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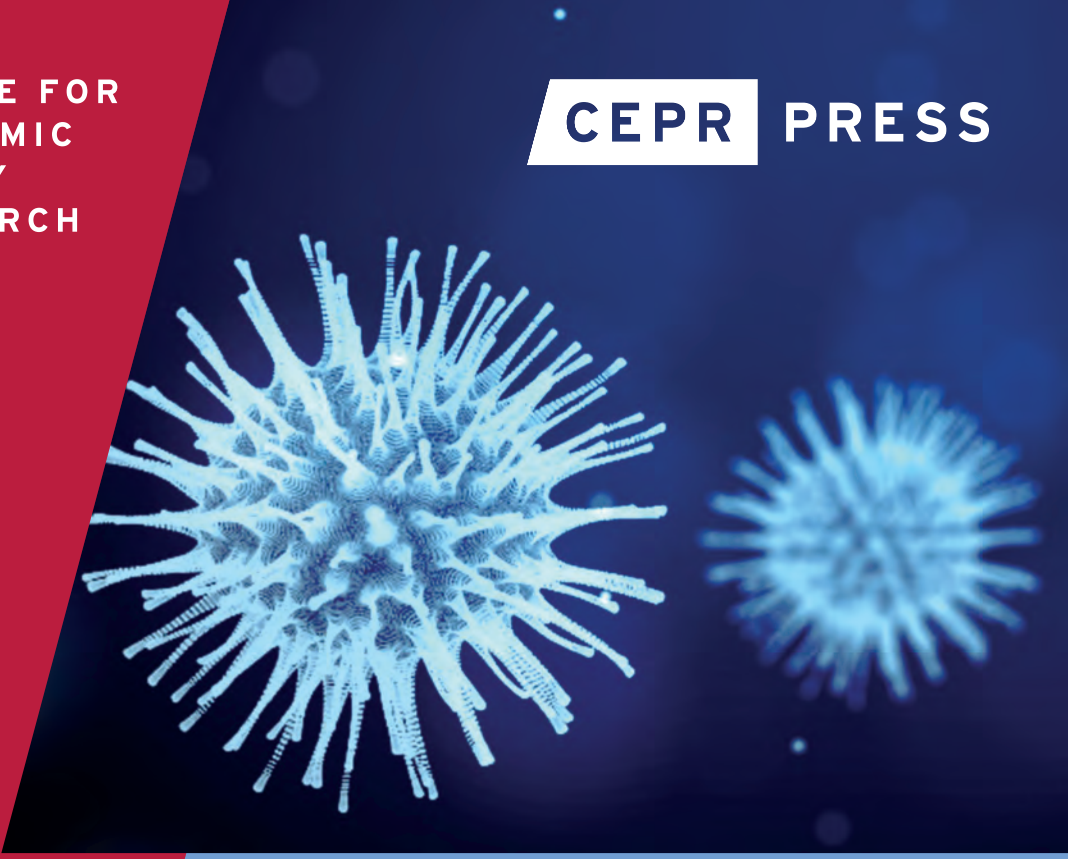

COVID ECONOMICS

VETTED AND REAL-TIME PAPERS

ISSUE 32
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Covid Economics
Vetted and Real-Time Papers

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

Founder: Beatrice Weder di Mauro, President of CEPR
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Contact: Submissions should be made at https://portal.cepr.org/call-papers-covid-economics. Other queries should be sent to covidecon@cepr.org.

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Ethics

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

Submission to professional journals

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

American Economic Review

American Economic Review, Applied Economics

American Economic Review, Insights

American Economic Review, Economic Policy

American Economic Review, Macroeconomics

American Economic Review, Microeconomics

American Journal of Health Economics

Canadian Journal of Economics

Economic Journal

Economics of Disasters and Climate Change

International Economic Review

Journal of Development Economics

*Journal of Econometrics**

Journal of Economic Growth

Journal of Economic Theory

*Journal of the European Economic Association**

Journal of Finance

Journal of Financial Economics

Journal of International Economics

*Journal of Labor Economics**

Journal of Monetary Economics

Journal of Public Economics

Journal of Political Economy

Journal of Population Economics

*Quarterly Journal of Economics**

Review of Economics and Statistics

*Review of Economic Studies**

Review of Financial Studies

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

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Spread of COVID-19 and telework: Evidence from Japan[1]

Toshihiro Okubo[2]

Date submitted: 23 June 2020; Date accepted: 23 June 2020

This paper investigates telework in Japan during the spread of COVID-19. Using unique survey data, we show which occupations are suited to telework. Our results show that the use of telework increased from 6% in January to 10% in March and reached 17% in June 2020, although remarkably the level is still lower than that of other developed countries (e.g. 37% in Europe). Furthermore, we found that some occupations such as services with face-to-face communication are the most unsuitable for telework. They tended to suffer from negative impacts, such as largely reduced incomes and working hours.

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1 I thank Keio University for funding and Naoto Mikawa for research assistance.
2 Professor, Faculty of Economics, Keio University and visiting research fellow, NIRA.

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1 Introduction

COVID-19 has spread throughout the world since January 2020, and people have been asked to stay at home and refrain from going out. Telework has emerged as an effective means of enabling people to keep working and preventing the spread of infectious diseases.

This paper investigates telework in Japan during the spread of COVID-19. The Japanese government asked all workers to utilize telework from home from February 2020. Then, the central government declared a national emergency on April 7, 2020, which continued until late May, and strongly suggested that all workers utilize telework from home, without the government enforcing a lock-down or penalties. It suggested some services such as retailers, hotel accommodation and restaurants to refrain from running their businesses. As a result, while economic activity was slowed down, the economy did not stop: the public transport system worked as normal and some people were allowed to commute. Importantly, the Japanese government has at no time enforced these restrictions through laws and penalties; instead, it has encouraged a so-called “soft” lock-down, unlike other developed countries.

The crucial issue is how many jobs can be carried out using a telework system. It is known that telework is suitable for some industries and occupations. Dingel and Neiman (2020) and Boeri et al. (2020) identified which occupations are potentially suitable for remote work. Telework involves numerous problems and difficulties as regards firm organization, work environment and individual workers in many industries and occupations. Furthermore, Mongey and Weinberg (2020) found that workers in occupations unsuitable for remote work tend to be less educated and to have lower incomes.

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In this paper, by using a survey on telework for the Japanese workers conducted by Keio University and NIRA, we investigate which occupations are suited to telework and discuss what problems are associated with telework in Japan. We found that the utilization rate of telework substantially increased from 6% in January, to 10% in March and to 17% in June 2020. Although the government suggested all workers should utilize telework from home, the use of telework still remains lower than in other countries.[2] For example, Eurofound (2020) reported 37% of workers began telework in Europe. Bick et al. (2020) found that number of those who worked from home in the United States went from 8% in February to 35% in May.[3]

We also found that the rate of utilization of telework varies across industries, occupations, regions and firm size. In the Greater Tokyo area, the rate of telework is much higher than the national average (33% as of June 2020). On the other hand, telework is hard to do in some occupations such as face-to-face services (e.g. food and drink, accommodation). In spite of this, these industries have been requested to refrain from doing business to aid the containment of COVID-19. Even though the government has asked people to adopt telework, workers in these industries cannot physically undertake telework. We found that more than half of workers in these service industries had reduced incomes and working hours.

2 COVID-19 and Telework in Japan

The COVID-19 virus commenced its worldwide spread in February 2020, and was

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[2] The largest shares of workers who began to work from home are around 60% in Finland and above 50% in Luxembourg, the Netherlands, Belgium and Denmark.

[3] https://www.eurofound.europa.eu/sites/default/files/ef_publication/field_ef_document/ef20058en.pdf Brynjolfsson et al. (2020) reported that around half of people were working from home in the United States. Bick et al. (2020) stated that the US level went from 8% in February to 35% in May 2020.

declared a pandemic in March 2020. Against this background, Japan is an exceptional case. The number of infections and deaths in Japan has been much lower than in the United States and Europe.[4] Japan has not completely closed its national borders nor locked down its cities. Rather than instituting a complete lock-down or attempting to control the population with penalties, the government's policy response has been to request people to refrain from leaving their houses without penalties and punishment (so-called "soft" lock-down), and to encourage telecommuting and telework. This is unheard of among the developed nations, with the exception of Sweden.[5]

At the same time, Japan is known to have the lowest use of telework among the developed countries. According to the Ministry of Land, Infrastructure, Transport and Tourism (MLIT) (2020), 16.6% of workers in Japan used telework in November 2019. In Japan, despite strong promotion of telework by the government and companies in recent years, the utilization rate has remained low. Therefore, Japan is an interesting case to investigate how the shock of the COVID-19 pandemic has led to the promotion of telework.

Possible reasons for the lower rate of telework persisting more in Japan than other countries are: 1) epidemic situation, 2) "soft" lock-down and 3) the Japanese corporate culture. First, Japan has seen much smaller numbers of patients and deaths than other OECD countries. Thus, this reduced the fears of workers about the epidemic risk more so than in other countries and thus they do not have a strong incentive to undertake telework. Second, the Japanese government did not institute a lock-down and thereby enabled economic activities to continue. The government just suggested that workers should use

[4] https://www.worldometers.info/coronavirus/country/japan/
[5] https://www.japantimes.co.jp/opinion/2020/04/14/commentary/japan-commentary/coronavirus-japans-constitution/#.Xu3jXUUzYcA

telework without imposing any penalties. Japan's "soft" lock-down is much less stringent than that of other countries. Third, only 11% of Japanese companies and enterprises introduced a telework system in Japan in 2019 (MLIT, 2020). Before the spread of COVID-19, most Japanese companies and enterprises had no experience of telework. Thus, working environments in many companies were not suited to telework, e.g. IT environment, employment system (flextime system) and wage system. In addition, the Japanese corporate culture emphasized the importance of working together in one place, paper-based documents and face-to-face communication.

Telework has recently attracted attention as a means of improving work styles and quality of life (e.g. Gajendran and Harrison, 2007; Dutcher, 2012; Bloom et al., 2015). Although the mechanisms that will fully enable telework are not yet in place, it is regarded as a means of increasing labor productivity and work efficiency by reducing commuting and increasing flexibility in working hours, giving workers more time for their daily lives.

As opposed to previous efforts to promote telework to enable better working styles, telework is currently promoted as a measure against the spread of infectious diseases. The Japanese government has requested citizens to exercise restraint in leaving their homes, in addition to calling for services such as restaurants and retail stores to restrict their activities or to close entirely. Instead, the Japanese government has asked all businesses to promote telework. A number of cases can be pointed to in which telework has been introduced at the request of employers. It may also be the case that even if some occupations and industries are not suited to telework, many workers have been forced to work in this way. It is extremely difficult to balance economic activities with measures against infectious diseases while dealing with institutional and environmental problems.

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3 Survey Results

3.1 Telework

Keio University and NIRA conducted a survey on telework in March and June 2020, entitled "Questionnaire Survey on the Effects of the Spread of COVID-19 on Telework-based Work Styles, Lifestyle, and Awareness." The sample was workers living in Japan. The sample size in the first wave (March) was 10,516 and 8,407 out of 10,516 answered in the second wave (June). The questionnaire asks about the employment status, living situation and awareness of workers as of January, March and June 2020.[6]

Here, we define telework: in general, telework refers to a way of working that is not bound by time and space, using information and communications technology (ICT). In our survey, telework is defined as working at a specific place (at home or in a public facility) for a specific number of hours using ICT. Our definition therefore does not include the use of ICT devices at locations such as stations, airports, public transportation (buses and trains) or the premises of business partners.

First of all, our survey found that the national average telework utilization rate was 10% in March and 17% in June, as compared with 6% in January. The utilization rate increased by 11 percentage point only in the course of five months. This is lower than that shown in the survey by MLIT (2020) of 16.6% as of November 2019 due to MLIT's broader definition of telework. MLIT's definition includes the number of workers who use ICT devices at public transportation spaces, public transportation and the premises of business partners.

[6] The questionnaire survey and data analysis were conducted by Toshihiro Okubo, Kiwamu Kato, Senior Architect for Future Corporation, and Atsushi Inoue, Kozue Sekijima, and Hironari Masuhara of NIRA. See also Okubo(2020) and Okubo and NIRA (2020a; 2020b). The survey was conducted in April 1st to 6th 2020 as well as June 5th to 18th 2020 on website-base by Nikkei Research, Co..

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The survey revealed three main findings regarding telework.

(1) There are more teleworkers in the information service industries and fewer among those involved in face-to-face service work and among manual laborers.

With regard to industry, communications and information services (46%) and information services and research (44%) have the highest telework utilization rates, while restaurants and accommodation (5%) and medical care and welfare (3%) have the lowest rates (Figure 1).

Turning to occupation, data processing workers (49%), management consultants (46%) and researchers (39%) display high rates of utilizing telework, while doctors, dentists, veterinarians and pharmacist (5%), carrying, cleaning, packaging and related workers (3%), food/drink and customer service workers (2%), manufacturing process industry workers (2%), and workers in family life support (1%) display low rates (Figure 2). This indicates that industries and occupations related to information have a comparatively high rate of the utilization of telework, while telework is not suited to face-to-face services and manual labor.

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Figure 1: Rate of utilization of telework by industry category.

