects were not present during the 2018 crisis, when the reduction in firms' demand did not translate into an increase in households' demand. While our empirical analysis does not go back to 2018, the longer span of our hourly data during the pandemic allows us to assess how the consumption patterns for firms and households responded to changes in the stringency of the lockdown measures, thereby reflecting changes in people's daily routines. The remainder of the paper is organized as follows. In Section 2 we describe our data, as well as our proposed method

Covid Economics 63, 7 January 2021: 159-185

CEPR PRESS

to decompose aggregate electricity demand into demand by firms and households. In Section 3 we describe the lockdown measures that were put in place in Spain. In Section 4 we perform our econometric analysis, analyzing both the evolution of daily demand across time as well as the changes in hourly demand patterns. Last, Section 5 concludes.

2 Decomposing Total Electricity Demand

We use hourly electricity demand data in Spain, from January 2015 until September 2020. Summing demand across hours of the day gives us the daily demand data, which we use in one of our empirical analyses. If data for at least one hour of the day is missing, we omit that date. We also omit those dates at the start or at the end of the daylight saving time (last Sunday in March and last Sunday in October, respectively).

We want to explore the behaviour of households and firms during the pandemic, as reflected in their electricity consumption. As these data are rarely available, we need to resort to other data sources to decompose aggregate electricity demand into the demand by firms and households. In particular, we use information on the type of tariff or market access that consumers are subject to, in order to infer whether they should be classified as either firms or households.[4]

In the Spanish electricity market, there are three options for buying power: (1) at default rates, (2) in the retail market, or (3) through direct market access. The first option is only available to households; in particular, only those households with a contracted capacity below 10kW have the choice of buying electricity at the so-called Voluntary Price for the Small Consumer,[5] which is computed as a pass-through of the hourly wholesale electricity prices. The second option, which is to buy electricity in the retail market at the prices offered by the electricity retailers, is available for both firms and households, regardless of their size. Using 2019 data, 95.2% of the buyers in the retail market are households, 4.2% are SMEs and 0.6% are large industrial consumers.[6] According to this data, in 2019 61% of all households bought electricity in the retail market. This number

[4]These data are provided by the Spanish System Operator, and they are publicly available through its website (Red Eléctrica de España, 2020). We use the series I3DIA02. The information is available after three days, showing the result of the P48 Schedule.

[5]More specifically, 99.9% of the users subject to the Voluntary Price for the Small Consumer are households. The remaining 0.1% are small and medium enterprises (SMEs).

[6]These data are provided on a quarterly basis by Comisión Nacional de los Mercados y la Competencia (2020). It provides the number of users of each type (either households, SMEs, or industrial buyers) and the number of users who buy electricity at either the default rates or in the retail market. The latest data available at the time of writing this paper belong to Q1-Q4 2019.

Covid Economics 63, 7 January 2021: 159-185

increased to 99% for firms. Last, while the third option is available for all consumers, only large firms decide to buy directly at the wholesale market given the large transaction costs involved.

Hence, all the electricity that is bought at the default rates can be classified as demand by households, while all the electricity that is bought through direct market access can be classified as demand by firms. It thus remains to decompose the retail market demand into demand by firms and by households. For this purpose, we assume that the average consumption of households is the same regardless of whether they choose to buy electricity at the default rate or in the retail market. This assumption would not be adequate if the characteristics of those households selecting into either option differed substantially. However, the evidence indicates this is not the case. For instance, Fabra et al. (2021) show that the observable characteristics of the households in these two groups are the same on average. This is consistent with survey data showing that 77% of the Spanish households are unaware of the differences between the two options, with 64% of them declaring not to know which one they are subject to.[7]

Let us use D_j^i to denote total electricity demand of households ($i = H$) or firms ($i = F$) who buy electricity at the default rates ($j = 1$), in the retail market ($j = 2$), or through direct market access ($j = 3$). We can thus decompose the demand under each type of access $j = 1, 2, 3$ as $D_j = D_j^H + D_j^F$. Likewise, let N_j denote the number of household users under each type of access j, with $N_1, N_2 > 0$ and $N_3 = 0$. It thus follows that

$$D^H = D_1^H + D_2^H = D_1 \left(1 + N_2/N_1\right)$$

where we have used the fact that all the consumers under the default rates are households, $D_1 = D_1^H$, and the fact that households have no direct market access, $D_3^H = 0$, together with the assumption that the average consumption of households in the two first groups is the same, i.e., $D_2^H = (N_2/N_1)D_1^H$.[8]

It follows that the electricity demand of firms can be constructed as

$$D^F = D_2^F + D_3^F = D_2 - (N_2/N_1)D_1 + D_3$$

where we have used the fact that $D_3^F = D_3$.

How good is our proposed decomposition of total demand into the demand by firms and households? In panels A and B of Figure 1, we have gathered information on electricity consumption by type of tariff, distinguishing between those tariffs that are

[7]See the Comisión Nacional de los Mercados y la Competencia (2019)'s household panel on electricity and gas, corresponding to Q2 2019.

[8]Using 2019 data, this ratio equals 1,61.

Covid Economics 63, 7 January 2021: 159-185

available for households (low voltage) and those that are available to firms (high voltage). These data are available on a daily basis from 2015 to the third quarter of 2019 (Red Eléctrica de España, 2020). We can see that our series capturing electricity demand by firms (panel A) and households (panel B) follow an almost one-to-one correlation with the demand at high and low voltage, respectively.

In panel C of Figure 1 we further explore the accuracy of the household electricity demand series by looking at the correlation with daily data television viewership. The latter is calculated with information on the number of viewers of the most watched evening news broadcast and its audience share.[9] We exclude the data points corresponding to July and August, since they fall within the peak of the holiday season. The figure shows a high correlation (0.53) between our estimated household power demand data and television viewership.

Last, in panel D of Figure 1 we explore the correlation between households' electricity demand and Google's Residential Community Mobility Index, which measures the time people spend at home with respect to a 'normal´ day.[10] Based on the time spent at certain places, the daily change in mobility is computed with respect to the median value of that day of week between January 3th and February 6th, 2020. The figure shows a strong positive correlation (0.83) between our estimated households electricity consumption data and the time people spend at home between March 14th (when the partial lockdown starts) and June 15th (which the new normal starts). Overall, we take the strong positive correlations between our estimated households' demand and the various measures as an indication of the validity of our decomposition.

Using our proposed decomposition, Figure 2 plots the relationship between the electricity demand by firms and households, on a daily basis before (panel A) and during (panel B) the pandemic. While the correlation between the two series before the pandemic is small (0.01), it turns negative (-0.38) during the pandemic. This suggests that the lockdown measures have moved electricity demand by firms and households in opposite directions.

This negative relationship between the two series suggests the importance of decomposing electricity consumption into the consumption by firms and households to obtain a good proxy for economic activity. Indeed, Figure 3 plots the relationship between the growth rate of the three series and GDP on a quarterly basis. Before the pandemic, the growth rates of electricity consumption by firms and households were similar, both be-

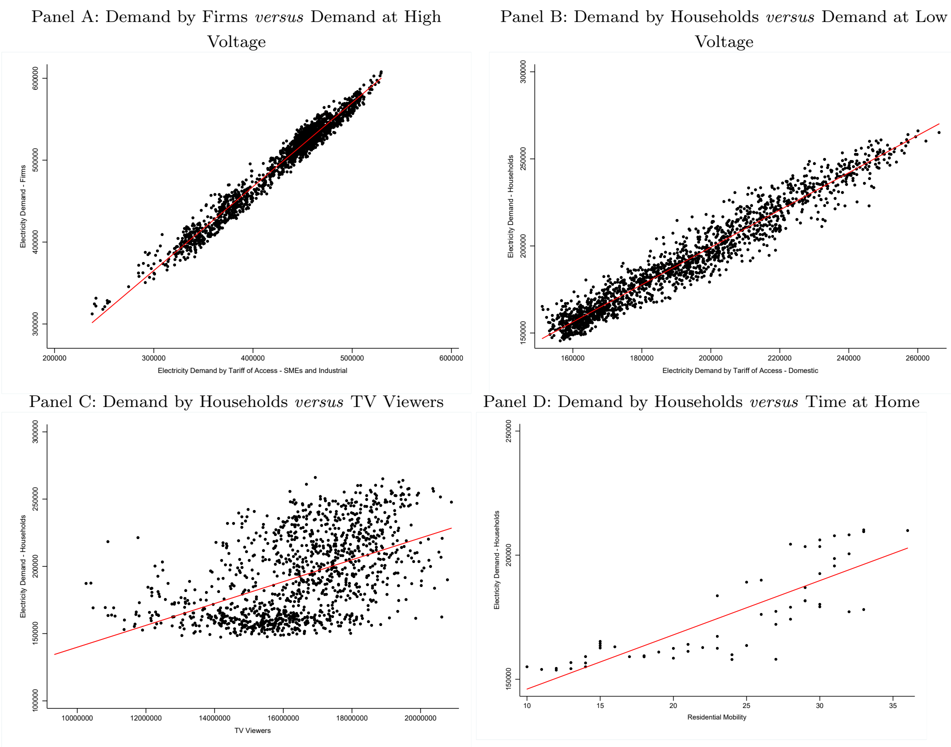
[9] The data source is Vertele! (2020). These data are available on a daily basis (with gaps) since late 2010.

[10] The data source is Google (2020). They are available on a daily basis since mid-February 2020, both for European countries as well as for the US.

Covid Economics 63, 7 January 2021: 159-185

Covid Economics 63, 7 January 2021: 159-185

Figure 1: Accuracy of the estimated firms' and households' electricity demand series



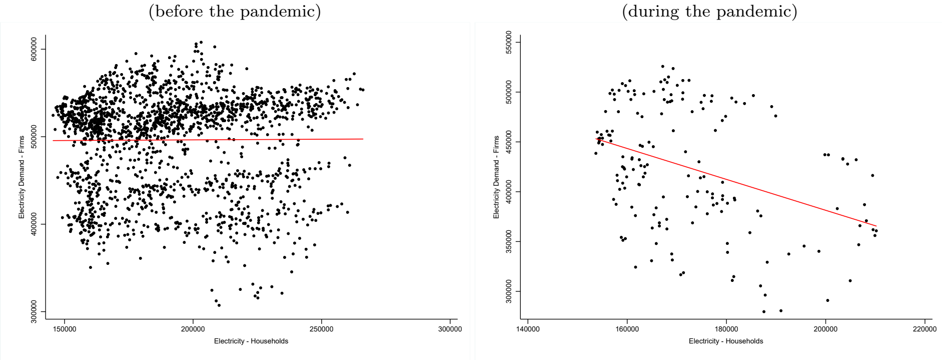
Notes: Panels A to C provide evidence about the accuracy of our proposed decomposition of aggregate electricity demand into demand by firms and households. Panel A,B,C reflect daily data, starting on January 2015 and ending either on September 2019 (panels A and B), or on July 2020 (panel C) . Panel A shows the correlation between the electricity demand by firms and the electricity demand at high voltage. Panel B shows the correlation between the electricity demand by households and the electricity demand at low voltage, while Panel C shows the correlation with TV audience. Last, panel D illustrates the correlation with the time people spend at home. It uses weekdays (excluding holidays) from March 14th until June 15th, 2020.

ing slightly below GDP growth. The Spanish System Operator has already documented that, since 2014, total electricity consumption has been growing at a lower pace relative to GDP (Red Eléctrica de España (2019)). They attribute this to several factors, including improvements in energy efficiency and electricity price increases. Our decomposition further reveals that, between 2016 and 2020, electricity consumption has added some noise to the evolution of total electricity consumption, as it has been more volatile than that of firms. Nevertheless, the most striking lesson of the figure is that during the pandemic, electricity consumption by firms has fallen down at the same rate as Spanish GDP. This is in contrast to the electricity consumption by households, which has started to grow

Covid Economics 63, 7 January 2021: 159-185

Figure 2: Relationship between the estimated firms' and households' electricity demand

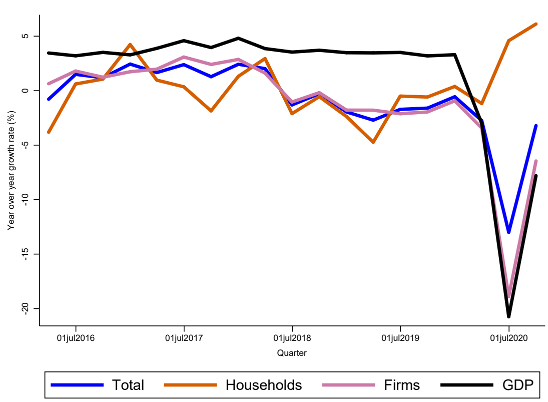
Panel A: Demand by firms *versus* Demand by households (before the pandemic) | Panel B: Demand by firms *versus* Demand by households (during the pandemic)



Notes: Panel A reflects daily data, starting on January 2015 and ending on February 14th, 2020. Panel B starts on February 15th and ends on November 1st; the summer period (July and August) is excluded.

at the same time as electricity consumption by firms collapsed. As a consequence, the fall in total electricity consumption has underestimated the fall in GDP. In sum, this evidence suggests that firms' electricity consumption is a better indicator for economic activity during the pandemic, as total electricity consumption is biased by the diverging behaviour of households' consumption.

Figure 3: Growth rates of the estimated firms' and households' electricity demand and GDP



Notes: This figure shows quarterly year over year growth rates, starting in Q1 2016 and ending in Q3 2020. The blue, pink and orange lines represent the growth rates of total electricity consumption, electricity consumption by firms and households, respectively, in the Spanish electricity market. The black line represents Spanish GDP growth.

In the following sections we analyze the recent evolution of the three electricity consumption series. Before we do so, we turn to describing the various lockdown measures that have been put in place in Spain.

3 Lockdown Measures

Similarly to most countries, several lockdown measures have been put in place in Spain during the COVID19 pandemic. Table 1 lists such measures.

Starting Monday, March 9th 2020, some regional governments started to close down kindergartens, schools and universities.[11] These measures were first supposed to last for 15 days. However, on Saturday March 14th, the Spanish government approved the state of alarm in order to centralize all decisions regarding the sanitarian crisis. It also decided to close down most retail shops, hotels, and restaurants as well all to cancel all sport events and recreational activities. Groceries and health centers were the only establishments allowed to stay open.[12] Moreover, strict mobility restrictions were imposed, only allowing people to go to work and to buy first necessity products. On Monday the 29th of March, those restrictions were strengthened, leading to a total lockdown of businesses other than those considered to be of first necessity,[13] or those that could rely on remote work. The total lockdown lasted until the end of Easter, on April 10th.

During the following month, the economy remained under a similar lockdown as the one that was initially imposed on March 14th. From then onward, the government put in place deescalation measures, organized in three phases, until reaching the so-called 'new normal' on June 21st. It was then when Madrid, Cataluña and Castilla León reached the last phase. The different phases differed in the degrees of stringency regarding mobility and businesses. On a regional basis, the decision to move from one phase to the next was based on the number of cases detected and the occupancy of the ICUs.

During the new normal, only mild restrictions were imposed. Establishments were

[11] On March 9th 2020 the Basque government closed all schools in La Bastida and some in the city of Vitoria. On the 10th these measures were extended to all schools in Vitoria. The regional government of Madrid and La Rioja approved on March 9th the closing of all schools in their regions to be effective on Wednesday March 11th. On Thursday 12th it was approved the school closing in Cataluña, Canarias, Castilla La-Mancha, Asturias and the rest of País Vasco to be effective on Friday 13th, while the rest of regions closed schools on Monday 16th.

[12] Article 10 in RDl 463/2020 listed the exceptions to this rule: food; beverages; first necessity products; pharmaceuticals; medical,optical and orthopedic products; hygiene products; hairdressers; press; automotive fuel; tobacco; technological and telecommunications equipment; pet food; establishments related to e-commerce or distribution by phone or mail; dry cleaners and laundries

[13] The annex of RDL 10/2020 defined the meaning of 'first necessity'.

Covid Economics 63, 7 January 2021: 159-185

CEPR PRESS

required to guarantee the minimum interpersonal distance of 1.5 meters, and the use of masks became compulsory. On August 14th, the risk of a second wave led the government and the regional governments to agree on additional restrictions for bars, restaurants and recreational activities.[14] After that date, some mobility restrictions were imposed on certain districts or municipalities, depending on the incidence of infections per 100.000 inhabitants as well as on the capacity of their hospital facilities. Schools and Universities re-opened under some restrictions.

4 Predictive Impact of the Pandemic on Electricity Consumption

To provide a formal analysis of the evolution of daily electricity consumption between March and October 2020, our sample spans from January 1st 2015 until October 31st 2020. Using information up to December 31st 2019, we first estimate the following equation in order to control for low frequency demand shifters, temperature and holiday differences:

$$\ln(q_{dt}) = \rho + \beta\tau_t + \beta_2\tau_t^2 + \gamma_t + \epsilon_{dt} \tag{1}$$

where γ_t includes time fixed effects (year and month of the year) and holiday indicators,[15] and τ_t is the average (weighted by electricity demand at the province level) of the maximum temperature within a day.[16] We then average out all the residuals happening in a particular day of the week during the pre-lockdown period, i.e., $\tilde{\epsilon}_{dt}$, for d running from Monday through Sunday before January 1st 2020. Finally, for days belonging to the lockdown period, we compare out of sample estimated residuals in each particular day of the week with those of the same day of the week during the pre-lockdown period. For example, for Wednesday April 1st, we plot the difference between $\hat{\epsilon}_{dt}$ for dt= Wednesday April 1st, minus $\tilde{\epsilon}_{dt}$ for dt=Wednesday prelockdown. Quantitatively, if this difference equals -10 on Wednesday April 1st, it means that electricity consumption was 10% lower as compared to a typical pre-pandemic Wednesday, controlling for temperature, year, month and holiday differences.

[14] In particular, regions agreed the closure of discos and dance halls. The closing time of terraces and restaurants was set at 1am at the very late, without being able to admit new clients after midnight.

[15] Holiday indicators are constructed in such a way that we include a 1 when there is a national holiday. Regional holidays are weighted by the regional electricity consumption, as kindly provided to us by Red Eléctrica de España (REE).

[16] Electricity consumption at the province level was kindly provided to us by REE.

Covid Economics 63, 7 January 2021: 159-185

Covid Economics 63, 7 January 2021: 159-185

Dates	Lockdowns	Legal documentation
March 11th-13th, Wednesday-Friday	Schools closed (starting in Madrid and La Rioja)	Regional legal texts
March 15th , Sunday	Partial lockdown (retail, hostel, restaurant, recreation)	RD 463/2020
March 29th, Sunday	Total lockdown (non essential, non-work from home)	RDL 10/2020
April 10th, Friday	Partial lockdown (retail, hostel, restaurant, recreation)	RDL 10/2020 (art. 2)
May 11th, Monday	Beginning deescalation (Phase I applied to Canarias, Baleares, Galicia, Asturias, Cantabria, País Vasco, La Rioja, Navarra, Aragón, Extremadura y Murcia, Andalucía except for Granada and Málaga, and Castilla la Mancha only in Cuenca and Guadalajara)	SND/399/2020
May 18th, Monday	Continuation deescalation (Phase I applied to all regions but Madrid, metropolitan area of Barcelona, and some regions in Castilla y León and Phase II applied to some islands - El Hierro, La Gomera, La Graciosa, Formentera)	SND/414/2020
May 25th, Monday	Continuation deescalation (Phase II applied to those in phase I the 11th of May and phase I rest)	SND/458/2020
June 1st, Monday	Continuation deescalation (Phase II applied to all regions but Madrid, and some regions in Cataluna, Castilla y León, Phase III applied to some islands - El Hierro, La Gomera, La Graciosa, Formentera)	RDL 21/2020
June 8th, Monday	Continuation deescalation (Phase III applied to all regions but Madrid, and some regions in Catalunya, Castilla y León, Castilla la Mancha and Comunidad Valenciana)	
June 15th, Monday	Continuation deescalation (new normal in Galicia, phase III applied to all regions but Madrid, metropolitan area of Barcelona, Lleida and some regions in Castilla y León)	
June 21th, Thursday	New normal	SND/458/2020
August 14th, Friday	Second wave	Central government and regions agreement

Table 1: Different lockdown measures in Spain

Figure 4 plots the estimated percentage change in electricity consumption (total, by firms or by households), and Table 2 summarizes the results.

4.1 Total electricity consumption

The stringency of the various lockdown measures had a strong effect on total electricity consumption (depicted in blue in the figure, and displayed on the first column of the table). Before March 10th, electricity consumption was slightly higher than what the model would have predicted, although differences not statistically significant. On average, during the first ten days of March, electricity consumption was 0.41% higher than the corresponding prediction. After March 10th, when the first lockdown measures were introduced, electricity consumption started to decline. The partial lockdown that started on March 11th strengthened the declining trend down to a -7.29% reduction on average. By Monday March 30th, electricity consumption had fallen sharply - by as much as as a 18.53% - and remained around that level until the end of the total lockdown on April 10th. The average fall during the total lockdown (between March 29th and April 10th) was -18.15%.