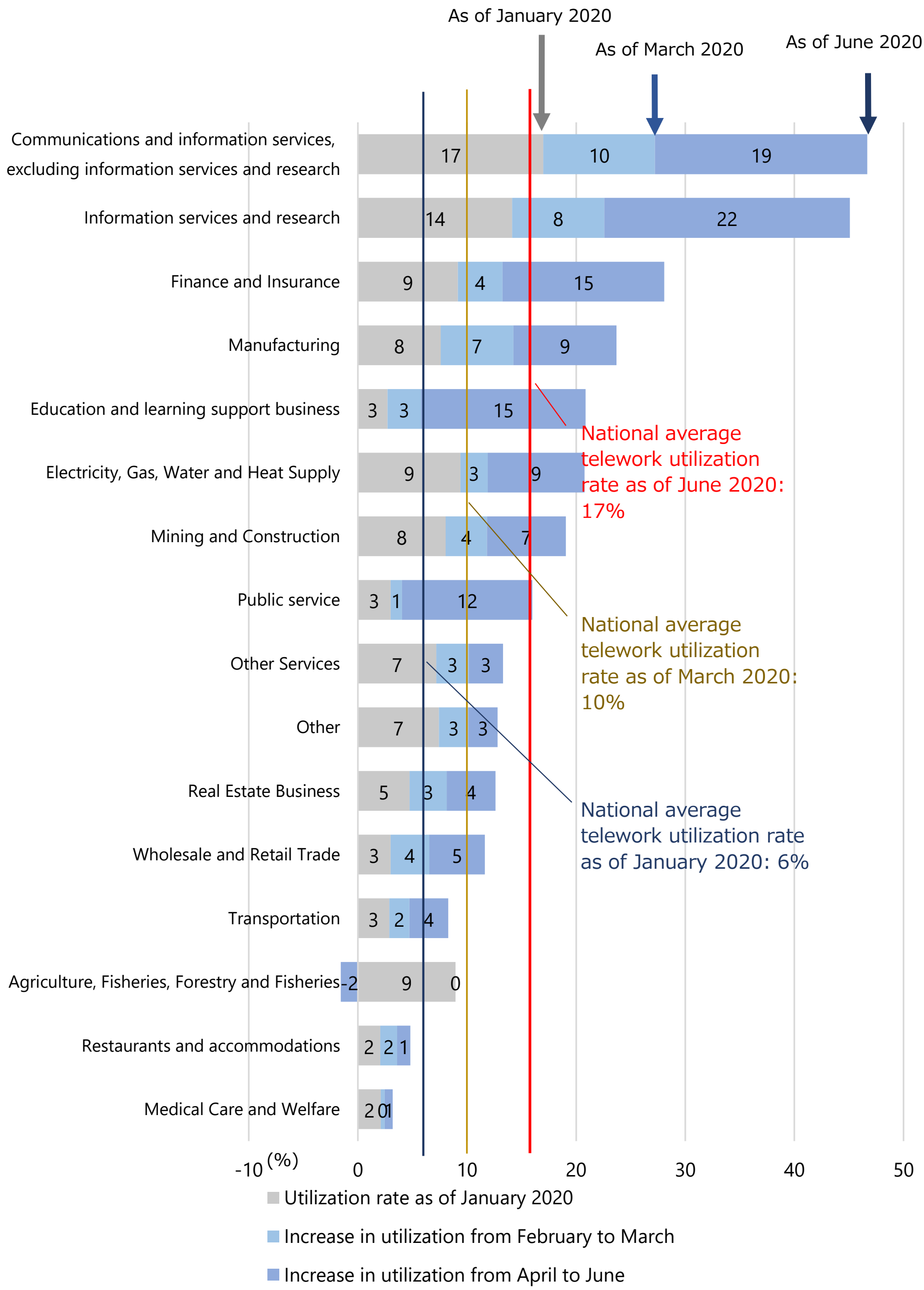
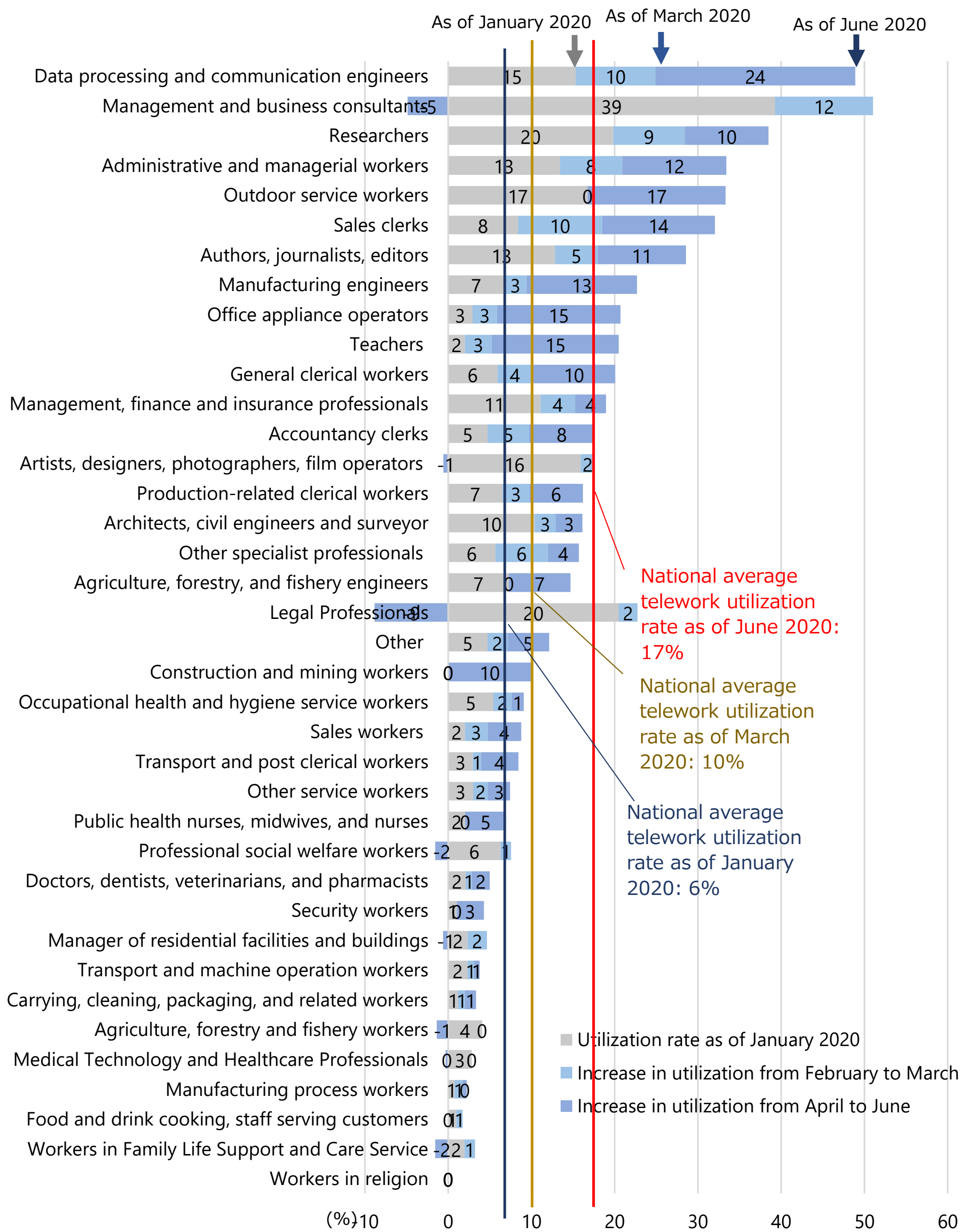


Figure 2: Rate of utilization of telework by occupational category.



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(2) There are more teleworkers in urban areas and fewer in rural areas

The rate of utilization of telework differs depending on region. Figure 3 shows the telework utilization rate by prefecture. Tokyo has the highest rate at 33%, followed by Kanagawa (26%), Saitama (25%) and Chiba (22%). Telework between January and June 2020 grew in Tokyo. The Tokyo metropolitan area features a concentration of large numbers of white-collar workers in corporate headquarter offices and service industries, all of which are well suited to telework.

Appendix Maps 1 and 2 focus on the Greater Tokyo (Tokyo, Chiba, Saitama and Kanagawa). The maps display the telework utilization rate at municipality level as of March 2020. Municipalities in central Tokyo see the highest utilization rates of telework in both maps. High values in Map 1 (based on place of work) are geographically more concentrated in central Tokyo than are those in Map 2 (based on place of residence). This indicates that people who live in the suburbs of Tokyo and commute to the central Tokyo area tend to use telework.

On the other hand, as shown in Figure 3, utilization rates are generally low in rural areas due largely to industrial structure. In prefectures that rely on agriculture, forestry and fisheries, it is less likely that telework is used.

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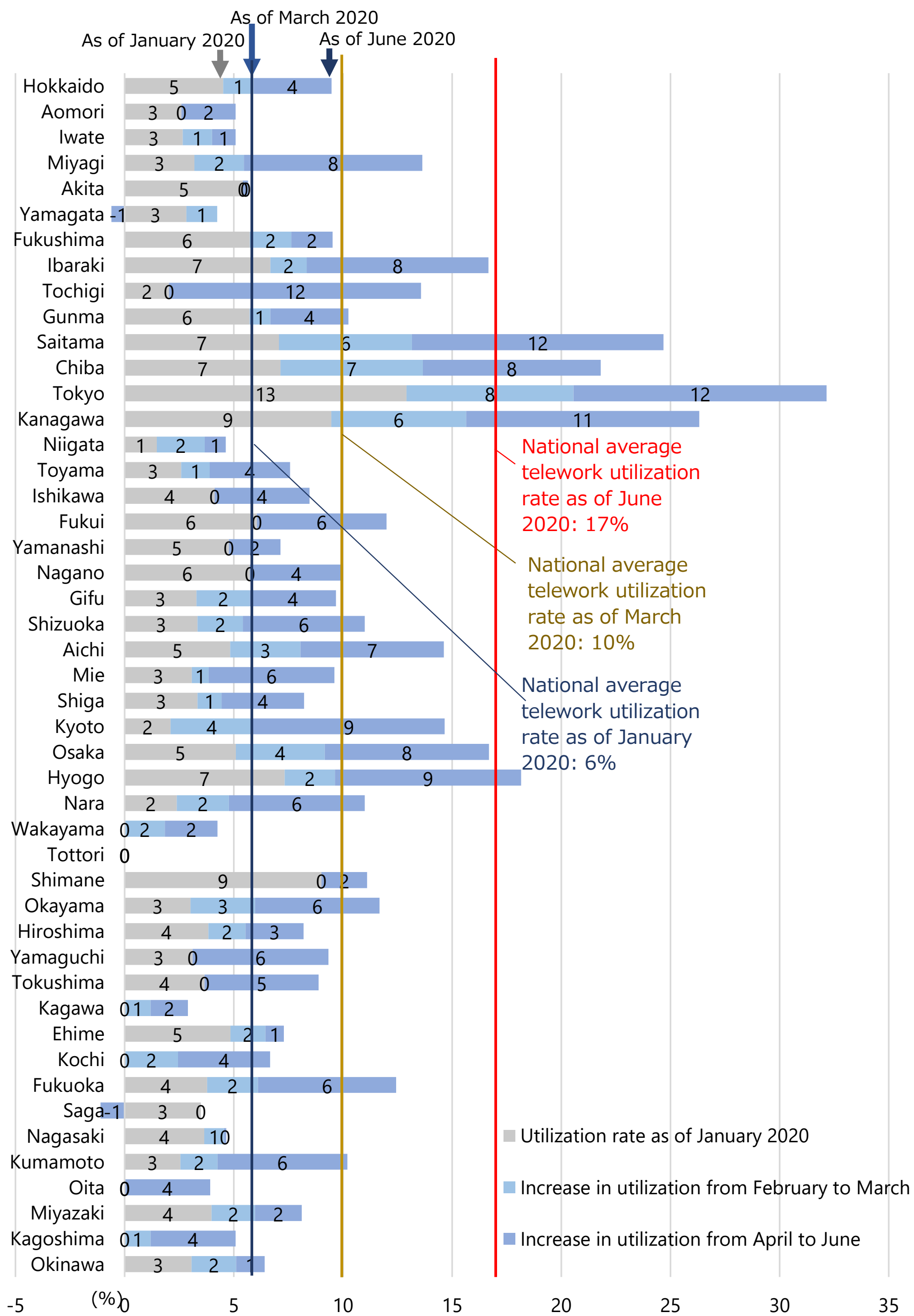
Figure 3: Telework utilization rate by prefecture (residential basis).



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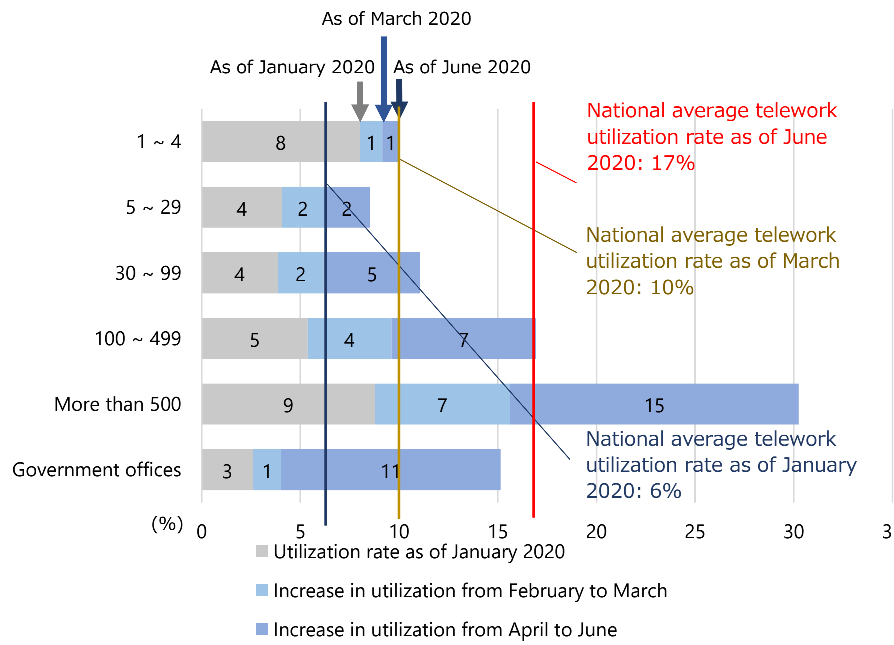
(3) There are fewer teleworkers in small and medium-sized enterprises

With regard to firm size, the rate of utilization of telework increases as the number of employees increases, reaching 31% in firms with 500 or more employees (Figure 4). The rate of utilization in firms with 5 to 29 employees is the lowest at 8%. The larger the firm, the more employees who commenced telework from January, March or June 2020. This is because large firms tend to have telework systems and enough ICT. On the other hand, the utilization of telework among SMEs remains the same, because the SMEs cannot afford to make an investment in ICT.

Figure 4: Telework utilization rate by enterprise size.



3.2 Three types of impediments to telework

As we discussed, the rate of telework use is lower than for other countries even during the spread of the virus. One of the reasons stems from impediments in the working environment. Now our survey asked workers about what problems and impediments workers have encountered while undertaking telework during the COVID-19 pandemic (Table 1). Impediments and problems were classified into three categories.

The first category includes a set of survey questions on problems related to firm organization. The impediments involve lack of file sharing, electronic payments, digitization of data and documents, and information security. The second category is a set of survey questions on the working environment. The questions address whether computers and peripheral devices are available at home, whether or not their children disturb them while they are teleworking, whether or not their colleagues and business partners can understand the progress and outcomes of work, and whether or not they receive a proper evaluation of their own outcomes. The third category is a set of survey questions on lack of ability of the individuals, e.g. their lack of ICT knowledge and feelings of anxiety.

As shown in Table 1, many problems and impediments that workers perceive do not always correspond with the suitability or unsuitability for telework of various occupations and industries. Table 1 shows the percentage of people for whom their job is suitable or unsuitable for telework (the first column), and the percentage of people experiencing impediments or problems within the three categories (the second to the fourth set of columns). In each survey question, gray cells indicate occupational categories with higher rates of problems facing the use of telework, and blue cells indicate occupational categories with lower rates.

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First, many workers in electricity, gas and water provision industries see many problems in all three impediment categories. A high percentage of workers in financial and insurance businesses also had many serious problems with telework. However, these industries saw relatively high utilization of telework as of March and June 2020, as shown in Figure 1. Despite their high utilization of telework, workers felt their jobs were unsuitable for telework (the first column of Table 1) as well as suffering from three types of impediments. Since government regulations in these industries are relatively stringent, stringent information security and heavy administrative procedures are likely to be impediments for teleworking.

Next, many workers in service industries such as food, restaurant and accommodation, education and medical industries felt that their tasks are unsuitable for telework (the first column of Table 1). In parallel, the telework utilization rate was extremely low in these industries (Figure 1). However, these industries face a few impediments in the three categories. In other words, it would be difficult for individuals in these industries to telework in the current circumstances, but it would be possible for management and human resources personnel to telework partially. Moreover, technological progress could solve problems. For example, new services of remote surgery or online diagnosis using robots or virtual reality (VR) will promote telework in the near future.

While a comparatively high percentage of workers in the real estate, mining and construction industries believe that their jobs are suited to telework, the actual use of telework is not high in these industries (Figure 1). In spite of there being a few impediments in their firm or organization, a considerable number of workers see some problems and impediments in their own ICT knowledge. It might be necessary to

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implement reforms such as upgrading the skills of the workers themselves.

Table 1: Problems and Impediments of Telework by Industry

		Related to company and organizational systems						Related to the working environment					Related to individual ability or awareness		
Industry	Telework does not suit one's profession or occupation	No external access to company or office servers or systems	No environment for sharing files	The environment for electronic approval, document processing and accounting is not in place	Materials and documents are not or cannot be digitized	Being burdened with one's own communications costs	Concerns about information security and information management	Difficulty in evaluating results from companies, customers, business partners, etc.	Difficulty in understanding the progress of work by other employees, customers, and business partners	Necessity of taking care of children and family when at home	PCs, printers, desks, etc., are not available for work at home	The Internet and communications environment at home is not adequate	Conducting meetings on the Web	Anxiety and discomfort about not being able to talk with colleagues	Insufficient knowledge of ICT (information and communication technology)
Information services and research (n = 332)	14%	17%	12%	12%	11%	9%	13%	7%	11%	6%	12%	8%	8%	10%	8%
Communications and information services, excluding	15%	16%	11%	12%	12%	11%	15%	10%	12%	11%	14%	9%	9%	12%	11%
Mining and construction (n = 608)	18%	13%	13%	11%	12%	10%	13%	9%	11%	9%	16%	9%	8%	13%	11%
Real estate business (n = 294)	18%	9%	12%	12%	11%	11%	12%	9%	10%	9%	15%	9%	6%	9%	13%
Transportation (n = 487)	19%	12%	10%	9%	11%	9%	10%	4%	8%	7%	10%	6%	5%	7%	9%
Other services (n = 1,681)	19%	10%	10%	10%	10%	7%	10%	6%	9%	6%	9%	6%	5%	8%	8%
Agriculture, forestry and fisheries (n = 123)	19%	10%	15%	15%	13%	12%	13%	11%	9%	12%	8%	11%	9%	11%	12%
Other (n = 483)	20%	9%	10%	12%	10%	7%	12%	8%	7%	6%	9%	5%	4%	10%	8%
Wholesale and retail trade (n = 1,239)	21%	11%	11%	12%	12%	8%	11%	8%	8%	7%	11%	5%	5%	8%	9%
Manufacturing (n = 1,742)	24%	14%	13%	15%	13%	8%	13%	10%	13%	9%	15%	8%	8%	13%	11%
Public service (n = 468)	25%	21%	17%	16%	17%	8%	18%	9%	10%	7%	14%	7%	5%	10%	8%
Electricity, gas, water, heating (n = 160)	26%	22%	19%	21%	18%	15%	20%	12%	13%	15%	20%	12%	10%	13%	16%
Restaurant and lodging (n = 390)	26%	7%	7%	7%	8%	10%	8%	5%	5%	7%	9%	5%	3%	8%	8%
Finance and insurance (n = 415)	27%	18%	15%	14%	16%	10%	20%	12%	15%	10%	17%	9%	10%	14%	11%
Education and learning support (n = 553)	28%	13%	13%	13%	10%	9%	14%	6%	8%	8%	10%	7%	6%	10%	10%
Medical care and welfare (n = 1,141)	28%	10%	11%	11%	10%	8%	11%	6%	7%	9%	8%	5%	4%	10%	9%

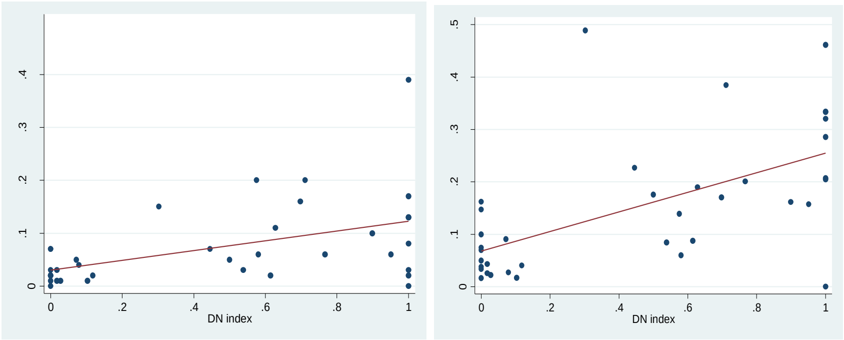
3.3 Potentially suitable jobs and teleworked jobs

The crucial issue in telework is how many jobs are suited to telework. Dingel and Neiman (2020) made a measurement of the jobs potentially suited to remote work. Using this, we made an index for the Japanese occupation classification.[7] Figure 5 plots telework use as of January 2020 (left panel) and as of June 2020 (right panel) in terms of Dingel and Neiman index. Overall, two values are positively correlated. People in

[7] To convert from the US to the Japanese classifications, we use the converters of Hamaguchi and Kondo (2018).

occupations potentially suited to telework tend to adopt telework. Correlation as of June 2020 is much clearer and steeper than that in January. This indicates that the spread of COVID-19 increased the amount of telework performed in jobs suitable for telework.

Figure 5: Dingel and Neiman index and telework (Left panel: January 2020, Right panel: June 2020).



3.4 Income and working hours

Teleworking varies across industries and occupations. Various problems arise in firms and organizations, across working environments and based on individual abilities. In fact, some specific industries saw a large decline in income and working hours. We found that some occupations were less suited to telework and some teleworkers tended to be more negatively impact by the COVID-19 pandemic shock. Figure 6 shows the rate of change in income from January to March as well as from March to June by industry. Likewise, Figure 7 shows changes in working hours.

Overall, more people had a greater reduction in income and working hours between

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April and June than between January and March. However, the negative impact was not widespread. Seventy-three percent of workers experienced no change during January–March 2020, whereas 67% experienced no change during March–June 2020. This is consistent with government surveys. According to the OECD, GDP growth in 2020 Q1 was only –0.56% in Japan, while it was –1.28% in the United States and –1.97% in the United Kingdom.[8] The unemployment rates did not increase so much in Japan, i.e. 2.4% in January and 2.6% in April 2020 (Labor Force Survey, Ministry of Internal Affairs and Communications, Japan). This is in sharp contrast to the United States and Europe. Unemployment in the United States increased drastically from 3.5% in January to 14.7% in April 2020. According to Eurofound (2020), more than one-quarter of respondents across the EU at this stage reported losing their job either temporarily (23%) or permanently (5%). One of the reasons for this difference is in Japan's "soft" lock-down, where Japanese companies did not stop operation and tended to keep their employees. The other reason is in the current Japanese labor market. In Japan, unemployment rates are low and stable over decades. Furthermore, Japan is now aging society and face serious labor shortage (Kawaguchi and Mori, 2017, 2019).

The negative impact was concentrated in specific industries and occupations. We found that about half of workers in the food and drink and accommodation industries saw a large decline in income and working hours. By contrast, workers in the information and communications, research and public service areas did not see large declines in income and working hours. Therefore, the negative impact of shock were already apparent as of March, but some specific occupations suffered serious negative impacts. Importantly, the occupations that had the most significantly negative impacts are those that utilized

[8] https://data.oecd.org/gdp/quarterly-gdp.htm

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telework the least (Figure 1), as well as being the most unsuitable for telework (Table 1).

The main measure for the prevention of infection during the current pandemic is the avoidance of person-to-person contact, and the utilization of telework has therefore been recommended. While face-to-face services in which person-to-person contact is fundamental have been a central focus of government requests for businesses to suspend their activities, tasks in these industries are also the least suited to telework. These industries had already suffered significant negative economic impacts. In nutshell, it is important to uniformly control socioeconomic activities as a countermeasure against infectious diseases, but at the same time, it is extremely difficult to uniformly promote telework and maintain economic activity. This is a typical contradiction between measures against infectious diseases and economic policy. More generous economic assistance will be an urgent requirement in order to prevent bankruptcies and unemployment in industries and occupations unsuited to telework.

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Figure 6: Changes in income (by industry).