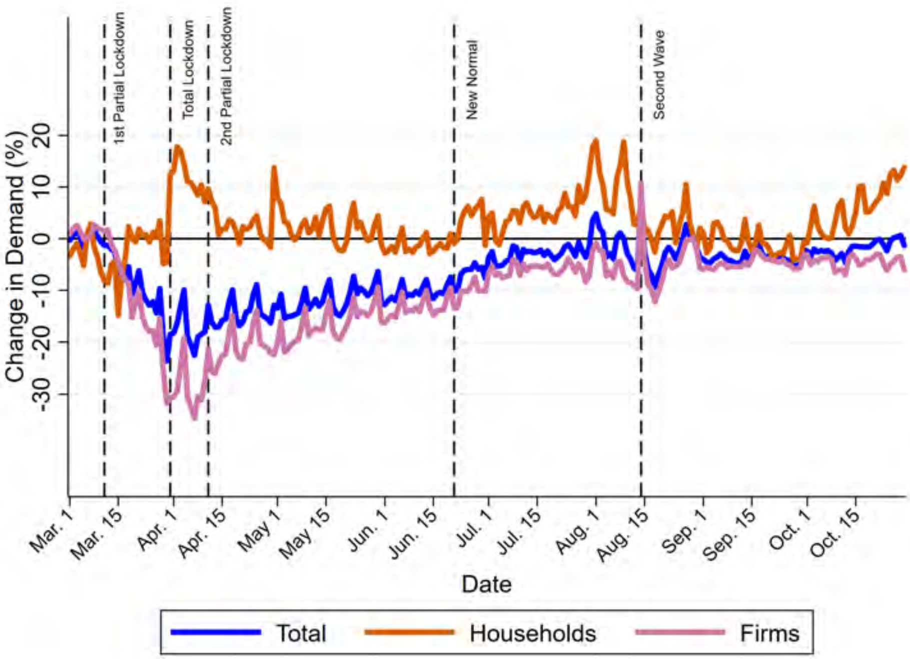
After that date, electricity consumption started to recover, but the recovery was more gradual than the fall initially observed in March. On average, electricity consumption during the first week of May showed a -13.94% decline as compared to the pre-crisis levels. This slow recovery towards the pre-crisis consumption levels was the norm along the deescalation. During the first two weeks of June, electricity consumption was 10.48% lower than before the crisis. Once the 'new normal' came into play, electricity consumption rapidly went back close to its predicted level. Despite the new restrictions that were introduced on August 14th, electricity consumption remained only slighlty below the predicted level during the second half of the month. From the beginning of October until the end of our data set and despite being in the middle of the second wave, total electricity demand has recovered from -3.35% at the beginning of the month to an average of -0,10% during the last week of October.

4.2 Electricity consumption by firms and households

Due to the economic crisis and due to the lockdown, several firms have gone bankrupt and others have temporarily ceased their activity, leading to permanent or temporary worker lay-offs. This should have reduced the electricity demand by firms while increasing the electricity demand by households. Therefore, because of this countervailing effect, using aggregate electricity consumption as a proxy for economic activity might under-estimate

Covid Economics 63, 7 January 2021: 159-185

Figure 4: The impact of the various lockdown measures on electricity consumption



Notes: This figure shows the estimated percentage change in total electricity consumption as compared to what the model would have predicted with 2015-2019 data. The effect on total electricity consumption appears in blue, on households' consumption in orange, and on firms' consumption in pink.

the true economic impact. Yet, other firms that have remained active have shifted their workers to remote work, which is expected to show up as an increase electricity demand by households. Hence, the true economic impact probably lies somewhere in between the impact on the electricity demand by firms and by households, but certainly below the impact on aggregate electricity demand.

For this reason, in this section we decompose the effects of the lockdown measures on electricity demand by firms and households, separately. Results are shown in Figure 4 (in pink and orange, respectively) and Table 2 (second and third columns of the table). According to the estimated effects, the level of electricity consumption by households remained close to the predictions of the model during March. Indeed, during the first partial lockdown, households even dropped their electricity consumption by 2.74% relative to what one would expect at the counterfactual. However, during the total lockdown period, people had to stay at home, which translated into a sharp increase in households electricity consumption, i.e., 9.60% above the counterfactual. During the deescalation,

Covid Economics 63, 7 January 2021: 159-185

Covid Economics 63, 7 January 2021: 159-185

	Total	Firms	Households
Pre-Lockdown			
(March 1st - March 10th)	0.41	1.13	-1.42
	(0.94)	(1.11)	(1.40)
1st Partial Lockdown			
(March 11th - March 28th)	-7.29***	-9.32***	-2.74***
	(0.68)	(0.83)	(1.05)
Total Lockdown			
(March 29th - April 10th)	-18.15***	-29.06***	9.60***
	(0.87)	(1.06)	(1.34)
2nd Partial Lockdown			
(April 11th - June 20th)	-12.28***	-17.08***	1.36***
	(0.35)	(0.42)	(0.53)
New Normal			
(June 21st - August 13th)	-3.21***	-6.74***	6.18***
	(0.39)	(0.48)	(0.60)
Second Wave			
(August 14th - October 31st)	-2.90***	-4.79***	2.36***
	(0.33)	(0.40)	(0.51)
Observations	2,071	2,071	2,071

Table 2: The impact of the various lockdown measures on electricity consumption

Notes: This table shows the estimated percentage change in total electricity consumption as compared to what the model would have predicted with 2015-2019 data. The coefficients and standard errors are obtained by regressing the daily differences on indicators for each lockdown period.Significance at 10%, 5%, and 1% is indicated by *, **, and ***, respectively.

households' electricity consumption remained slightly above the counterfactual (again, approximately 1.36% above the pre-crisis levels). It is interesting to see that after Monday June 22st and up to Friday August 14th, households' electricity consumption jumped again. Indeed, during the first half of August, in average, it remained around 10% above the pre-crisis levels. This is consistent with people spending more time at home during the summertime as compared to previous years. Afterwards, households' consumption stabilized at around 2% above the usual level up until October 1st, and it then started to increase sharply during the second wave, reaching almost 14% above the pre-crisis level by the end of October.

Electricity demand by firms is almost a mirror image of that of households. According to the estimates, during the first half of March, the demand by firms behaved similarly to what one would expect with 2015-2019 data. During the partial lockdown that started on March 11th, it initiated a decreasing trend. This effect was slightly higher than that on total electricity consumption given the mild drop in households' consumption. The total lockdown made things worse, leading to a fall in the electricity demand by firms of 30.68% by March 30th. This low level was maintained up to April 10th. The week after the total lockdown, the electricity demand by firms started to gradually recover, yet reaching a level that was 21.94% below the pre-crisis level. It remained low until the start of the deescalation on May 11th. From that moment onward, there was a partial recovery of firms' electricity demand, which nevertheless remained below its normal level. For instance, on June 21st, it was 14.78% lower than expected. The new normal pushed firms' electricity demand to a level -6.74% in average, and by the end of August it fluctuated between 0 and -5% below its normal level. Electricity demand by firms remained around -5% its normal level until the end of October.

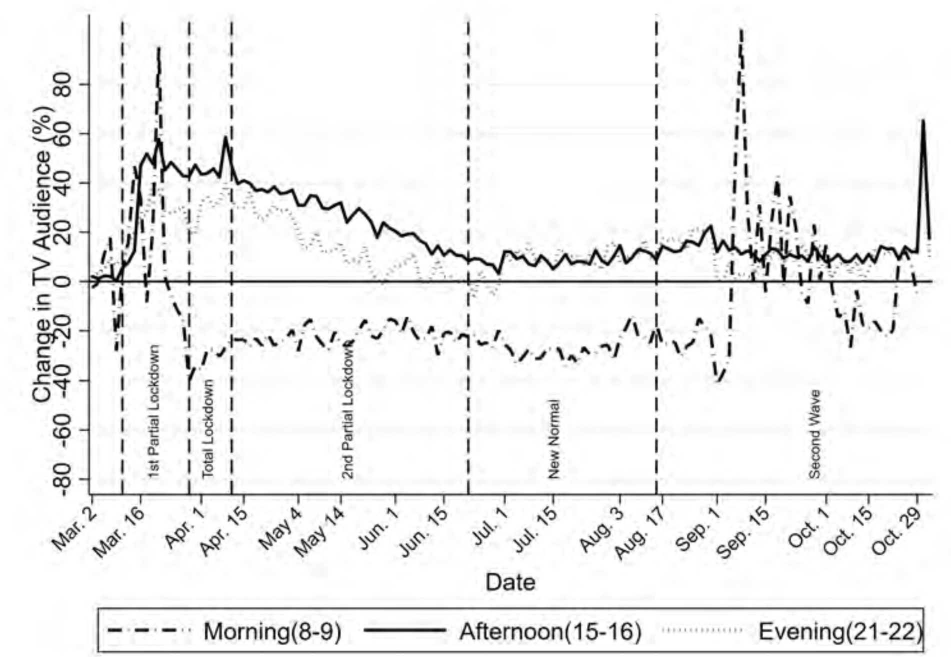
We conclude this section analyzing daily data by providing further evidence on the drivers of increased households' electricity consumption. In particular, we have obtained TV audience data at three different times corresponding to the daily News (8-9am, 3-4pm and 9-10pm), during weekdays.[17] We identify the normal audience at each day and time using a similar model as the one we used for electricity demand, (1). In particular, the model incorporates year, month, and day dummies, as well as temperature and holidays. Figure 5 plots the estimated percentage change in TV audience with respect to the normal audience. As it is clear from the figure, more households turn on the TV during the first days of confinement at news broadcasts. From that moment onward, audiences in the afternoon and evening remain abnormally high, although they converge towards their normal level by the end of June. This is in line with our estimates of households' electricity demand, as both pieces of evidence suggest that people spend more time at home due to the lockdown measures. On the contrary, TV audiences during the morning were abnormally low during the lockdown. In turn, this is consistent with people getting up later as kids did not have to go to school and adults could work remotely, thus replacing travelling times with extra sleep. During the summer, the audience raised again in the afternoon and evening, and it dropped again after September. During the second wage the audience in the afternoon and evening was still 10% above its normal level. On the

[17]The data source ObjetivoTV (2020). Our dataset contains daily information on the number (and share) of TV viewers watching a particular TV program at a particular time. We consider the news programs of the channel A3 (leader in that type of program) in the usual three tranches during the day. We divide the number of people watching those programs by the corresponding share to obtain the total number of people watching TV at a particular time of the day.

Covid Economics 63, 7 January 2021: 159-185

contrary, in September, when schools re-opened, the morning audiences jumped back to normal. This suggests that a finer analysis of the changes in electricity demand on an hourly level would also reflect changes in peoples' habits during the pandemic. We turn to this issue next.