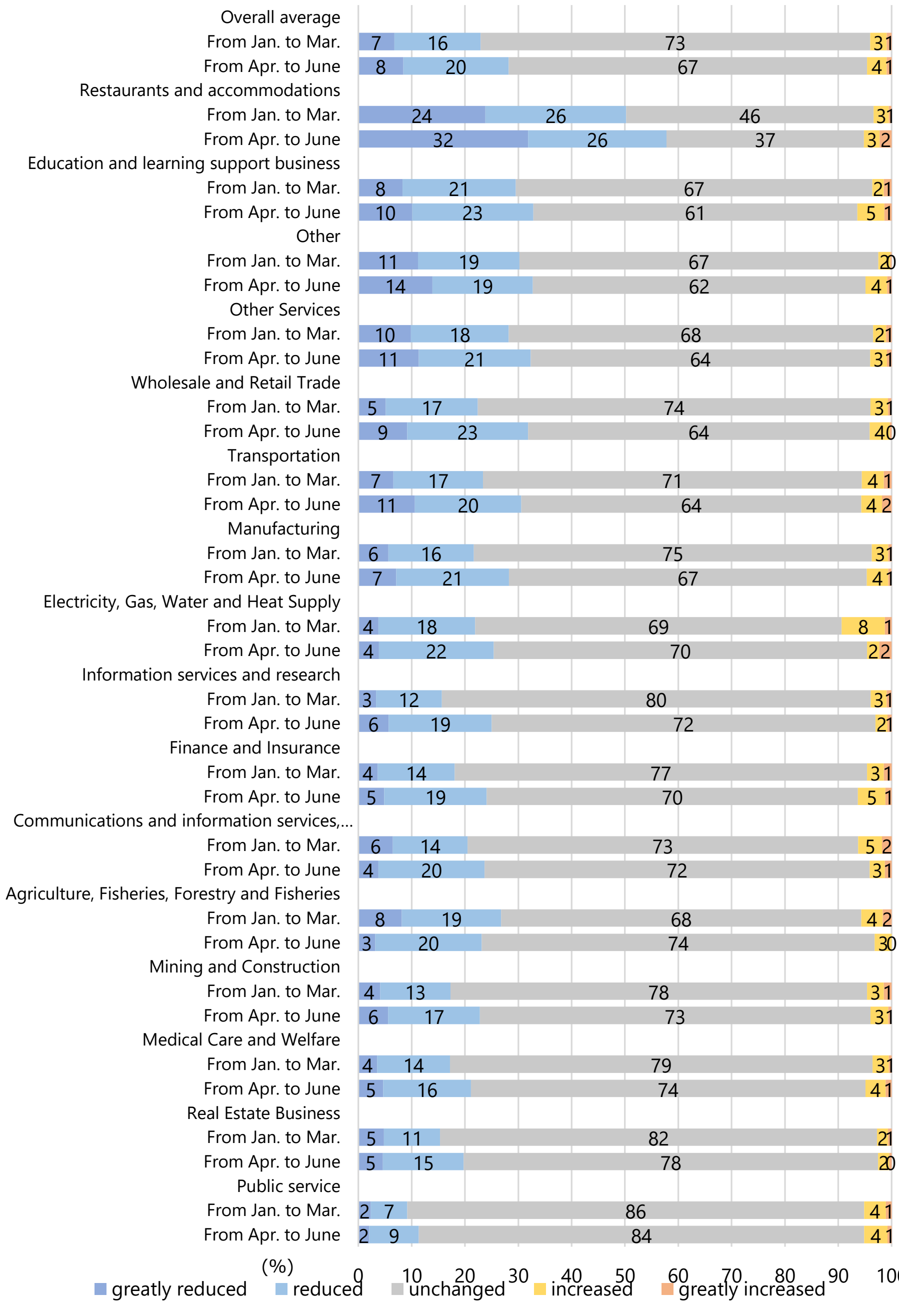
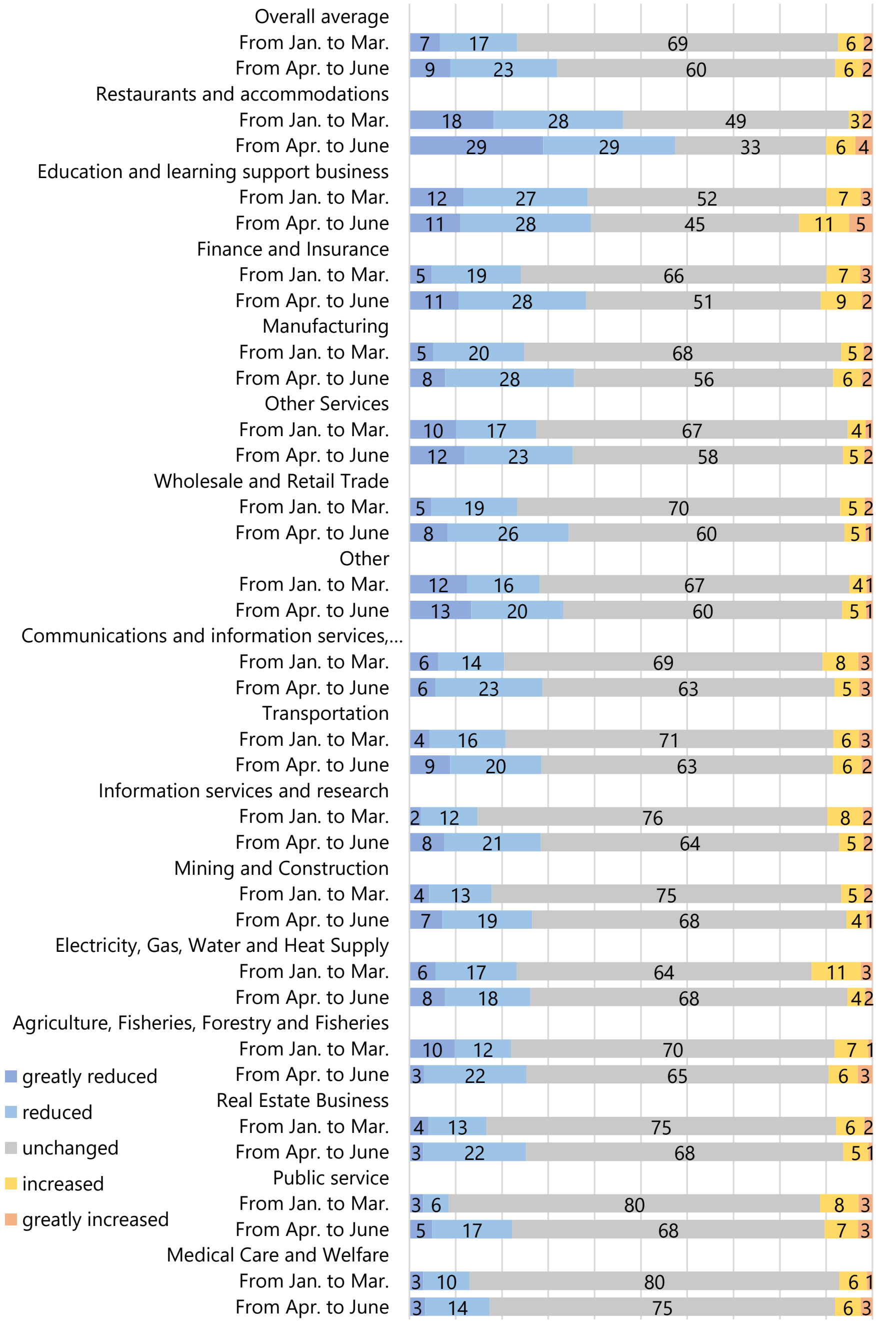


Figure 7: Changes in working hours (by industry).



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4 Policy Implications

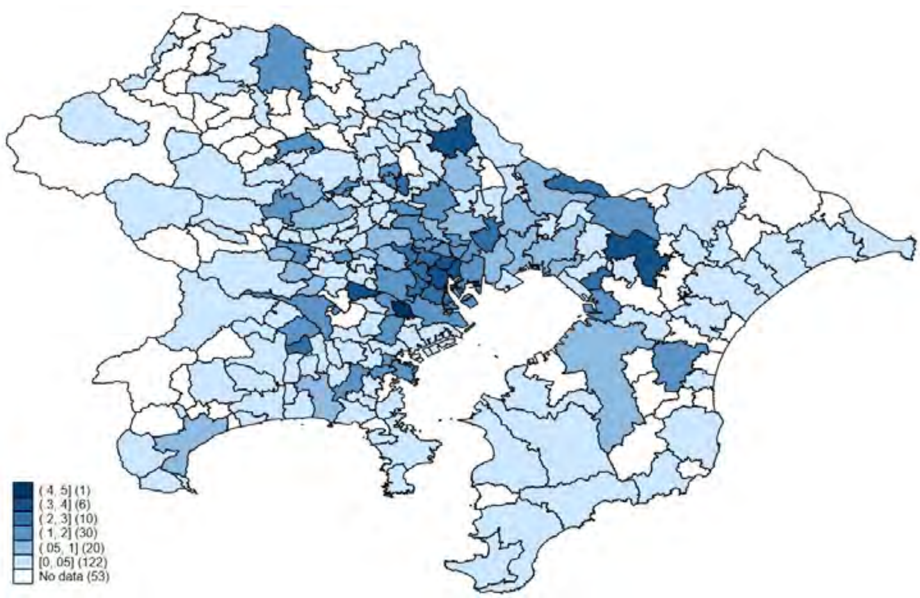
During the spread of COVID-19, while the rate of telework use increased, it still remains lower than in other countries. There are several reasons as mentioned above, but this section discusses one of the reasons, the Japanese corporate culture.[9] Many Japanese firms have retained traditional business culture whereby face-to-face communication and human relationships are fostered. Good examples of this are the exchange of visiting cards, many face-to-face meetings and many drinking meetings with the boss and colleagues. However, in the face of COVID-19, many Japanese firms have had to rethink their traditional labor practices and customs in the Japanese business culture.[10] Some things need to change, including the extensive use of paper documents, the holding of lengthy formal meetings, and numerous other outdated practices such as the use of stamps ("Inkan") and visiting cards. It will be necessary to focus on the creation of a new employment environment to facilitate telework (for example, the establishment of flextime systems and evaluation-based systems for job advancement). With regard to issues related to the working environment and the abilities of workers, it will be necessary to improve the ICT environment and provide ICT training. In addition, protecting information, guaranteeing privacy and ensuring security are expected to become more difficult when workers are teleworking from home.

[9] https://www.japantimes.co.jp/news/2020/04/13/business/corporate-business/traditional-japanese-seal-system-hampers-telework/#.Xu4XvUUzYcA
[10] See, e.g. https://www.nytimes.com/2020/04/14/business/japan-coronavirus-telework.html; https://www.cnn.com/2020/04/02/business/japan-coronavirus-work-lockdown-guilt-hnk-intl/index.html

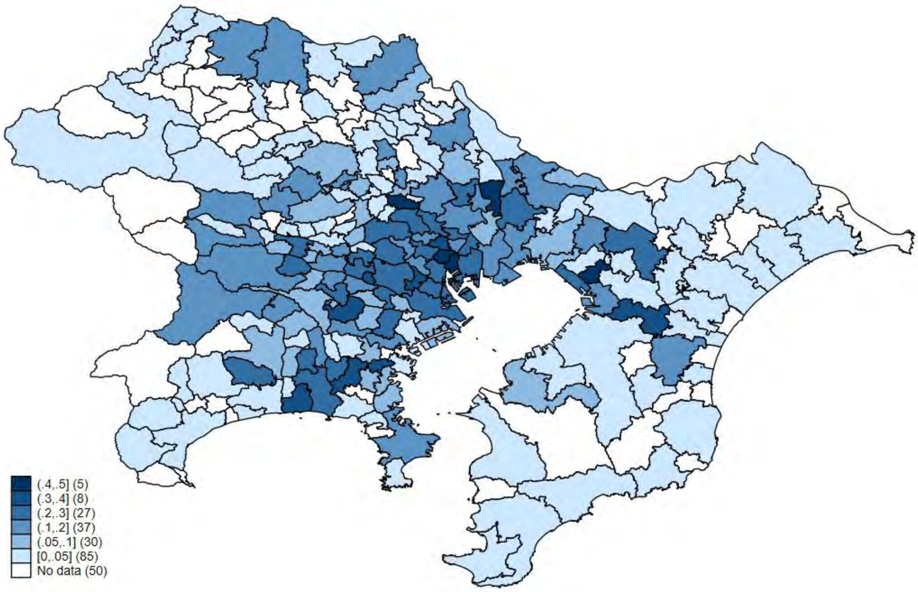
5 Conclusion

This paper has shown through a unique survey how telework has been adopted in Japan during the COVID-19 pandemic. As a result of the survey, we found that some occupations are unsuitable for telework and face a negative impact from COVID-19. These results concur with those of previous studies, e.g. Dingel and Neiman (2020). In particular, services with face-to-face communication, which are the most unsuitable for telework, tended to suffer from the negative impacts of the virus and saw largely reduced income and working hours.

Appendix Map 1: Telework utilization rates in the Greater Tokyo area (working place basis).



Appendix Map 2: Telework utilization rate in the Greater Tokyo area (residential basis).



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Were stay-at-home orders during Covid-19 harmful for business? The market's view[1]

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We study the market reactions following staggered lockdown events across U.S. states during Covid-19. We find that returns on firms located in lockdown states are higher following the lockdown. We interpret these market reactions as reflecting updated beliefs of market participants in the light of events that follow the lockdowns, such as compliance with stay-at-home orders. The effect is (a) only significant when the firm's county has a high number of infections, (b) larger for firms in essential industries, and (c) larger for states with Democratic trifecta. While lockdown extension announcements are associated with negative market reactions, the reaction is still positive when the county's number of infections is high. These findings suggest that the market perceives Non-Pharmaceutical Interventions, when effective, to be beneficial for businesses.

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Introduction

One of the most intriguing aspects of government policy response to the Covid-19 pandemic is how varied it has been.[1] As the pandemic unfolded, some governments (e.g., China, South Korea, Hong Kong SAR, Taiwan, Germany, Austria) moved early and imposed strict restrictions on citizens' activities (henceforth referred to as Non-Pharmaceutical Interventions or NPI), backed by monitoring measures such as testing and contact tracing, and succeeded in limiting the spread relatively quickly. Others (most notably, Sweden, and the U.K. and the Netherlands in early stages) aimed for herd-immunity, and imposed only mild restrictions. Most other countries gradually increased the stringency of interventions as the number of deaths increased (e.g., Italy, France, Spain). Within countries as well, there has been significant variation in the stringency of NPIs, as in the case of China and the U.S.

The choice of how soon to intervene and if so, to what degree, has possibly been affected by several factors, or trade-offs. The capacity of a country or a region's health system (medical supplies, hospital beds, availability of trained health care workers) or the potential of containing contagion (population density, living conditions, etc.) has been a major motivation for some countries to move swiftly. Other countries, on the other hand, have taken into consideration the feasibility of monitoring the spread of the infection, the population's propensity for compliance, and the costs associated with restrictions on personal and economic freedom, and chosen a more graduated response. As the personal and economic costs from longer periods of more stringent NPIs have mounted, the question of what level of containment is appropriate for relaxation of interventions has become a highly contentious issue.