Figure 5: The impact of the various lockdown measures on TV audience



Notes: This figure shows the estimated percentage change in total audience as compared to what the model would have predicted with 2016-2019 data. The effect on morning news (8-9am) appears in a dash-dot black line, on afternoon news (3-4pm) appears in a solid black, and on evening news (9-10pm) appears in a dotted black line.

4.3 Analysis of hourly data

In this section we analyze the hourly demand response to the various lockdown measures. To this end, we exploit differences in hourly electricity consumption across the day during the lockdown period as compared to the average electricity consumption of the same average day of the week in the pre-lockdown period. We use a similar model than the one used in the previous sections but making extensive use of hourly data:

$$\ln(q_{hdt}) = \rho + \beta\tau_t + \beta_2\tau_t^2 + \gamma_t + \epsilon_{hdt} \tag{2}$$

Covid Economics 63, 7 January 2021: 159-185

where similarly to (1), γ_t includes time fixed effects (year and month of the year) and holiday indicators, and τ_t is a weighted average of the maximum temperature within a day in each province. We then average out all the residuals happening every single hour h in each particular day d of the week during the pre-lockdown period, i.e., $\tilde{\epsilon}_{hdt}$, for d running from Monday through Sunday before March 10th. For the averaging, we consider two subsets within the year: winter days (from the last Sunday in October to the last Sunday in March the following year) or summer days (from the last Sunday in March to the last Sunday in October each year). Finally, for days belonging to the lockdown period we compare the residuals in each particular hour with the average of the residuals for that same hour and day of week during the pre-lockdown period. For example, for each hour of h during Wednesday April 1st, we plot the difference between $\hat{\epsilon}_{hdt}$ for $dt=$ Wednesday April 1st, minus $\tilde{\epsilon}_{hdt}$ for dt=Wednesday for that same hour h. Quantitatively, finding a -10 between 8am and 9am during Wednesday April 1st would mean that electricity consumption was 10% lower as compared to that same hour during a typical pre-pandemic Wednesday, controlling for temperature, year, month and holiday differences.

Figure 6 shows the evolution of those residuals along the day for firms and households. Days are grouped in four types of periods that differ on the stringency of the lockdown measures in place (weekends and holidays are excluded). Table 3 summarizes the results by reporting the changes in electricity demand during representative hours.[18]

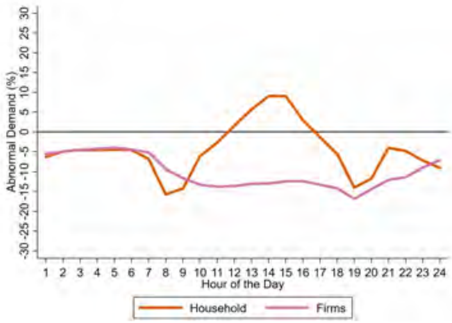
Consistently with our previous analysis, electricity demand by households went up, while electricity demand by firms went down, particularly so during the total lockdown period. Therefore, changes in total demand (as shown in Figure 8 in the Appendix) hide the opposite movements in the two series. The effects are not uniform across all hours of the day, or across time as the stringency of the lockdown measures changed. Indeed, the effects on households' electricity demand patterns reflect changes in their habits during the pandemic. The reduction in demand at around 8-9am and the increase in demand at around 10-11pm is consistent with people getting up later but also going to be bed later (as also suggested by the TV audience data). The increase in the households' electricity demand is more pronounced during working hours, which is also when we observe the strongest reduction in firms' electricity demand. The most striking difference between the two series is observed during the total lockdown period at 2pm, when households increase their electricity demand by almost 19% while firms reduce theirs by almost 25%.

[18]The choice of hours also coincides with the timing of TV news, allowing us to check whether the changes in households' demand and TV viewership are consistent with each other.

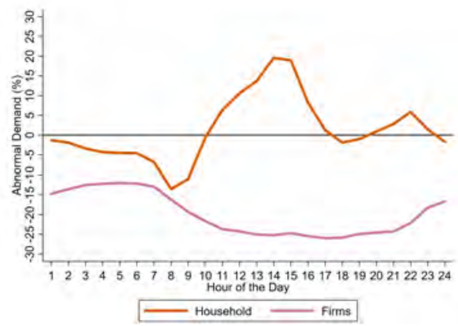
Covid Economics 63, 7 January 2021: 159-185

Figure 6: Changes in firms' and households' hourly electricity consumption relative to pre-lockdown

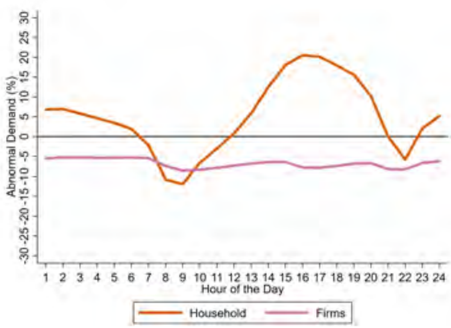
Panel A: 1st Partial Lockdown



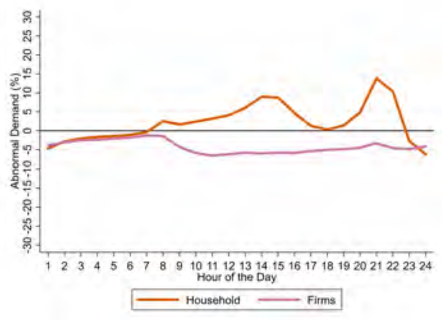
Panel B: Total and 2nd partial lockdown



Panel C: New normal



Panel D: Second wave



Notes: These figures show the estimated percentage change in hourly electricity consumption by firms and households as compared to what the model would have predicted with 2015-2019 data. Only weekdays and non-holidays are considered.

Covid Economics 63, 7 January 2021: 159-185

Covid Economics 63, 7 January 2021: 159-185

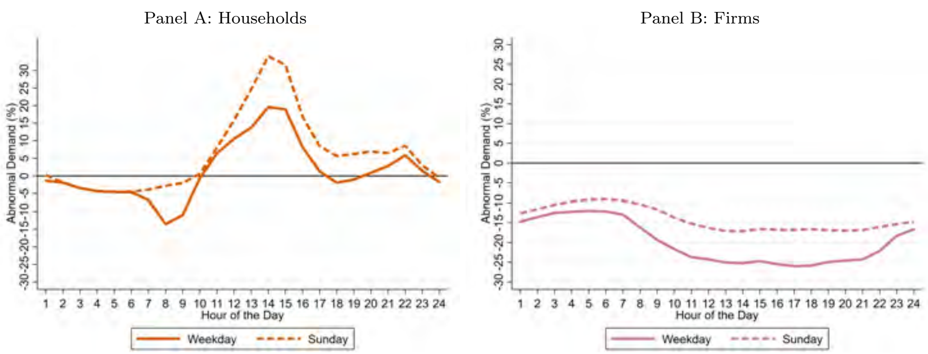
	8 am		2 pm		10 pm	
	Households	Firms	Households	Firms	Households	Firms
1st Partial Lockdown						
(March 11th - March 28th)	-14.20***	-11.57***	9.01	-12.40***	-7.29***	-9.06***
	(2.12)	(2.94)	(5.17)	(3.19)	(1.40)	(2.09)
Total and 2nd Partial Lockdowns						
(March 29th - June 20th)	-10.98***	-19.35***	18.95***	-24.74***	1.44	-18.29***
	(0.76)	(0.85)	(1.16)	(0.96)	(0.97)	(0.63)
New Normal						
(June 21st - August 13th)	-11.88***	-8.67***	18.04***	-6.46***	2.01*	-6.70***
	(0.65)	(0.58)	(0.91)	(0.60)	(0.92)	(0.49)
Second Wave						
(August 14th - October 31st)	1.66	-4.30***	8.75***	-5.80***	-2.75*	-4.82***
	(1.32)	(0.44)	(1.36)	(0.34)	(1.14)	(0.22)

Table 3: Abnormal Energy Demand for Selected Hours of the Day

Notes: This table shows the estimated percentage change in hourly electricity consumption compared to what the model would have predicted with 2015-2019 data. The coefficients and standard errors are obtained by regressing the hourly differences on indicators for each lockdown period. Significance at 10%, 5%, and 1% is indicated by *, **, and ***, respectively.

Figure 7 compares the evolution of those residuals on weekends versus Sundays during the period of total and 2nd partial lockdowns. For firms, the effects are milder during Sundays, although still negative (note that some industrial activity takes place non-stop). On the contrary, the increase in the households' electricity demand is more pronounced during Sundays. Again, this is consistent with a change in habits: where people would often go out on Sundays, they now have to stay home. Last, note that the dip in morning demand is not present, as under normal conditions people would not get up early on Sundays in any event.

Figure 7: Changes in firms' and households' hourly electricity consumption relative to pre-lockdown



Notes: These figures show the estimated percentage change in hourly electricity consumption by firms and households as compared to what the model would have predicted with 2015-2019 data. Both weekdays and Sundays that were no holiday are considered separately.

Covid Economics 63, 7 January 2021: 159-185

CEPR PRESS

Covid Economics 63, 7 January 2021: 159-185

5 Conclusions

In this paper we have analyzed the impact of the COVID-19 lockdown measures on Spanish electricity consumption. We have highlighted the importance of decomposing total electricity consumption into consumption by firms and households, to better understand the economic and social impacts of the crisis. While electricity demand by firms has fallen substantially, the demand by households has gone up, with both effects being stronger under more stringent lockdown measures. These countervailing effects have implications for indicators of economic activity that rely on total electricity consumption as an input. The full economic impacts of the pandemic might be masked by those indicators - see for instance, Lewis, Mertens and Stock (2020).

Understanding the relationship between electricity consumption and economic activity will become increasingly complex, as the drivers of electricity consumption are likely to evolve over time. On the one hand, the energy transition will heavily rely on electrification as a means to reduce emissions in many polluting sectors (notably, transport and residential heating and cooling), and *ceteris paribus* this will lead to greater electricity needs. On the other, this will be partly offset by improvements in energy efficiency. The long term trend of electricity demand will likely depend more on the interplay between these two countervailing factors than on the state of the economy.

The strength of these drivers will also differ between firms and households, depending on their scope to electrify their energy needs and improve their energy efficiency. Electric vehicles are a category of important growth, which will likely affect electricity demand by households relatively more than that of firms. A confounding effect will be the deployment of rooftop solar photovoltaics, which are also expected to grow rapidly over the coming years both at industrial sites as well as at homes. Electricity consumption is measured net of any onsite generation, so the increase in rooftop solar generation will confound the true electricity consumption.

These issues do not imply that electricity consumption will no longer be informative of economic activity. Rather, they point at current and future challenges to understand the changing link between the two. By decomposing the change in electricity demand during the pandemic, this paper illustrates how such challenges can be, at least partly, overcome.

Covid Economics 63, 7 January 2021: 159-185

References

Banco de España. 2020. *Escenarios macroeconómicos para la economía española 2020-2022.*

Benatia, David. 2020*a*. "Reaching New Lows? The Pandemic's Consequences for Electricity Markets." Center for Research in Economics and Statistics Working Papers 2020-12.

Benatia, David. 2020*b*. "Ring the Alarm! Electricity Markets, Renewables, and the Pandemic." *USAEE Working Paper*, , (20-473).

Buera, Francisco J., and Joseph P. Kaboski. 2012. "The Rise of the Service Economy." *American Economic Review*, 102(6): 2540–69.

Cheshmehzangi, Ali. 2020. "COVID-19 and household energy implications: what are the main impacts on energy use?" *Heliyon*, 6(10): e05202.

Cicala, S. 2020*a*. "Early Economic Impacts of COVID-19 in Europe: A View from the Grid."

Cicala, Steve. 2020*b*. "Powering Work from Home." National Bureau of Economic Research Working Paper 27937.

Comisión Nacional de los Mercados y la Competencia. 2019. "Panel de Hogares CNMC sobre electricidad y gas del primer semestre de 2019."

Comisión Nacional de los Mercados y la Competencia. 2020. "Informe de Supervisión de los Cambios de Comercializador - Año 2019."

Davis, Lucas W. 2017. "Evidence of a decline in electricity use by U.S. households." *Economics Bulletin*, 37(2): 1098–1105.

Dingel, Jonathan I., and Brent Neiman. 2020. "How many jobs can be done at home?" *Journal of Public Economics*, 189: 104235.

Fabra, Natalia, Aitor Lacuesta, and Mateus Souza. 2020. "Degrowth versus Decoupling: Competing Strategies for Carbon Abatement?" *EnergyEcoLab*, Working Paper(109).

Fabra, Natalia, David Rapson, Mar Reguant, and Jingyuan Wang. 2021. "Estimating the Elasticity to Real Time Pricing: Evidence from the Spanish Electricity Market." *American Economic Association Papers and Proceedings*, forthcoming.

Fezzi, Carlo, and Valeria Fanghella. 2020. "Real-time estimation of the short-run impact of COVID-19 on economic activity using electricity market data." DEM Working Papers, Universita degli Studi di Trento Working Paper 2020/8.

Ghiani, Emilio, Marco Galici, Mario Mureddu, and Fabrizio Pilo. 2020. "Impact on Electricity Consumption and Market Pricing of Energy and Ancillary Services during Pandemic of COVID-19 in Italy." *Energies*, 13(13): 1–19.

Google. 2020. "COVID-19 Community Mobility Reports."

Henderson, J. Vernon, Adam Storeygard, and David N. Weil. 2012. "Measuring Economic Growth from Outer Space." *American Economic Review*, 102(2): 994–1028.

Hirsh, Richard F., and Jonathan G. Koomey. 2015. "Electricity Consumption and Economic Growth: A New Relationship with Significant Consequences?" *Electricity Journal*, 28(9): 72–84.

IMF. 2020. *World Economic Outlook, October 2020: A Long and Difficult Ascent.*

INE. 2020. "Quarterly Spanish National Accounts: main aggregates."

Kraft, John, and Arthur Kraft. 1978. "On the Relationship Between Energy and GNP." *The Journal of Energy and Development*, 3(2): 401–403.

Leach, Andrew, Nic Rivers, and Blake Shaffer. 2020. "Canadian electricity markets during the COVID-19 pandemic: An initial assessment." *Canadian Public Policy*, 46(S2).

Lewis, Daniel, Karel Mertens, and James H Stock. 2020. "U.S. Economic Activity During the Early Weeks of the SARS-Cov-2 Outbreak." National Bureau of Economic Research Working Paper 26954.

McWilliams, B., and G. Zachmann. 2020. "Bruegel electricity tracker of COVID-19 lockdown effects." Bruegel Datasets.

Metcalf, Gilbert E. 2008. "An Empirical Analysis of Energy Intensity and Its Determinants at the State Level." *The Energy Journal*, 29(3): 1–26.

ObjetivoTV. 2020. "Objetivo TV: Indice de Audiencias."

Red Eléctrica de España. 2019. "Demanda eléctrica y actividad económica: ¿cambio de paradigma?"

Covid Economics 63, 7 January 2021: 159-185

Red Eléctrica de España. 2020. "ESIOS: Information System of the Spanish Electricity System Operator."

Ruan, Guangchun, Dongqi Wu, Xiangtian Zheng, Haiwang Zhong, Chongqing Kang, Munther A. Dahleh, S. Sivaranjani, and Le Xie. 2020. "A Cross-Domain Approach to Analyzing the Short-Run Impact of COVID-19 on the US Electricity Sector." *Joule*, 4(11): 2322 – 2337.

Stern, David I. 2018. "Energy-GDP Relationship." *The New Palgrave Dictionary of Economics*, 3697–3714. London:Palgrave Macmillan UK.

Vertele! 2020. "Vertele!: Indices de Audiencias."

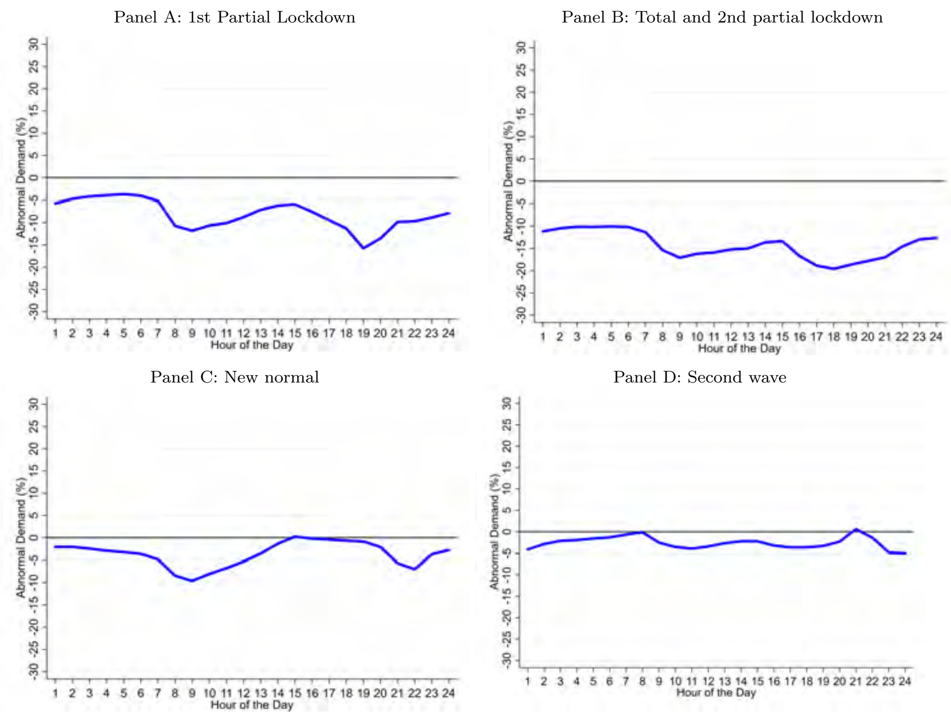
Covid Economics 63, 7 January 2021: 159-185

Covid Economics 63, 7 January 2021: 159-185

Appendix: Additional Figures

For completeness, we report here the evolution of residuals along the day for total electricity consumption. Days are grouped in four types of periods that differ on the stringency of the lockdown measures in place (weekends and holidays are excluded).

Figure 8: Changes in total hourly electricity consumption relative to pre-lockdown



Notes: These figures show the estimated percentage change in hourly electricity consumption adding up firms and households as compared to what the model would have predicted with 2015-2019 data. Only weekdays and non-holidays are considered.

The impact of the first wave of the COVID-19 crisis on small and medium-sized enterprises and credit guarantee responses: Early lessons from Japan[1]

Nobuyoshi Yamori[2] and Tomoko Aizawa[3]

Date submitted: 17 December 2020; Date accepted: 20 December 2020

Covid Economics 63, 7 January 2021: 186-200

Small and medium-sized enterprises (SMEs) have been severely affected by the first wave of the COVID-19 crisis, which struck from January to July 2020. The COVID-19 crisis has had an impact on every industry, with unprecedently profound effects. It has also led to policy responses of a scale never seen before, which has curbed the number of failed SMEs. The expansion of the public credit guarantee system has contributed tremendously to SME financing. We investigated credit guarantee trends in relation to the first wave of the COVID-19 crisis and found that the spread of COVID-19 led to increased use of credit guarantees. The introduction of the new system that eliminated guarantee fees and interest costs, in particular, resulted in an explosive rise in credit guarantee use from May 2020 onwards. This enabled SMEs to borrow despite the significant decline of the macroeconomy. In terms of individual business types, there was a particularly marked rise in the usage of credit guarantees by companies in the restaurant industry, which has been catastrophically affected by the pandemic. The loans accompanied by credit guarantees are being used to make up for revenue deficits, not for profitable capital investment, so many companies will likely have difficulty paying off these loans in the future unless they successfully transform their business model for the post- COVID-19 era.

1 This work was supported by JSPS KAKENHI (Grant Numbers 16H02027, 17H02533 and 19H01505) as well as Kobe University Center for Social Systems Innovation.
2 Professor, Research Institute for Economics and Business Administration, Kobe University
3 Assistant Professor, College of Commerce, Nihon University

1. Introduction

At the start of 2020, COVID-19 began spreading around the world. In addition to the direct damage caused by infections, it also had a significant negative impact on the global economy due to the measures used to contain it (such as movement restrictions). According to the IMF's World Economic Outlook, as of January 2020, the global economy was expected to grow by 3.3% in 2020. Still, in April, this forecast was revised, reducing the growth rate significantly to -3.0%. In June, it was revised again, lowering it further to -4.9%. According to the IMF, Japan's growth forecast for 2020 was 0.7% as of January, but then fell to -5.2% in April, and further to -5.8% in June.

SMEs are especially susceptible to the adverse effects of crises such as these[1]. For example, Bartik et al. [2020] presented the tentative evaluation of the size of impacts of the COVID-19 on the U.S, which showed 43 percent of surveyed SMEs were temporarily closed. This paper analyzes the impact of the COVID-19 crisis on Japanese SMEs and examines the public financial assistance provided to SMEs, especially assistance that uses the credit guarantee system[2]. We analyze what the Japanese public guarantee system worked during the period from January to July 2020[3]. For the sake of convenience, we refer to this period as the first wave of the COVID-19 crisis.