Perhaps nowhere else has this been more evident than in the U.S., where the authority to implement NPIs largely is vested with individual states. The "health versus economic/personal freedom" issue has taken the center stage here. While it is well known that political ideology is a major determinant of which side of this debate one is likely to be in, a large-scale survey conducted in late May suggests sharp

[1] See, for example, Gibney (2020) for a review of government policy responses.

differences along gender and racial lines as well. Fear persists, even though close to 40 million people are out of a job.[2]

Against this backdrop, it is useful to know how the financial markets evaluate the costs and benefits of NPIs. Financial markets do not explicitly take into account the "value" of a human life; however, how the market responds to the adoption of NPIs at least gives a timely indication of how the social costs and benefits of these NPIs are shared. For example, for the current pandemic, the experiences of Sweden and the U.K. raise questions about the feasibility of limiting the loss of human lives via relaxed policies aiming at "herd immunity" (especially when there are limits on the capacity of the health system and when socio-economic factors could cause certain groups of society to be more vulnerable). Thus, NPIs such as lockdown or stay-at-home measures save more lives, and if lockdowns are also favored by firms' shareholders, such policies are easier to defend. Of course, numerous caveats would still remain – for example, the economic benefits could be very uneven and the set of government economic policy initiatives are likely to be crucial for the larger economic impact of NPIs. However, the market's reaction to NPIs is still likely to be extremely useful in understanding the likely impact of these measures on economic activity.

There are several reasons why, ex ante, it is not obvious how markets are expected to respond to lockdowns – especially as market participants observe whether the interventions are effective and how they are affecting behavior. First, the answer is likely to be context-specific – depending on the pandemic, the socio-economic environment, the institutional environment. For example, it is a truism that, absent any health issues, lockdowns cannot be good for the economy. Thus, lockdowns are good for the economy only if the immediate economic costs are outweighed by the future economic costs that are potentially avoided by a better control of the spread of the epidemic today. How this particular trade-off works out depends on all the aforementioned factors. Second, as noted, since governments can have heterogenous ideologies and could weigh the value of saving lives versus economic benefits differently, not all lockdowns are expected to be "good news" for the market. Third, and related, even among the U.S. states, we observe a wide variation in the severity of

[2] Washington Post-ABC poll results announced on June 1, 2020.

NPIs. This raises the question of whether these variations are systematically related to the trade-offs, represent idiosyncratic variations, or are half-hearted attempts that cater to multiple constituencies. Finally, some sectors of a local economy may be more exposed to the effects of the pandemic or to those of NPIs than others.

In the U.S., California was the first state to announce a stay-at-home or lockdown order on March 19, and New York followed the next day. From then until April 3 (Alabama and Missouri), all states except Arkansas, Iowa, Nebraska, North Dakota, South Dakota, Utah, and Wyoming issued some form of stay-at-home order. This staggered adoption of lockdowns provides an ideal opportunity to examine the market's reaction to lockdowns, which is the main issue we address in this paper. We also examine the market's reaction to lockdown extensions, which a number of states announced later.

Specifically, we examine, in a (stacked) difference-in-difference setting, how lockdown announcement and implementation impacted the daily abnormal stock returns of firms headquartered in a state imposing a lockdown, over a five-trading day window following the lockdown, compared to a five-trading day window before the lockdown. The control group of firms are those headquartered in states that did not experience any lockdown within a [-10, +10] day window. [3] In our regressions, we include, for each cohort, day and firm fixed effects. Inclusion of day fixed effect effectively filters out same-day events that may not be fully captured in the market index, while inclusion of firm fixed effect absorbs time-invariant firm characteristics that could affect daily returns. The focus of attention is an indicator variable "lockdown", which takes a value of 1 for the firms headquartered in states that experience a lockdown in the five-day post-lockdown announcement (alternatively, implementation) period, and zero otherwise. Our main result is that the coefficient of the lockdown variable is significantly positive: the stock market reacts favorably following lockdown announcements. In addition, we find that the significant positive effect is confined to states where the number of infections at the time of announcement

[3] In our sample of lockdowns, 94.03% (88.98%) of firms have their headquarters and the biggest plant located in the same state (county). Thus, lockdowns, to the extent that they influence workforce participation, are material for the firm's operations.

is above median for the cohort (i.e., all the firms in the treated and control groups corresponding to a particular lockdown event), and insignificant for the below median sub-sample.

In our sample, 37 percent of the announcements are immediate (effective the same day), while 44 percent are effective the following day. The remaining 19 percent are effective two days after the announcement day. When we center our [-5, +5] window on the effective day of the lockdown and separate the distinct announcement day from the effective day, we find that the announcement day effect is positive, though marginally insignificant. We believe this could be due to inadequate information on exactly when the announcement was made (in particular, whether it was made after trading hours or not)—in contrast, we were able to find more definitive information on exactly when the lockdown was supposed to become effective. We find that a dummy variable which takes a value of 1 for the firms headquartered in the lockdown states for the five days after the lockdown becomes effective, and zero otherwise, is significantly positive. This suggests that the implementation resolves uncertainty – the market, while favoring lockdowns, reserves judgment until the lockdown is implemented successfully. For our remaining results, we primarily rely on this setting, and refer to this dummy variable as the post-lockdown dummy or simply the lockdown dummy.

Lockdowns are clearly endogenous decisions that reflect many factors such as the number of infections in the state, the rate of increase of infections, the capacity of the health system in the state, the political leadership, the likely economic costs, and so on. Our intention is not so much to make a causal statement that lockdowns directly cause abnormal returns in the next five days to be higher. Rather, our interpretation of these results is that the market reacts positively to events that occur immediately following lockdown announcements. The most plausible events are the outcomes of social distancing measures. We conjecture that the market participants observe whether these social distancing measures are successful or unsuccessful, and revise their priors about the likely economic impact of the lockdowns. Although we do not directly test how social distancing is affected by lockdowns, we provide evidence suggesting that success in social distancing is associated with more positive market

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reaction.[4] For example, as discussed below, it has been widely reported that social distancing was more successful in states with Democratic leaning than those with Republican leaning. Our results are significantly stronger for Democratic states.[5]

States differ in terms of the range of restrictive measures that were included as part of the lockdown announcement. We construct a "score" of lockdown strictness by assigning weights to different aspects of these restrictive measures. When we replace the lockdown dummy by the score (which assumes a value corresponding to the score when the lockdown comes into effect for all firms in that state, and is zero otherwise), the score has a significantly positive effect on the firms' subsequent abnormal returns.

As further evidence that the lockdowns mattered more for businesses that stood to lose more from wider spread of the infection in the state, we consider separately the market reactions of firms that were deemed "essential" versus "non-essential". Firms deemed non-essential were directly affected by not being able to continue during lockdown. Moreover, while they would benefit from being able to resume full-scale operations if the spread of the infection were brought under control, in this sector, there is more scope for employees to work from home. We find that, while the stock prices of firms in the non-essential sector responded positively to lockdowns, consistent with our expectation, the magnitude of the coefficient on the lockdown dummy is larger for the essential sector.

Next, we examine whether a state's political orientation has any impact on the market reaction subsequent to lockdown. We classify a state as "Democratic" or "Republican" if it has a Democratic or Republican trifecta status (i.e., one political party holds the governorship, a majority in the state senate, and a majority in the state

[4] Reports suggest that except for a few early cases (e.g. California), compliance with lockdown orders was generally good. We discuss this further in Section 3.

[5] One may still worry that factors that trigger lockdown decisions also affect subsequent abnormal returns. If such factors are in the public domain, these should already be reflected in stock prices, and should not matter for subsequent abnormal returns. If these factors are private information to policy makers, then they have to be salient and manifest in the short window of the next five days. While this cannot be ruled out, even in this scenario, such factors (e.g., potential immediate jump in mortality rates) are likely to affect returns negatively. Our reading of the events leading to the spate of lockdowns that followed in quick succession is that several state governors (who are known to hold regular conference calls) had evaluated the scientific advice and decided to act. Delays in preparation time possibly created a quasi-random timing of lockdowns.

house in a state's government). The control group associated with states with each type of political orientation comes from those that have divided trifecta. We find that while the post-lockdown dummy is positive and significant for each type of orientation, it is twice as large for Democratic states. This is consistent with evidence (discussed in Section 3) that (a) lockdowns were more comprehensive and (b) compliance was more complete in the Democratic states, and suggests that information revelation about compliance with the stay-at-home orders is a possible explanation for the overall positive market response that we find.

Finally, when we turn to announcements of lockdown extensions, we find consistent results. Lockdown extension announcements are associated with positive market reaction in the next five days when the number of infection cases is high. However, the market reaction is negative when the number of cases is low. The latter result suggests that the market is sensitive to the short-run economic costs of lockdowns. When incurring these costs do not seem justified given lower infection numbers, the market favors relaxing the restrictions so that the local economy can get back on track sooner.

Our paper addresses a core issue in the policy debate relating to pandemics – the so-called "health versus wealth" trade-off – by examining the stock market's reaction to social distancing measures. To the best of our knowledge, research on the economic benefits of NPIs in a pandemic is limited. A paper that is related to the core issue we investigate in this paper (Correia, Luck, and Verner, 2020) examines the economic impact of the 1918 influenza pandemic and how regional economic impact was related to the adoption of NPIs in different U.S. cities. The authors find that while the pandemic reduced manufacturing output by 18 percent, early and more aggressive adoption of NPIs not only reduced mortality, but also had a positive impact on employment creation after the pandemic. Lin, and Meissner (2020) conduct a county-level border discontinuity analysis and surprisingly find that local (state) NPIs have at best weak effects on the growth of confirmed cases. Individual choices regarding the "health versus wealth" trade-off are examined in an experimental setting by Heap, Koop, Matakos, Unan, and Weber (2020).

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Second, we address a very recent literature on the effect of policy announcements and infection spread during pandemics on asset prices. Ding, Fan and Lin (2020) conduct an event-study analysis to examine the effect of the lockdown in Hubei province in China and the subsequent spread of the Covid-19 pandemic to Northern Italy on the stock prices of Chinese firms. They find that Chinese firms with exposure (production links) to Hubei experienced negative market reaction to the Hubei lockdown relative to firms with international exposure; however, this effect was reversed when the pandemic spread to Northern Italy. Overall Chinese stock market response to the Hubei lockdown is negative, while that to the spread to Northern Italy is positive. Croce, Farroni, and Wolfskeil (2020) examine intraday returns in a ±90-minute window around announcements for countries, where more than 100 infection cases have been reported, and find that cumulative equity returns are higher immediately after the announcement but fall afterwards. They attribute this pattern to resolution of uncertainty as in Ai and Bansal (2018). Baker, Bloom, Davis, Kost, Sammon, and Viratyosin (2020) find that, unlike any other pandemic, news about Covid-19 developments and policy responses accounted for 15 or 16 of the 18 U.S. stock market jumps between February 24 to March 24. Gormsen and Koijen (2020) use data on stock market returns and dividend futures to assess how investors growth expectations evolve in response to economic policy announcements. Ramelli and Wagner (2020) examine the how the CAPM-adjusted cumulative abnormal returns of U.S. firms were affected during different phases of the Covid-19 pandemic, starting with the early spread of the pandemic in China, its subsequent spread in Europe, and eventual spread in the U.S. until the third week of March. They identify which industries were relative winners versus losers. Firms with exposure to China and international exposure generally underperformed during the entire period; some of these effects were already visible during the spread in China. Finally, the authors find that when the pandemic spread to the U.S., firms with high leverage and lower cash holdings experienced lower CARs.

Acharya and Steffen (2020) provide evidence that firms with access to liquidity (i.e., either through cash or lines of credit) perform better during the first quarter of 2020. Ding, Levine, Lin, and Xie (2020) study which firm characteristics soften the

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impact of the spread of the pandemic on weekly stock returns across 56 countries by interacting several firm characteristics with the weekly growth of infection rates due to Covid-19 in the country. Albuquerque, Koskinen, Yang, and Zhang (2020) find that firms with high Environmental and Social (ES) ratings and high advertisement spending perform better in the first quarter of 2020. Pagano, Wagner, and Zechner (2020) also examine the relationship between a firm's resilience to a pandemic (as measured by the extent to which a firm's operations are compatible with social distancing) and excess returns. Not only do they find that more resilient firms outperform less resilient firms after the onset of the pandemic, this relationship actually emerges several years before the pandemic, reflecting that investors became aware of a pandemic threat as early as 2014. Finally, Alfaro, Chari, Greenland, and Schott (2020) find that unanticipated changes in predicted infection rate (which they interpret as a proxy for the infection-related labor supply shock) during the Covid-19 pandemic and the SARS 2003 epidemic affect the aggregate stock market in the U.S. even after controlling for the most recent change in infection cases. Moreover, they find that firms more likely to be affected by social distancing experience more negative returns when unexpected changes in the predicted infection rate occur than those that are less likely to be affected.

The rest of the paper is organized as follows. Section 1 discusses the data, and sections 2 and 3 discuss, respectively, our methodology and results. Finally, Section 4 concludes.

1. Data

We construct our sample from several sources. First, we collect daily stock prices for common shares from Compustat North America Daily database retrieved via the Wharton Research Data Services (WRDS) for the period from January 2019 to May 2020. Following Frazzini and Pedersen (2014), we use the security type indicator in Compustat (TPCI=0) to restrict our sample to common shares only.[6] We merge these

[6] From our correspondence with a WRDS data analyst, the quality of Compustat Daily market data over the last decade is on par with the daily market data of the Center for Research in Security and Prices (CRSP). An advantage of using Compustat is that this database is updated on a daily basis,

data with Compustat Quarterly Fundamentals database to obtain up-to-date information on headquarters locations.