This paper is composed of the following sections. Section 2 looks at the impact the first wave had on SMEs. Section 3 provides a brief overview of the public financial assistance available to SMEs, including credit guarantees. Section 4 analyzes the actual state of financing support provided through the credit guarantee system. One of the distinctive features of this paper is that it uses data from credit guarantee associations to explore, in-depth, how credit guarantee responded to the first wave. Section 5 presents our conclusions.

2. The impact of the first wave of the COVID-19 crisis on SMEs

(1) Sudden decline in sales

Each month, the Japan Finance Corporation conducts a survey regarding SMEs (the Monthly

[1] OECD [2020] surveyed OECD member countries' SME supporting policies. Furthermore, Gourinchas et al. (2020), analyzing SMEs in seventeen countries including Japan, estimated a large increase in the failure rate of SMEs under COVID-19 of nearly 9 percentage points without government support.

[2] Yoshino and Hendriyetty (2020) discuss wide range of Japanese government's supports for SMEs.

[3] Core and De Marco [2020] examines Italian public guarantees and Corredera-Catalán et al. [2020] examines Spanish case. Yamori [2019] provided the brief explanation of Japanese public credit guarantee scheme.

Covid Economics 63, 7 January 2021: 186-200

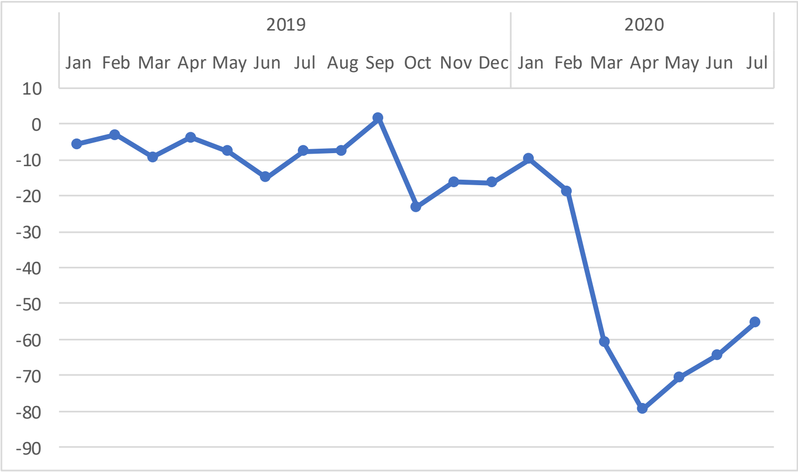
Survey on SME Trends)[4]. Figure 1, based on this survey, shows the sales DI trend during the first wave of the COVID-19 crisis. In comparison, Figure 2 shows the sales DI trend during the global financial crisis (around September 2008). The sales DI in this study is determined by subtracting the percentage of companies for which sales fell year-on-year from the percentage of companies for which sales rose year-on-year. The negative value of DI is that companies with increased year-on-year sales are less than companies with decreased year-on-year sales.

There are three notable features of the COVID-19 crisis in comparison to the global financial crisis. First, during the global financial crisis, sales DI also fell significantly, but the downturn was a steady one, starting in January 2008. However, in the case of the COVID-19 crisis, there was a sharp decline in March and April 2020, indicating a sudden crisis. This shows that, for companies, this crisis came on suddenly.

Second, the sales DI reached a low point of -50 during the global financial crisis but has fallen as far as -80 in the COVID-19 crisis. In other words, a huge number of companies have been negatively affected.

Third, this paper uses data for the period leading up to July, and during that period, the number bottomed out in April, after which it recovered nearly 30 points. However, even given that, July's sales DI is still lower than the lowest point of the global financial crisis. In other words, this crisis is a protracted one.

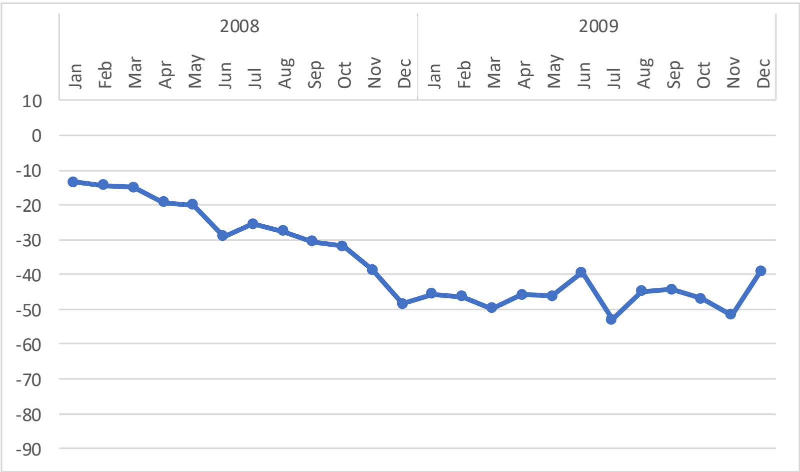
Figure 1 Sales DI during the COVID-19 crisis (seasonally adjusted)



Source: Japan Finance Corporation "Monthly Survey on Micro and Small Business Trends"

4 About 1,300 companies submitted questionnaire responses.

Figure 2 Sales DI during the global financial crisis (seasonally adjusted)



Source: Japan Finance Corporation "Monthly Survey on Micro and Small Business Trends"

(2) Differences in impact by business type

Table 1 shows the sales DI by business type in January, April, and July 2020. The restaurant industry's sales DI fell to -100 in April 2020, and all companies were negatively affected. In January 2020, the sales DI had been positive, which shows the tremendous change in sales suffered in just three months. Comparing manufacturing and non-manufacturing business segments, the table indicates that non-manufacturing business segments had a more considerable decline. However, looking at the April to July period, while conditions grew even worse for the construction industry, other industries recovered. Furthermore, while the sales DI was roughly -60 for many industries, it was -47 for the wholesaling industry, indicating a relatively small downturn.

The notable features of the impact of the first wave of the COVID-19 crisis on SME operations were that sales fell suddenly and dramatically. This state of affairs continued for an extended period, and the crisis significantly hurt all industries; the degree and timing varied by industry.

Covid Economics 63, 7 January 2021: 186-200

Table 1 Sales DI by industry

	Jan	Apr	Jul	Change (from Jan. to Apr.)	Change (from Apr. to Jul.)
All	-9.8	-79.5	-55.4	-69.7	24.1
Manufacturing	-21.0	-69.0	-60.0	-48.0	9.0
Wholesaling	-14.7	-67.8	-46.7	-53.1	21.1
Retail	-19.5	-76.9	-51.1	-57.4	25.8
Restaurant	2.2	-100.0	-60.1	-102.2	39.9
Service	-4.2	-87.4	-60.4	-83.2	27.0
Construction (order volume)	-13.5	-43.7	-50.2	-30.2	-6.5
Transportation	-7.5	-75.4	-57.8	-67.9	17.6
Non-manufacturing	-8.9	-81.0	-54.9	-72.1	26.1

Source: Japan Finance Corporation "Monthly Survey on Micro and Small Business Trends"

3. Public financial assistance for SMEs

(1) Three important policies

The severe impact of the first wave prompted the government to implement various policies. These can be divided into three categories, as shown in Table 2. The first was the expansion of direct financing by governmental financial institutions. The second was the expansion of the credit guarantee system. The third was the request that private financial institutions relax their financing and repayment terms.

Table 2 Policies related to the first wave of the COVID-19 crisis

Expansion of direct financing by governmental financial institutions
COVID-19 Special Loans
Shoko Chukin Crisis Response Loans
COVID-19 Managerial Improvement Fund Loans
Interest Subsidy Program (effectively zero-interest)
Relaxation of terms of Safety Net Loans
Expansion of credit guarantee system
Safety Net Guarantee No. 4 and No. 5
Crisis-related Guarantee
Effectively interest-free and collateral-free loans by private financial institutions
Requests to private financial institutions

Note: Created based on materials from the Ministry of Economy, Trade, and Industry website https://www.meti.go.jp/english/covid-19/index.html

Covid Economics 63, 7 January 2021: 186-200

(2) Direct financing by governmental financial institutions

Governmental financial institutions such as the Japan Finance Corporation (JFC), the Development Bank of Japan (DBJ), and the Shoko Chukin Bank (SCB) have expanded their direct financing. Of these, the JFC has played a central role[5].

Table 3 shows how the financing provided by the Micro Business and Individual Unit of the Japan Finance Corporation has changed over time[6]. From January to April, the number of loans doubled each month. In June, 209,000 loans were given, for a total of 2.4 trillion yen. On year earlier, the number of loans in June 2019 was 23,000, for a total of 152.4 billion yen. The number of loans, therefore, grew 9.0-fold, and the amount loaned increased 15.8-fold.

Table 3 Financing provided by the Micro Business and Individual Unit of the Japan Finance Corporation (2020)

	Number of Responses	Monetary amount (billion yen)
Jan	19434	106.2
Feb	32029	148.3
Mar	60791	320.5
Apr	127675	1070.0
May	183017	1701.8
Jun	208576	2402.2
Jul	120151	1417.9
Aug	55782	606.1

Source: Japan Finance Corporation website materials.

https://www.jfc.go.jp/n/company/national/g_gaikyo.html

(3) Relaxation of repayment conditions by private financial institutions

Requests to private financial institutions can be broadly divided into requests for the relaxation of the terms of repayment on existing loans and requests for the provision of new loans.

On March 6, 2020, Finance Minister and Minister of State for Financial Services Taro Aso issued a statement entitled "Cash Flow Support for Companies as Impact of COVID-19 (Novel Coronavirus) Outbreak Grows." He also requested that financial institutions "follow up carefully on circumstances at companies that have existing loans and be quick and flexible in changing loan conditions, e.g., offering concessions on principal/interest repayment." He also requested that private financial institutions submit reports on their efforts to the Financial Services Agency.

[5] The JFC is a public corporation wholly owned by the Japanese government, established on October 1, 2008.

[6] The Micro Business and Individual Unit of the JFC provides business loans to micro/small businesses and business start-ups, and educational loans to individuals who are in need of funds for school entrance fees and other educational expenses.

Covid Economics 63, 7 January 2021: 186-200

CEPR PRESS

Table 4 shows changes to bank loan terms. There were roughly 50,000 loan applications in April. Less than 1% of these were declined, and term changes were granted for most companies that applied as an examining process needs some time. The largest number of applications was in April, and in August, the number of applications had fallen to roughly 60% of April's level.

Table 4 Changes to terms of loans to SMEs (banks)

	Number of Applications	Implemented (A)	Declined (B)
Mar	26592	9963	33
Apr	49312	31725	52
May	39793	36056	63
Jun	40362	45282	445
Jul	36466	37287	616
Aug	31447	32159	460

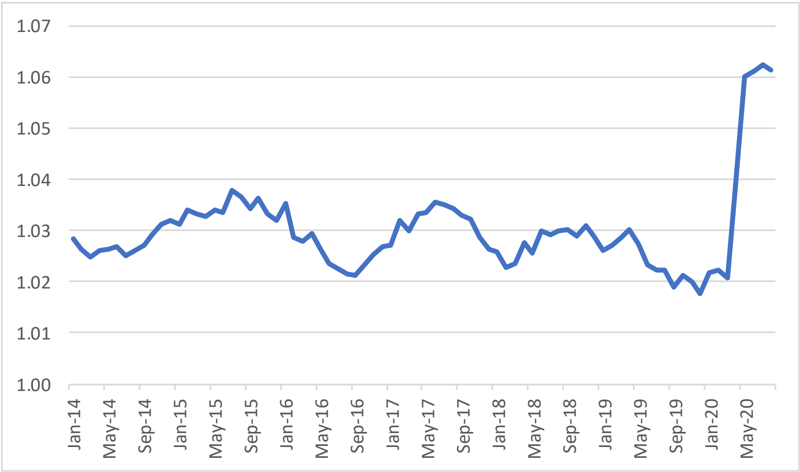
Source: The Financial Services Agency.

(4) Loans by private financial institutions

Looking at Figure 3, it is apparent that loans by private financial institutions also increased suddenly during the first wave. However, this rapid rise was supported by governmental credit enhancement. The growth of loans from May was boosted, in particular, by government subsidies that enabled financial institutions to charge no interest for the first three years and require no guarantee fees, as well as providing a grace period of up to five years.

The enhancement provided by credit guarantees is discussed in detail in Section 4.

Figure 3 Loan balances of private banks (year-on-year)



Source: The Bank of Japan.

Covid Economics 63, 7 January 2021: 186-200

4. Financing support by the credit guarantee system during the first wave of the COVID-19 pandemic

(1) Expansion of credit guarantee system

As the COVID-19 crisis grew more severe, the government expanded the credit guarantee system. Table 5 provides an overview. First, it began with Safety Net Guarantee No. 4 (for companies whose revenue declines due to sudden disasters).

However, this was not sufficient to fully address the issue, so the government put the Crisis-related Guarantee into effect in March. This Crisis-related Guarantee was introduced as part of the credit guarantee system reforms of 2018, but this was the first time it was put into action. Under this system, SMEs and micro-scale companies with rapidly falling net sales can make use of general guarantees (up to 280 million yen), the Safety Net Guarantee (up to 280 million yen), and the separate Crisis-related Guarantee (up to 280 million yen), for a total of 840 million yen. The Safety Net Guarantee No. 4 and the Crisis-related Guarantee are not included in the responsibility-sharing system's scope (in other words, banks have no risks on these loans).

Table 5 Expansion of credit guarantee system

February 28, 2020	Put Safety Net Guarantee No. 4 into operation
March 6, 2020	Emergency addition of 40 business types (inns and hotels, cafeterias, restaurants, fitness clubs, etc.) to Safety Net Guarantee No. 5 scope
March 11, 2020	Put Crisis-related Guarantee System into operation for the first time
March 11, 2020	Added 316 business types to the Safety Net Guarantee No. 5 scope
March 23, 2020	Designated 587 business types as the Safety Net Guarantee No. 5 scope for the first quarter of 2020
April 8, 2020	Designated additional business types as within the Safety Net Guarantee No. 5 scope
May 1, 2020	Implemented measures to eliminate guarantee fees for private loans

(2) Nationwide status of the use of the guarantee system

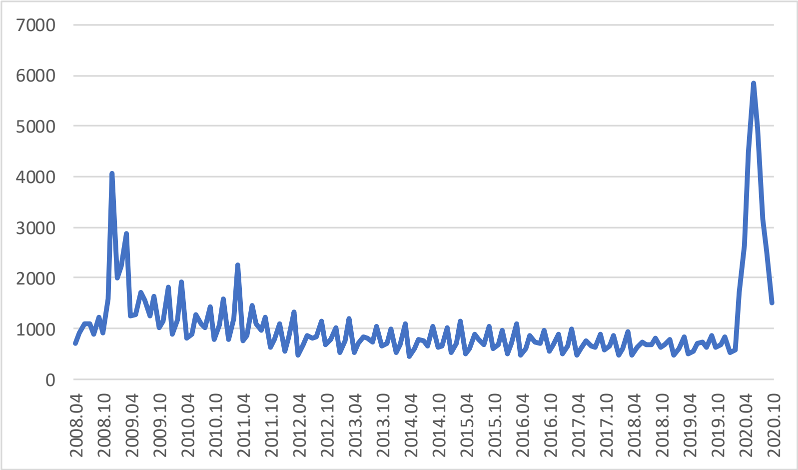
Figure 4 shows monthly changes in approved guarantee amounts by credit guarantee corporations nationwide between April 2008 and July 2020. Over two trillion yen were approved in a single month three times -- during the global financial crisis, between December 2008 and March 2009, after the Great East Japan Earthquake in March 2011, and during the first wave of the COVID-19 crisis (i.e., from April to September 2020).

Covid Economics 63, 7 January 2021: 186-200

Let's compare the impact of the global financial crisis and the first wave in terms of credit guarantee approval amounts[7]. The peak during the global financial crisis was 4.1 trillion yen in December 2008. In the four-month period from December 2008 to March 2009, the total was 11.2 trillion yen. The peak during the first wave was 5.8 trillion yen in June 2020. In the four-month period from April to July 2020, the total was 17.9 trillion yen. The peak month of the first wave was 1.4 times larger than that of the global financial crisis, and the four-month period around the peak was 1.6 times larger. The impact of the COVID-19 crisis is clearly without precedent.

Figure 4 Credit guarantee approval amounts

(Unit: billion yen)



Source: Japan Federation of Credit Guarantee Corporations (JFC)

Figure 5 shows monthly changes in subrogation. Subrogation means that a credit guarantee corporation repays a financial institution on behalf of a borrower unable to repay its debt. Therefore, it can be considered a proxy variable for the number of company bankruptcies. During the global financial crisis, from December 2008 to December 2009, there were multiple cases of subrogation in excess of 100 billion yen within a single month. After December 2009, there were sudden increases in subrogation in March[8], but the number declined thereafter. In other words, during the global financial crisis, the number of subrogations increased at almost the same time as

[7] Yamori [2015] and Yamori et al. [2013] analyzed how the Japanese credit guarantee system responded to the global financial crisis.

[8] Japanese firms' fiscal years usually end on March 31.

Covid Economics 63, 7 January 2021: 186-200

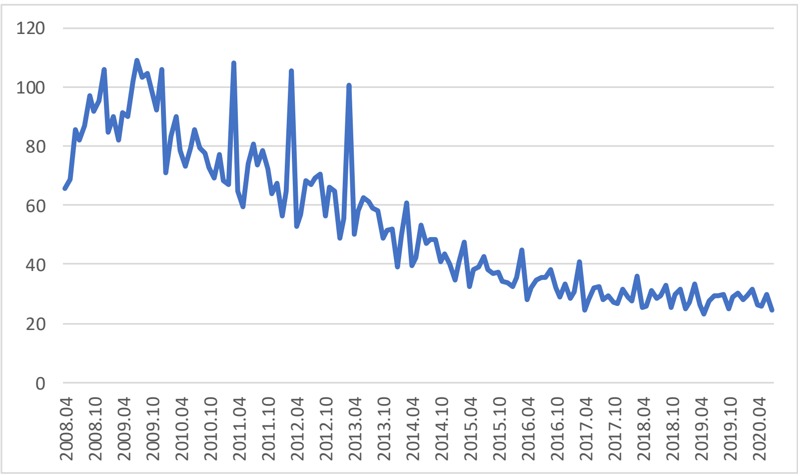
Covid Economics 63, 7 January 2021: 186-200

the crisis itself, and the number of subrogations remained high for roughly a year from the peak guarantee usage period (December 2008 to March 2009).

In the case of the first wave, there were no notable changes in the number of subrogation through July 2020, which is markedly different than the situation during the global financial crisis. Compared to the global financial crisis, there has been powerful financing support, which can be considered to have successfully kept down the number of bankruptcies.

Figure 5 Subrogation amounts

(Unit: billion yen)



Source: Japan Federation of Credit Guarantee Corporations (JFC)

(3) Usage by business type

Unfortunately, nationwide monthly data broken down by business type has not been released. Of the major credit guarantee corporations, Hyogo Prefecture Credit Guarantee Corporation (CGC), Aichi Prefecture CGC, and Nagoya City CGC have released monthly data broken down by business type. Both Aichi-Prefecture CGC and Nagoya City CGC are in Aichi Prefecture. To get the whole figures of Aichi Prefecture, we add figures of these two CGCs. So, let us look at usage by business type using this data.

In March 2020, year-on-year approved guarantee amounts rose suddenly for all business types in Hyogo Prefecture, as shown inTable 6. In particular, approved guarantee amounts for restaurants rose 315.6% year-on-year in March 2020 and 1144.7% year-on-year in April 2020, far more than any other business type. The growth level declined from May onwards, showing that the restaurant industry required funding from an early stage. In July 2020, the growth rate of approved guarantee amounts was the highest for the service industry, but the growth rates declined across all business types.

Looking at approved guarantee amounts by business type in Aichi Prefecture (Table 7), in May 2020, the approved guarantee amount for restaurants rose 2055.8% year-on-year. Amounts were roughly ten times greater than the same month of the previous year for most business types in the table.

To recapitulate, in Hyogo Prefecture, the approved guarantee amounts rose rapidly for the restaurant industry in April. They peaked in May or June for other industries, which shows that the restaurant industry was affected to an extremely great degree from an early stage. Comparing Hyogo Prefecture and Aichi Prefecture, credit guarantee usage by the restaurant industry in Aichi Prefecture peaked in May, later than in Hyogo Prefecture. There were also differences in the heights of these peaks. The peak in Aichi Prefecture was in May, at over 20 times the same month of the previous year, while in Hyogo Prefecture, it was in April, at 11 times that of the same month of the previous year. There are several possible reasons for this, such as a difference in infection growth, in the financial condition of local firms, or in the local economic environment. This will require more in-depth exploration in the future.