We also obtain the daily cumulative count of coronavirus cases at the county level from The New York Times, who, in turn, compiles the data from local governments, health departments, as well as timely updates and validations from its journalists located throughout the U.S.[7]

Our empirical tests require the information on the announcement date and effective date of state-level lockdown directives and orders, which is collected from The New York Times, The Wall St. Journal, The Washington Post, the National Association of Counties, and state governments' websites.[8] Almost all U.S. states issued statewide stay-at-home directives, except Arkansas, Iowa, Nebraska, North Dakota, South Dakota, Utah, and Wyoming. California was the first state to announce a stay-at-home order, effective immediately. New York followed the next day. The last state to announce a stay-at-home order was South Carolina on April 6, effective the following day. Figure 1 in the Appendix gives the date of the first trading day when the lockdown first became effective in the state, sorted according to whether the state has a Republican or Democratic or divided trifecta.

From these public sources, we also quantify the extent of lockdown in a given state based on three prominent types of social and business restrictions, namely, stay-at-home restriction score, public gathering restriction score, and business activity restriction score. Specifically, the stay-at-home restriction score ranges from 0 to 2, where a score of 2 represents a statewide order to stay at home; a score of 1 denotes the state directive to stay at home (e.g., "safer-at-home" directive); and a zero score is

which is a desirable feature given the timeliness of our study, whereas the CRSP Daily database is updated on a monthly basis at best.

[7] The NY Times data are available at https://github.com/nytimes/covid-19-data.

[8] The NY Times: https://www.nytimes.com/interactive/2020/us/states-reopen-map-coronavirus.html
The Wall St. Journal: https://www.wsj.com/articles/a-state-by-state-guide-to-coronavirus-lockdowns-11584749351
The Washington Post: https://www.washingtonpost.com/health/2020/04/06/coronavirus-stay-at-home-by-state/#kentucky
The National Association of Counties: https://ce.naco.org/?dset=COVID-19&ind=State%20Declaration%20Types

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assigned to states without any stay-at-home directives (i.e., Arkansas, Iowa, Nebraska, North Dakota, South Dakota, Utah and Wyoming).

Similarly, the public gathering score ranges from 0 to 3, representing the increasing restriction in a state. For example, Minnesota is the only state without any statewide directive on gathering restrictions and is thus given a score of zero. A score of 1 means that the state limits a gathering to be fewer than 20 people, while a score of 2 represents the limit of maximum 10 people. States that prohibited all social gatherings are given a score of 3.

The third prominent aspect of restriction is related to the extent of non-essential business operations. Specifically, the business restriction score is equal to 1 if only entertainment-related businesses are closed (bars, theaters, restaurants, and other entertainments). The score is equal to 2 if, in addition to entertainment businesses, non-essential retail stores are also required to be closed. If a state bans all non-essential businesses, then it has a score of 3.

Having quantify the extent of restrictions in a state, we construct an aggregate measure of lockdown scope as the sum of the three scores above.

2. Methodology

To examine how the imposition of statewide lockdowns are associated with stock price reactions, we conduct a stacked difference-in-differences analysis around a state's lockdown event. We focus, in turn, on three types of events, i.e., announcement date of lockdown, effective date of lockdown, and announcement date of lockdown extension. Following Gormley and Matsa (2011), for each type of lockdown event, we construct a cohort of treated firms (i.e., those headquartered states where a lockdown event occurs on a particular day) and control firms using observations over a [-5, 5] window (i.e., the five days before and five days after the lockdown event). Control firms are those located in states that do not experience the same lockdown event over the 10 days after the treated firms' lockdown event and firms located in states that have already experienced lockdown more than 10 days prior to the treated firms' lockdown event.

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For cohorts centered around lockdown announcement and effective dates, the requirement that control firms are drawn from states where such events did not occur within ± 10 days means that for a majority of the dates, the control sample comprises mostly of firms in the seven states that never imposed lockdowns. Collectively, there are 130 firms headquartered in these states. In one of the robustness tests reported in Section 3.7, we relax the requirement for control group selection to no events occurring within [-10, +5] days, which allows more firms to be included in the control samples. We also remove cohorts that are highly unbalanced in terms of the number of treated and control firms.

We pool all the cohorts across all lockdown events and estimate the following regression:

$$AR_{i,s,c,t} = \alpha + \beta_1 Post\ Event_{s,c,t} + \delta_{c,i} + \varphi_{c,t} + \varepsilon_{i,s,c,t}, \qquad (1)$$

where $AR_{i,s,c,t}$ is the daily abnormal return on firm i headquartered in state s over the window of [-5, 5] days around a lockdown event. Abnormal returns are computed as the difference between realized excess returns (over the risk-free rate) and the expected return from the Capital Asset Pricing Model estimated using 2019 return data.[9] $Post\ Event_{s,c,t}$ is a dummy variable, which is equal to one for the five days after the lockdown event date of state s in cohort c and is equal to zero for the five days before the lockdown event date of a treatment state, for firms in states that do not experience lockdown over the 10 days after the lockdown event of state s and for firms in states that have already been in lockdown at least 10 days before the lockdown event of state s. In our empirical tests, *Post Event* represents *Post Announcement*, *Post Lockdown*, and *Post AnnExtension*, which are the announcement of lockdown, the effective lockdown, and the announcement of lockdown extension events, respectively.[10] $\delta_{c,i}$ represents cohort-by-firm fixed effects; and $\varphi_{c,t}$ denotes cohort-by-

[9] Our results do not qualitatively change if we use raw daily stock returns. The Fama-French factors updated to April just became available for us to replicate our baseline tests after the first draft of this paper was completed, and all our baseline results continue to hold if we use the 5-factor model. However, we do not have updated factors for the tests on lockdown extensions in May. For consistency, all tests reported here are for CAPM-adjusted abnormal returns.
[10] If the event time is after the exchange trading hours, we use the next trading date.

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date fixed effects. As noted by Gormley and Matsa (2011), these interactions of fixed effects are more conservative than the simple firm and date fixed effects, since they allow unobservable differences between treated firms and control firms to vary by cohort on a daily basis. These fixed effects also control for time-varying marketwide factors that could affect both treated firms and control firms. (We confirm that our results do not qualitatively change when using the simple firm and date fixed effects).[11] We do not control accounting variables due to the lack of time variations in these variables over our sample period. However, we also estimate regression (1) by including a stock's past abnormal returns as a control variable, which is computed as the continuously compounded abnormal return on the stock over the past one month. To account for the potential cross-sectional covariance across firms, we cluster the standard errors at the firm level.[12]

3. Results

3.1 Market Reaction Following Lockdowns

We start by examining, in our "stacked difference-in-differences" setting, the effect of a lockdown announcement in a [-5, +5] window around the announcement date. The key variable of interest is the *Post Announcement* dummy, which takes a value of 1 in the five days after the announcement date for firms headquartered in the state for which the lockdown announcement applies, and zero for all other firm-days (which includes all days in this window for control firms and the pre-announcement days in this window for the treated firms). As discussed, the dependent variable is CAPM-adjusted daily abnormal returns. We control for firm×cohort and date×cohort fixed effects.

Panel A of Table 1 shows that the coefficient of *Post Announcement* is significantly positive. This implies that the market responds positively to events following the lockdown announcement (e.g., improved social distancing). In Panel B, we split the sample of firms in each cohort and each state into "high" and "low"

[11] McLean and Pontiff (2016) point out that including date fixed effects can help filter out common trends in stock returns.

[12] Our results do not qualitatively change if we cluster standard errors by firm and industry or by firm and date, or by state.

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infection groups ("more cases" versus "fewer cases") based on the number of infections scaled by the population in the county where the firms are headquartered on the day of the announcement. We find that the lockdown announcement is associated with a significant positive return only when the number of infections is high. These results are consistent with idea that the economic concern of market participants is related to the potential for the outbreak to affect more individuals locally. The health of the local population matters for how well companies headquartered there are able to operate. Plausible channels through which could be relevant is the impact on employees – factory workers or management – who might not be able to function effectively if the infection spreads locally.

As discussed in the introductory section, the exact timing of announcements is sometimes not readily available – in particular, whether or not they occur within trading hours of that particular day. Given that more than 80 percent of the lockdowns are effective either the same day or on the next trading day, and the remaining ones are effective after another trading day, for the rest of our analysis, we focus on the [-5, +5] window surrounding the effective date. In Panel A of Table 2, we first separate out the announcement date, and create an indicator variable *Announcement* for that date. We also construct a dummy variable *AnnounceToEffective,* which equals 1 for the trading days between the announcement date and the effective date. *Post Lockdown* is a dummy variable that takes the value of 1 for any firm in the lockdown state in any of the five days after the lockdown becomes effective, and zero for any other firm-days. The market reaction on the date of announcement, with the caveat that the announcement date is identified with noise, is positive, though not significant at conventional levels. However, *Post Lockdown* has a positive and highly significant coefficient. We conjecture that the market reaction to the lockdown announcement continues and perhaps becomes stronger in the post-effective date period because the market reserves judgment on the efficacy of the lockdown (i.e., if stay-at-home orders

Table 1: Announcement of Lockdown and Stock Abnormal Returns
This table presents the stacked difference-in-differences regression results surrounding the announcement date of lockdown. The sample period is from March 12, 2020 to April 13, 2020. For each announcement date of lockdown, we construct a cohort of treated firms (i.e., those headquartered in a state that announced lockdown) and control firms using observations over a [-5, 5] window (i.e., the five days before and five days after the announcement date of lockdown). *AR* is the abnormal return computed as the difference between realized excess returns (over the risk-free rate) and the expected return from the Capital Asset Pricing Model estimated using 2019 return data. *Post Announcement* is a dummy variable equal to one for the five days after the announcement date of lockdown for firms located in a treatment state , and is equal to zero for the five days before the announcement date of lockdown for firms in a treatment state, for firms in states that do not announce lockdown over the 10 days after the announcement date of lockdown of the treatment state, and for firms in states that have already announced a lockdown at least 10 days before the announcement date of lockdown of the treatment state. Panel A reports the results for the full sample of lockdown announcement analysis. Panel B reports the results for the subsample analysis based on the number of infections scaled by the population in the county where the firm located on the cohort's lockdown announcement date. Both cohort-by-firm fixed effects and cohort-by-date fixed effects are included in all regressions. Standard errors are clustered at the firm level. *t*-statistics are presented in parentheses. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Full Sample of Lockdown Announcement

	Dependent Variable: *AR*	
Variable	(1)	(2)
Post Announcement	0.501***	0.486***
	(3.756)	(3.682)
Past AR		-0.082***
		(-27.739)
Firm × Cohort FE	Yes	Yes
Date × Cohort FE	Yes	Yes
Number of Obs	120,332	120,310
Adjusted R^2	0.022	0.037

Panel B: Subsample Analysis

	Dependent Variable: *AR*			
	(1)	(2)	(3)	(4)
Variable	Fewer Cases	More Cases	Fewer Cases	More Cases
Post Announcement	0.233	0.718***	0.165	0.733***
	(1.075)	(4.190)	(0.770)	(4.328)
Past AR			-0.078***	-0.086***
			(-19.148)	(-19.834)
Firm × Cohort FE	Yes	Yes	Yes	Yes
Date × Cohort FE	Yes	Yes	Yes	Yes
Number of Obs	63,706	56,626	63,692	56,618
Adjusted R^2	0.024	0.028	0.037	0.045

are being followed or not). Academic studies and reports suggest that most of the early stay-at-home orders were effective.[13]

In the last two columns in Panel A, we examine whether there are any pre-trends. While anticipation effects could cause the returns of the treated firms to already start to diverge from those of the control firms prior to the announcement date or the effective date, there could also be persistent diverging trends. The latter is especially a concern in our setting, because the requirement that the control firms be drawn from states that do not implement any lockdown within a ±10 day window of the event date means that a significant part of the control sample for the events occurring between March 24 and April 2 is drawn from the seven states that do not implement a lockdown.[14] To check for the existence of pre-trends, we include three indicator variables corresponding to one, two and three days before the lockdown announcement, and interact these with the treated firm dummy. The baseline is the day occurring four days before the lockdown announcement day. The post-lockdown dummy remains significantly positive, while none of the other interactions prior to the effective lockdown date are significant. This suggests our results do not reflect a continuation of pre-trends.

In Panel B, we only consider the cases where the announcement and effective dates are the same. Here also, the coefficient of *Post Lockdown* is positive and significant.

For the remainder of the results reported in the paper, we consider the effective day of the lockdown as the event day. In Panel A of Table 3, we present univariate comparisons of the cumulative average abnormal returns (*CAR*) for the 5 days before and after the effective date, for the control firms and treated firms, respectively. Except for the treated firms in the post-lockdown period, the *CAR*s are negative. While both sets of firms experience higher *CAR*s in the post-event 5-day period, the difference is larger and more significant for the treated group, and the difference-in-difference of

[13] Analysing cellphone-based geolocation data, Engel, Stromme and Zhou (2020) find that an official stay-at-home order reduces mobility by 7.87 percent. Painter and Qiu (2020) report similar findings. Based on data from 15 million cellphone users, The New York Times reports that "Stay-at-home orders have nearly halted travel for most Americans" ("Where America Didn't Stay at Home Even as the Virus Spread", The New York Times, April 2, 2020).