Table 6 Changes in approved guarantee amounts by business type in Hyogo Prefecture (year-on-year)

	Jan	Feb	Mar	Apr	May	Jun	Jul
Manufacturing	116.6	91.1	162.8	260.0	636.3	578.3	522.2
Construction	111.0	104.6	165.8	235.1	478.8	527.8	424.1
Wholesaling	115.1	89.5	194.6	373.8	624.2	467.3	447.4
Retail	93.2	106.5	180.2	258.8	564.1	542.2	348.2
Restaurant	104.2	63.9	315.6	1144.7	1084.5	896.5	458.1
Real estate	90.2	124.8	239.0	313.0	382.9	459.3	331.7
Transportation and warehousing	120.6	76.8	217.5	257.4	620.6	618.9	435.3
Service	124.2	79.7	183.4	267.9	587.3	767.3	587.2

Source: Credit Guarantee Corporation of Hyogo-ken “Guarantee Conditions.”

Covid Economics 63, 7 January 2021: 186-200

Table 7 Changes in approved guarantee amounts by business type in Aichi Prefecture (year-on-year)

	Jan	Feb	Mar	Apr	May	Jun	Jul
Manufacturing	90.2	91.7	287.5	602.2	1051.8	933.1	888.1
Construction	115.8	90.0	281.2	659.8	1116.8	795.1	776.4
Wholesaling	104.6	81.3	322.4	533.2	1034.2	702.1	714.2
Retail	112.7	96.3	341.8	568.7	907.2	773.6	604.5
Restaurant	66.3	135.3	528.3	1166.4	2055.8	1103.1	1156.3
Real estate	109.5	182.7	312.8	626.2	805.7	526.2	539.3
Transportation and warehousing	91.0	61.6	350.7	575.0	1218.1	576.0	793.0
Service	103.6	86.7	304.8	527.2	1104.3	1073.8	1057.3

Source: Aichi Prefecture Credit Guarantee Corporation “Aichi Guarantee Report” and “Business Overview Monthly Report,” Nagoya City Credit Guarantee Corporation “Business Overview Report.”

(4) Usage objectives in Hyogo Prefecture and Aichi Prefecture

The credit guarantee corporations in Hyogo Prefecture and Aichi Prefecture both disclose whether money was borrowed for capital investment (equipment funds) or operating capital (operation funds).

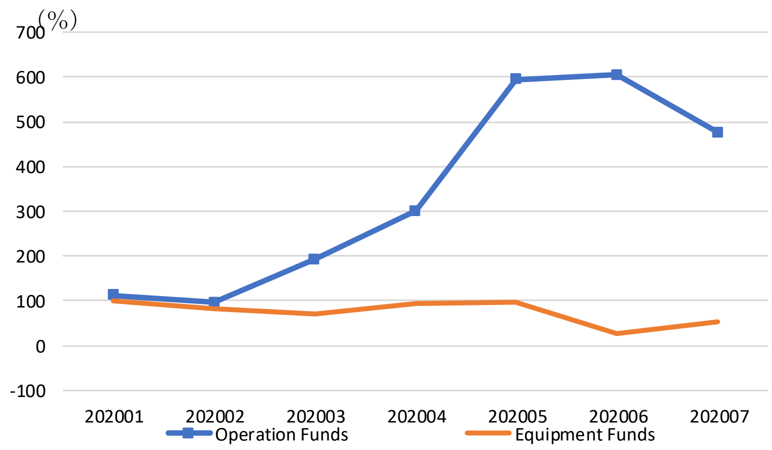
Looking at data from Hyogo Prefecture, there was little year-on-year change in capital investment through May, and in June, the amount fell year-on-year. Approved guarantee amounts for operating capital, on the other hand, rose rapidly from March, peaking in June, and the growth rate stopped increasing in July.

In Aichi Prefecture, like Hyogo Prefecture, approved guarantee amounts for operating capital rose year-on-year from March. However, unlike Hyogo Prefecture, the growth rate peaked in May 2020, and the growth rate itself was higher. In June 2020, the growth rate for approved capital investments was 118.6% but was negative during other months, indicating an economic environment in which funds could not be directed toward capital investment.

As the above shows, the large number of funds suddenly procured through the credit guarantee system during the COVID-19 crisis were primarily used as operating capital. Funds procured through borrowing with credit guarantees were used to pay employee wages and rent. These funds were necessary to keep companies in operation, but, unlike capital investment, they do not generate new cash flow. Financial institutions must support borrowers to enable them to generate profits and pay back the money they borrowed.

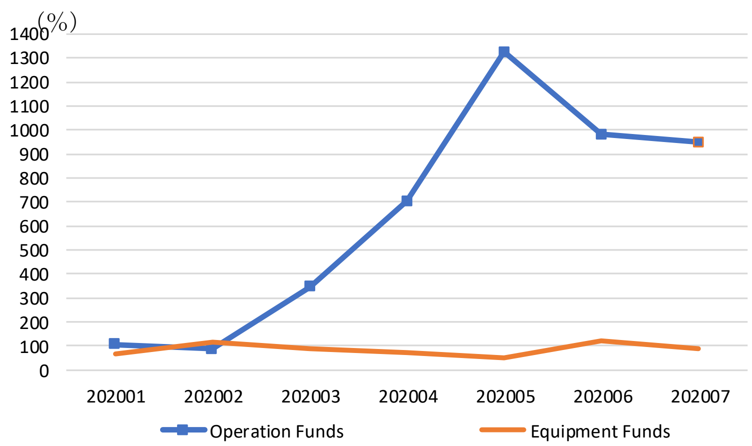
Covid Economics 63, 7 January 2021: 186-200

Figure 6 Changes in approved guarantee amounts by fund usage purpose in Hyogo Prefecture (year-on-year)



Source: Credit Guarantee Corporation of Hyogo-ken "Guarantee Conditions"

Figure 7 Changes in approved guarantee amounts by fund usage purpose in Aichi Prefecture (year-on-year)



Source: Aichi Prefecture Credit Guarantee Corporation "Aichi Guarantee Report" and "Business Overview Monthly Report," Nagoya City Credit Guarantee Corporation "Business Overview Report"

5. Evaluation and future challenges

The amount of credit guarantees provided during the first wave of the COVID-19 crisis have far exceeded those of the global financial crisis[9]. This has succeeded in supporting the financing of SMEs. As a result, as of July 2020, there has been a consistently low level of subrogation, and this approach has prevented a rise in bankruptcies.

The rapid growth of lending and the expansion of the credit guarantee amounts that make this possible have provided financing for numerous SMEs. Still, borrowing companies will now need to repay a tremendous amount of money. For the restaurant industry, in particular, the first wave had a significant impact, but companies cannot go back to operating as they did before the pandemic, so they must produce profits and repay loans using new methods of operation. This will be a tough challenge. Financial institutions must support the business reforms of companies.

The rapid increase in lending in a short period has also produced a sudden rise in the number of companies that financial institutions should support. There are concerns that they will exceed the support capacities of those financial institutions. It will be essential to coordinate with experts such as tax accountants and collaborate with government agencies.

Credit guarantees back many of the loans provided by private financial institutions during the COVID-19 crisis. Credit guarantee corporations will entirely bear losses from failure to repay these loans. There is, therefore, a risk that financial institutions will not have incentives to provide full-fledged support to companies. Furthermore, grace periods may be up to five years long, so the government provides subsidies that enable companies to pay back only interest for the first five years and have effective zero interest rates for the first three years. This will make it difficult for financial institutions to realize when borrowers' businesses are struggling. Furthermore, Gobbi et al. [2020] pointed out that banks prefer not to roll over the debt and foreclose guaranteed loans maturing close to the expiration date of the guarantee scheme if the borrowers are in financial difficulties. For financial institutions to actively keep aware of borrowers' conditions, monitoring by supervisory authorities will also need to be reinforced.

References

Bartik, Alexander; Marianne Bertrand; Zoe Cullen; Edward Glaeser; Michael Luca; and Christopher Stanton, [2020] "How are small businesses adjusting to Covid-19? Early evidence from a survey," NBER Working Paper 26989.

[9] Corredera-Catalán, et al. [2020], analyzing Spanish credit guarantee scheme, concluded the use of credit guarantee was very cost effective to improve SMEs' access to financing during the COVID-19 crisis. However, it takes a considerable amount of time to determine the final cost of the credit guarantee.

Core, Fabrizio and Filippo De Marco, [2020] “Public Guarantees for Small Businesses in Italy during COVID-19,” SSRN 3604114. https://ssrn.com/abstract=3604114 or http://dx.doi.org/10.2139/ssrn.3604114.

Corredera-Catalán, Felix; di Pietro, Filippo and Trujillo-Ponce, Antonio, [2020] Post COVID-19 SME Financing Constraints and the Credit Guarantee Scheme Solution in Spain: A Note” SSRN 3732460 : https://ssrn.com/abstract=3732460 or http://dx.doi.org/10.2139/ssrn.3732460

Gobbi, Giorgio; Francesco Palazzo; and Anatoli Segura [2020] “Unintended effects of loan guarantees during the Covid-19 crisis,” April 2020, VOX, CEPR Policy Portal. https://voxeu.org/article/unintended-effects-loan-guarantees

Gourinchas, Pierre-Olivier; Kalemli-Özcan, Şebnem; Penciakova, Veronika; and Sander, Nick [2020] "COVID-19 and SME Failures", National Bureau of Economic Research Working Paper Series 27877.

OECD [2020] “Coronavirus (COVID-19): SME Policy Responses,” July 2020. https://read.oecd-ilibrary.org/view/?ref=119_119680-di6h3qgi4x&title=Covid-19_SME_Policy_Responses

Yamori, Nobuyoshi, [2015] “Japanese SMEs and the Credit Guarantee System after the Global Financial Crisis,” *Cogent Economics and Finance* 3: 1002600 pp.1-18 http://dx.doi.org/10.1080/23322039.2014.1002600

Yamori, Nobuyoshi, [2019] “Japan’s Credit Guarantee System Reform of 2017 and New Functions of Credit Guarantee Associations,” in Yamori, Nobuyoshi; Yoshihiro Asai; Masao. Ojima; Kei Tomimura; Koji Yoneda [2019] *Roles of Financial Institutions and Credit Guarantees in Regional Revitalization in Japan*. The Springer Briefs in Economics Book Series (BRIEFSECONOMICS) and Kobe University Social Science Research Series, Springer, Singapore. pp.1-92.

Yamori, Nobuyoshi; Kazumine Kondo; Kei Tomimura; Yuko Shindo; Kenya Takaku, [2013] “Japanese Banking Regulations and SME Finance under the Global Financial Crisis,” *Japanese Journal of Monetary and Financial Economics* 1(1), pp.59-90.

Yoshino, Naoyuki and Nella Hendriyetty [2020] “The COVID-19 Crisis: Policy Recommendations for Japan” The Economists’ Voice 17(1).