[14] We relax the ±10 day window in robustness tests discussed later in this section.

Table 2: Announcement and Effective Date of Lockdown

This table presents the stacked difference-in-difference regression results surrounding the effective date of lockdown. The sample period is from March 12, 2020 to April 14, 2020. For each effective date of lockdown, we construct a cohort of treated firms (i.e., those headquartered in a state that experienced lockdown) and control firms using observations over a [-5, 5] window (i.e., the five days before and five days after the lockdown). *Post Lockdown* is a dummy variable equal to one for the five days after the effective date of lockdown of a treatment state where a firm located, and equal to zero for the five days before the effective date of lockdown of a treatment state, for firms in states that do not experience lockdown over the 10 days after the effective date of lockdown of the treatment state, for firms in states that have already been in lockdown at least 10 days before after the effective date of lockdown of the treatment state. *AnnounceToEffective* is a dummy variable equal to one for the days after announcement date and before effective date of lockdown for firms in a treatment state, and zero otherwise. *Announcement* is a dummy variable equal to one for the announcement date of lockdown for firms in a treatment state, and zero otherwise. *Pre Announce 1*, *Pre Announce 2*, and *Pre Announce 3* are dummy variables that take a value of 1 for one, two and three days before the announcement date of lockdown for firms in treatment states, respectively, and zero otherwise. Panel A reports the results for the full sample of effective lockdown analysis. Panel B reports the results for the subsample of treated firms located in the states that announced lockdown effective immediately and controls firms in the same cohort as these treated firms. Both cohort-by-firm fixed effects and cohort-by-date fixed effects are included in all regressions. Standard errors are clustered at the firm level. *t*-statistics are presented in parentheses. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Full Sample of Effective Lockdown

	Dependent Variable: *AR*					
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Post Lockdown	0.379***	0.396***	0.413***	0.438***	0.357**	0.370**
	(3.391)	(3.571)	(3.552)	(3.798)	(2.081)	(2.192)
AnnounceToEffective	-0.252	-0.247	-0.173	-0.149	-0.253	-0.240
	(-0.876)	(-0.860)	(-0.591)	(-0.511)	(-0.821)	(-0.780)
Announcement			0.242	0.299	0.158	0.202
			(1.265)	(1.566)	(0.664)	(0.857)
Pre Announce 1					-0.019	-0.023
					(-0.090)	(-0.111)
Pre Announce 2					-0.176	-0.183
					(-0.849)	(-0.894)
Pre Announce 3					-0.083	-0.074
					(-0.434)	(-0.395)
Past AR		-0.067***		-0.067***		-0.066***
		(-25.117)		(-25.124)		(-27.529)
Firm × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Date × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs	138,968	138,940	138,968	138,940	138,968	138,940
Adjusted R^2	0.026	0.036	0.026	0.036	0.032	0.043

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Panel B: Subsample of Lockdown Effective Immediately

	Dependent Variable: *AR*	
Variable	(1)	(2)
Post Announcement	0.421**	0.406**
	(2.168)	(2.103)
Past AR		-0.062***
		(-10.771)
Firm × Cohort FE	Yes	Yes
Date × Cohort FE	Yes	Yes
Number of Obs	31,293	31,292
Adjusted R^2	0.001	0.015

the *CAR*s is positive and highly significant. The difference between treated and control firms in the pre-period is driven by the treated firms for the events in California and New York, and becomes insignificant once we remove them. However, the difference-in-difference remains positive and highly significant.

Panel B of Table 3 reports results similar to Table 1 except that the [-5, +5] window is centered around the effective lockdown date. Findings are very similar. The coefficient of the *Post Lockdown* dummy is positive and significant at the 1 percent level, and the magnitude slightly smaller than that of the *Post Announcement* dummy in Table 1. In Panel C, we split the cohorts based on the number of infections at the county (scaled by population) where the firm is headquartered. Again, we find that the Post-Lockdown dummy is only significant for the subsample where the infections are high (above median).

Hereafter, the specifications reported in Table 3 are our baseline specifications, and all results are reported for the window centered on the effective date.

Before leaving this subsection, we note that the specifications in columns (1) and (2) include a very large number of fixed effects (cohort*day and cohort*firm fixed effects). Even after accommodation such a large number of regressors, the adjusted R-squares are 2 percent and 3 percent respectively in columns (1) and (2). The unadjusted R-squares are 12 percent and 14 percent, respectively. The cohort*day fixed effects contribute significantly to the explanatory power (but not the cohort*firm fixed

Table 3: Effective Date of Lockdown and Stock Abnormal Returns

This table presents the stacked difference-in-difference regression results surrounding the effective date of lockdown. The sample period is from March 12, 2020 to April 14, 2020. For each effective date of lockdown, we construct a cohort of treated firms (i.e., those headquartered in a state that experienced lockdown) and control firms using observations over a [-5, 5] window (i.e., the five days before and five days after the lockdown). *Post Lockdown* is a dummy variable equal to one for the five days after the effective date of lockdown of a treatment state where a firm located, and equal to zero for the five days before the effective date of lockdown of a treatment state, for firms in states that do not experience lockdown over the 10 days after the effective date of lockdown of the treatment state, for firms in states that have already been in lockdown at least 10 days before the effective date of lockdown of the treatment state. Panel A reports the results for the univariate analysis of cumulative abnormal returns (*CAR*) for the 5 days before and after the effective date, for the control firms and treated firms, respectively. Panel B reports the results for the full sample of effective lockdown analysis. Panel C reports the results for the subsample analysis based on the number of infections scaled by the population in the county where the firm located on the cohort's lockdown effective date. Both cohort-by-firm fixed effects and cohort-by-date fixed effects are included in all regressions. Standard errors are clustered at the firm level. *t*-statistics are presented in parentheses. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Univariate Analysis of CAR around the Effective Date of Lockdown

	Treatment		Control	
	Pre-event	Post-event	Pre-event	Post-event
CAR	-0.999	0.309	-0.571	-0.430
Difference: Post-Pre	1.308***		0.141**	
Diff-in-Diff	1.167***			

Panel B: Full Sample of Effective Date of Lockdown

	Dependent Variable: *AR*	
Variable	(1)	(2)
Post Lockdown	0.374***	0.393***
	(3.267)	(3.461)
Past AR		-0.063***
		(-22.098)
Firm × Cohort FE	Yes	Yes
Date × Cohort FE	Yes	Yes
Number of Obs	138,968	138,940
Adjusted R^2	0.019	0.029

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Panel C: Subsample Analysis

	Dependent Variable: *AR*			
	(1)	(2)	(3)	(4)
Variable	Fewer Cases	More Cases	Fewer Cases	More Cases
Post Lockdown	0.249	0.464***	0.217	0.517***
	(1.347)	(3.126)	(1.185)	(3.512)
Past AR			-0.059***	-0.066***
			(-15.618)	(-15.172)
Firm × Cohort FE	Yes	Yes	Yes	Yes
Date × Cohort FE	Yes	Yes	Yes	Yes
Number of Obs	72,927	66,041	72,909	66,031
Adjusted R^2	0.022	0.022	0.031	0.034

effects). In tests not reported in a table, we find that an F-test that the fixed effects are insignificant is strongly rejected at less than 1 percent level of significance.

3.2 A "Placebo" Test

To ensure that our findings of the effect of lockdown on returns are not spurious and not driven by chance, we conduct a placebo test. Specifically, for each effective lockdown date, we identify control firms in states that did not implement lockdown over the ±10 day window. We then select a random subset of states (no more than four for each lockdown date) from the control group and assume that these states were placed under lockdown on the same date as the treatment states. We estimate our baseline regression using this *Post Pseudo Lockdown* variable, which is equal to one for the five days after the pseudo-event of the selected control firms and zero for other control firms. (We do not consider firms headquartered in the actual treatment state in this analysis). We repeat this procedure 200 times and report the distribution of the coefficient estimates on *Post Pseudo Lockdown* in Table 4.

The mean and median coefficient estimates are -0.045 and 0.003, respectively. About one-half of the coefficients are positive. However, the chance that we estimate a coefficient as large as that in our baseline model in column (1) of Table 3, Panel A is less than 5 percent: 95 percent of the coefficient estimates are less than the coefficient estimate in our baseline model. The 95th percentile value of the coefficient of *Post Pseudo Lockdown* is 0.262, which is well below the coefficient of 0.374 in column (1) of

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Table 3, Panel B. Thus, these results suggest that our headline findings are unlikely to spurious.

Table 4: Placebo Analysis

The table reports the distribution of the coefficient on *Post Pseudo Lockdown* variable. For each actual lockdown event date, we select a random subset of states in the control group (defined in Table 3) and assume that these states were placed under lockdown on the same date as the treatment state (i.e., *Post Pseudo Lockdown*). We estimate the baseline regression (Column 2 of Table 3 Panel A) using the *Post Pseudo Lockdown* dummy (excluding firms in the actual treatment states from the sample). We repeat this procedure 200 times to obtain the distribution of estimated coefficients and the associated *t*-statistics on the pseudo-lockdown event. The corresponding robust *t*-statistics are presented in parentheses.

	Coefficient on *Post Pseudo Lockdown*
Statistics	(1)
Mean	-0.045
	(-0.223)
Min	-0.709
	(-5.267)
1%	-0.676
	(-4.861)
5%	-0.540
	(-3.446)
25%	-0.147
	(-1.326)
Median	0.003
	(0.033)
75%	0.120
	(1.161)
95%	0.262
	(2.319)
99%	0.440
	(2.834)
Max	0.477
	(3.614)
SD	0.241
	(1.790)

3.3 *Endogeneity of Lockdowns and Interpretation of Results*

The decision to impose a lockdown likely depends on many factors, including the number of infections and their rate of spread, the capabilities of the health system, decisions by neighboring states, the demographic composition of the state, the likely economic impact, and the political orientation of the state. To the extent that information about these factors are in the public domain, their likely impact on

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business should already be impounded in stock prices and should not affect abnormal returns subsequent to lockdown announcement. However, policy makers may have private information that may trigger a lockdown, e.g., a sudden anticipated increase in the mortality rate or shortages that might cripple the hospital system. If these events materialize immediately after the lockdown, they would affect abnormal returns and create an endogeneity problem. We think it is unlikely that our results reflect such a problem, for several reasons. First, if anything, the presence of such private information would cause returns to be lower, rather than higher, after lockdowns. Second, given the close clustering of the lockdown announcements, it is likely that rather than being guided by private information, state governments were sharing information and responding to guidance from health officials at more or less the same time. With random differences in preparation time, at least for all the Democratic states, this almost creates a quasi-random timing of lockdown events.

Nonetheless, we do not contend that lockdowns directly caused the positive market reaction – i.e., we are not documenting a market reaction to the lockdown announcement *per se* over the next five days. Rather, we argue that our results are consistent with the market reacting to events that followed. In particular, we argue that the market participants updated their prior beliefs in the next several days as to how successful the stay-at-home policies would be, whether workers would be willing to come to work in essential sectors, and whether they would be able to work from home in non-essential sectors. This is salient because, as noted in the introductory section, for close to 90 percent of the firms in our sample, the state or county where the firm is headquartered is also the state or county of location of its largest plant. Thus, for manufacturing firms, the spread of the infection within the community is likely to affect workforce participation, while for firms in non-traded sectors service sectors, it is more likely to affect demand. As we show below, the market reaction was more positive in states where compliance with stay-at-home orders was more successful.[15,16]

3.4 State Political Orientation and Strictness of Lockdown

We next examine whether the market reaction to a state's lockdown depends on the state's political orientation. It has been widely reported that compliance with social distancing was less evident in Republican states.[17] The extent of lockdown restrictions also tends to be less strict in these states. We classify states as Republican or Democratic based on whether they have a Republican or Democratic trifecta status (i.e., one political party holds the governorship, a majority in the state senate, and a majority in the state house in a state's government).

We perform two separate regressions – one for the lockdowns of states with a Democratic trifecta status and the other regression for the lockdowns of states with a Republican trifecta status. Firms located in states that never announce a lockdown and those in states that have a divided trifecta status are included the control group. Results reported in Table 5 show that, while the subsequent market reaction is positive for both types of lockdowns, the magnitude and significance of the coefficient of *Post Lockdown* is higher when a Democratic state announces a lockdown. This result is consistent with our argument that information revelation regarding compliance and revision of the market's priors regarding the effectiveness of stay-at-home orders is a possible reason why abnormal returns are higher immediately after the lockdown becomes effective.

[15] Two alternative reasons for our results could be that (i) as people stay at home, retail traders trade "home stocks" more, and (ii) the higher returns post-lockdown reflect higher risk premium. In tests that we do not report in a table, we find that when a downstream firms' state comes under lockdown, its suppliers in states that have not yet experienced lockdowns also experience higher returns, which is not consistent with the home-bias explanation. Moreover, the market response is higher for states which did better in terms of compliance with stay-at-home orders, which is difficult to explain in terms of a risk-based argument.

[16] In unreported tests, we find that if we isolate the day the lockdown becomes effective, the market reaction on that day is insignificant, which is consistent with our interpretation that the market responding to events immediately following the lockdown.

[17] "Where America Didn't Stay at Home Even as the Virus Spread", The New York Times, April 2, 2020.

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Table 5: Political Orientation and Effective Lockdown
This table presents the results for the regression of Table 3 in two subsamples split based on state's political orientation. A state is deemed to be a democratic (republican) state if the state has a democratic (republican) trifecta status. States that never announced a lockdown and those with a divided trifecta status (i.e., more balanced power between the two political parties) are classified into the control group (*Post Lockdown* = 0). The sample period is from March 12, 2020 to April 14, 2020. Both cohort-by-firm fixed effects and cohort-by-date fixed effects are included in all regressions. Standard errors are clustered at the firm level. *t*-statistics are presented in parentheses. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent Variable: *AR*			
	(1)	(2)	(3)	(4)
Variable	Democratic	Republican	Democratic	Republican
Post Lockdown	0.903***	0.483**	0.869***	0.598**
	(3.145)	(2.355)	(3.075)	(2.303)
Past AR			-0.066***	-0.070***
			(-18.893)	(-3.553)
Firm × Cohort FE	Yes	Yes	Yes	Yes
Date × Cohort FE	Yes	Yes	Yes	Yes
Number of Obs	95,193	43,435	95,192	43,418
Adjusted R^2	0.030	0.023	0.040	0.035

There was a significant variation in the extent of restrictions associated with lockdowns in different states. As discussed in Section 1, we collect information on how strict the lockdowns were on different dimensions and construct our own score of "lockdown strictness". In Table 6, we create a variable *Post Lockdown Score*, which is the interaction between the *Post Lockdown* dummy variable and the lockdown score (i.e., this essentially means that *Post Lockdown Score* replaces the *Post Lockdown* dummy variable). The coefficient on *Post Lockdown Score* is positive and significant. These results are consistent with the idea that the market responded more positively when the social distancing was more comprehensive.

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Table 6: Strictness of Lockdown Restrictions
This table presents the stacked difference-in-difference regression results surrounding the effective date of lockdown. The sample period is from March 12, 2020 to April 14, 2020. *Post Lockdown Score* is computed as *Post Lockdown* times the total restriction scores of lockdowns. The total restriction scores are the sum of stay-at-home restriction score, public gathering restriction score, and business activity restriction score. Stay-at-home, public gathering, and business activity restriction score range from 0 to 2, from 0 to 3, and from 1 to 3, respectively, with higher score capturing a higher level of restriction. Panel A reports the results for the full sample of effective lockdown analysis. Panel B reports the results for the subsample analysis based on the number of infections scaled by the population in the county where the firm located on the cohort's lockdown effective date. Both cohort-by-firm fixed effects and cohort-by-date fixed effects are included in all regressions. Standard errors are clustered at the firm level. *t*-statistics are presented in parentheses. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent Variable: *AR*	
Variable	(1)	(2)
Post Lockdown Score	0.060***	0.058***
	(3.591)	(3.529)
Past AR		-0.063***
		(-22.081)
Firm × Cohort FE	Yes	Yes
Date × Cohort FE	Yes	Yes
Number of Obs	138,968	138,940
Adjusted R^2	0.019	0.029

3.5 Essential versus Non-Essential Industries

Most lockdowns allowed establishments in "essential sectors" to stay open, but those deemed "non-essential" were to either close or carry on only those operations that were deemed absolutely necessary, with workers directed to work from home. In Table 7, we examine whether the market reaction subsequent to lockdowns was more muted for firms in these so-called "non-essential" sectors. This might be expected because (a) the work disruption due to lockdowns in the short-term is likely to be more severe for these firms, and (b) in the absence of lockdowns, these firms might still continue to operate because of the possibility of work from home. We partition firms into those belonging to essential and non-essential sectors, respectively.[18]

[18] Essential industries are defined by the Department of Homeland Security based on 4-digit NAICS, which are available at https://www.cisa.gov/publication/guidance-essential-critical-infrastructure-workforce.

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Results reported in Table 7 show that the coefficient of *Post Lockdown* for the subsample comprising the firms in the non-essential sectors is smaller and about half the magnitude of that for the subsample comprising firms in the essential sectors, though still significant at the 10 percent level.

Table 7: Essential vs. Non-Essential Industries

This table presents the industry analysis of the effective lockdown events. The sample period is from March 12, 2020 to April 14, 2020. The sample is divided into two subsamples based on whether firm's industry is classified as essential or non-essential industries. Essential industries are defined by the Department of Homeland Security based on 4-digit NAICS, which are available at https://www.cisa.gov/publication/guidance-essential-critical-infrastructure-workforce. Both cohort-by-firm fixed effects and cohort-by-date fixed effects are included in all regressions. Standard errors are clustered at the firm level. *t*-statistics are presented in parentheses. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent Variable: *AR*			
	(1)	(2)	(3)	(4)
Variable	Non-Essential	Essential	Non-Essential	Essential
Post Lockdown	0.266*	0.431**	0.271*	0.470***
	(1.687)	(2.528)	(1.739)	(2.768)
Past AR			-0.072***	-0.055***
			(-17.140)	(-14.220)
Firm × Cohort FE	Yes	Yes	Yes	Yes
Date × Cohort FE	Yes	Yes	Yes	Yes
Number of Obs	60,995	77,973	60,995	77,945
Adjusted R^2	0.027	0.016	0.039	0.024

3.6 Lockdown Extensions

In Table 8, we examine the effect of lockdown extension announcements. These regressions are also done in a stacked difference-in-difference setting. The control samples comprise firms in all states that do not announce lockdown extension over the next 10 days, and firms in states that have already announced lockdown extension at least 10 days earlier. On average, the market reaction subsequent to extension announcements is negative, as shown in Panel A of Table 8. It is possible that the market participants by the time these extensions were announced had revised the benefit-cost trade-offs of lockdowns, since there is now updated information about the effectiveness of government support programs for business, the likely impact of the

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spread of infection on business, the awareness of individuals to infection risk and their capacity to exercise voluntary self-distancing, etc. Thus, it appears that, on average, the market participants by this time were leaning towards discontinuation of the lockdown measures. In Panel B, however, a more nuanced picture emerges: while lockdown extensions are associated with more negative market reaction when the number of infections in the state announcing the extension is low, the opposite is the case when this is high. These results are consistent with the notion that market participants viewed lockdowns as an effective form of intervention that, in mitigating the spread of infections, would be ultimately beneficial for business.

Table 8: Announcement of Lockdown Extension and Abnormal Returns

This table presents the stacked difference-in-difference regression results surrounding the announcement of lockdown extension. The sample period is from March 26, 2020 to May 8, 2020. For each announcement date of lockdown extension, we construct a cohort of treated firms (i.e., those headquartered in a state that announced lockdown extension) and control firms using observations over a [-5, 5] window (i.e., the five days before and five days after the announcement of lockdown extension). *Post AnnExtension* is a dummy variable equal to one for the five days after the announcement date of lockdown extension of a treatment state where a firm located, and equal to zero for the five days before the announcement date of lockdown extension of a treatment state, for firms in states that do not announce lockdown extension over the 10 days after the announcement date of lockdown extension of the treatment state, for firms in states that have already announced lockdown extension at least 10 days before the announcement date of lockdown extension of the treatment state. Panel A reports the results for the full sample analysis. Panel B reports the results for the subsample analysis based on the number of infections scaled by the population in the county where the firm located on the cohort's announcement date of lockdown extension. Both cohort-by-firm fixed effects and cohort-by-date fixed effects are included in all regressions. Standard errors are clustered at the firm level. *t*-statistics are presented in parentheses. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Full Sample of Announcement Date of Lockdown Extension

	Dependent Variable: *AR*	
Variable	(1)	(2)
Post AnnExtension	-0.101**	-0.087*
	(-2.150)	(-1.860)
Past AR		-0.034***
		(-40.815)
Firm × Cohort FE	Yes	Yes
Date × Cohort FE	Yes	Yes
Number of Obs	601,173	601,038
Adjusted R^2	0.045	0.052

Panel B: Subsample Analysis

	Dependent Variable: *AR*			
	(1)	(2)	(3)	(4)
Variable	Fewer Cases	More Cases	Fewer Cases	More Cases
Post AnnExtension	-0.215***	0.149***	-0.176***	0.124**
	(-4.059)	(2.589)	(-3.332)	(2.170)
Past AR			-0.025***	-0.028***
			(-30.944)	(-33.995)
Firm × Cohort FE	Yes	Yes	Yes	Yes
Date × Cohort FE	Yes	Yes	Yes	Yes
Number of Obs	279,259	321,914	279,224	321,814
Adjusted R^2	0.049	0.065	0.055	0.073

3.7 Robustness

The lockdown announcements are closely clustered over the period March 19-April 6. This makes the composition of the control samples sensitive to the requirement that for firms in a state to belong to the control sample for a specific event day, that state must not experience a lockdown within ±10 trading days of that event day. Moreover, this requirement also leads to a few highly unbalanced cohorts in terms of the number of firms in the treated and control. To see whether our results are sensitive to these choices, we first change the requirement that, to be included in the control sample for an event, another state must not experience a lockdown within 10 days, to within 5 days. We also drop the states of Alabama, Missouri and South Carolina, which were among the last ones to announce lockdowns, from the treated group since their inclusion means that New York and California enter the control group and the cohorts become highly unbalanced. Table 9 Panel A reports the results. The post-lockdown dummy remains highly significant and the magnitude of the coefficient estimate is similar to that in Table 3.

Next, in Panel B of Table 9, we only include the two largest (and the first) states to announce lockdowns – California and New York – as the treated states. All other states that experience lockdowns after 5 days are included in the corresponding control samples. The coefficient of the post-lockdown dummy remains positive and significant in Panel B.

In Panel C (Panel D), we drop New York entirely (consider Friday, March 20 to be the effective day for New York's lockdown, although the order was only effective after trading hours that day). The latter change also balances the cohort as more states are retained in the control sample. Again, the coefficient of the post-lockdown dummy remains positive and highly significant. In Panel B, its magnitude is very similar to that in Table 3. Clearly, excluding the state with the greatest number of firms has little effect on our results. The coefficient is also positive and significant, though somewhat larger, in Panel C.

Table 9: Robustness Tests

This table presents the results for robustness tests of the stacked difference-in-difference regression surrounding the effective date of lockdown. Panel A reports the results for the first robustness test in which we change the requirement that, to be included in the control sample for an event, another state must not experience a lockdown within 10 days, to within 5 days following the event [*Relaxed Criteria*]. We also drop the states of Alabama, Missouri and South Carolina from the treated group. In Panel B, we only include the two largest (and the first) states that experience lockdowns – California and New York – as the treated states and maintain the relaxed criteria for inclusion in the control group. In Panel C and D, we drop the states of New York, Alabama, Missouri and South Carolina from the treated group and use the same method to construct control group as in Table 3. In Panel D, the lockdown effective date of New York is redefined as March 20, 2020. Both cohort-by-firm fixed effects and cohort-by-date fixed effects are included in all regressions. Standard errors are clustered at the firm level. *t*-statistics are presented in parentheses. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Relax Criteria for Control Sample and Drop the Lockdown Events in Alabama, Missouri, and South Carolina

	Dependent Variable: *AR*	
Variable	(1)	(2)
Post Lockdown	0.460***	0.399***
	(5.044)	(4.430)
Past AR		-0.097***
		(-31.064)
Firm × Cohort FE	Yes	Yes
Date × Cohort FE	Yes	Yes
Number of Obs	154,488	154,425
Adjusted R^2	0.009	0.028

Panel B: Subsample of Lockdown Events in California and New York [Relaxed Criteria for Control Sample

	Dependent Variable: *AR*	
Variable	(1)	(2)
Post Lockdown	0.464***	0.226*
	(3.535)	(1.766)
Past AR		-0.179***
		(-37.261)
Firm × Cohort FE	Yes	Yes
Date × Cohort FE	Yes	Yes
Number of Obs	60,835	60,819
Adjusted R^2	0.001	0.041

Panel C: Drop the Lockdown Events in New York, Alabama, Missouri, and South Carolina

	Dependent Variable: *AR*	
Variable	(1)	(2)
Post Lockdown	0.371***	0.393***
	(3.087)	(3.290)
Past AR		-0.076***
		(-20.244)
Firm × Cohort FE	Yes	Yes
Date × Cohort FE	Yes	Yes
Number of Obs	83,841	83,813
Adjusted R^2	0.016	0.030

Panel D: Redefine the Event in New York and Drop Events in Alabama, Missouri, and South Carolina

	Dependent Variable: *AR*	
Variable	(1)	(2)
Post Lockdown	0.518***	0.500***
	(4.462)	(4.348)
Past AR		-0.082***
		(-22.674)
Firm × Cohort FE	Yes	Yes
Date × Cohort FE	Yes	Yes
Number of Obs	96,781	96,753
Adjusted R^2	0.013	0.029

4 Conclusions

One of the key issues in the "health versus wealth" debate surrounding the implementation of Non-Pharmaceutical Interventions such as stay-at-home orders in a pandemic is whether such policies push mitigation to a point where they impose net economic costs on society. A complete answer to this question is difficult and possibly highly context-specific. We examine how market participants evaluate the adoption of such measures in U.S. states during the Covid-19 pandemic. Our main finding is that, on average, irrespective of whether the state adopting a lockdown is Democratic or Republican, the subsequent market response to the adoption of lockdowns is positive. The reaction is more positive if the state adopting the lockdowns has relatively more infections at the time. Even extensions of lockdowns are received positively by the market when the infections are relatively high; however, when a county's infections are low, lockdown extensions are associated with negative market reactions. Overall, these results suggest that market participants have regarded NPIs, when successful in implementing social distancing, as having positive net effects on business activity even though the short-term consequences are very likely to be adverse. This is possibly because such restrictions are viewed as necessary for arresting the spread of the infection and making subsequent labor participation possible in the local economies.

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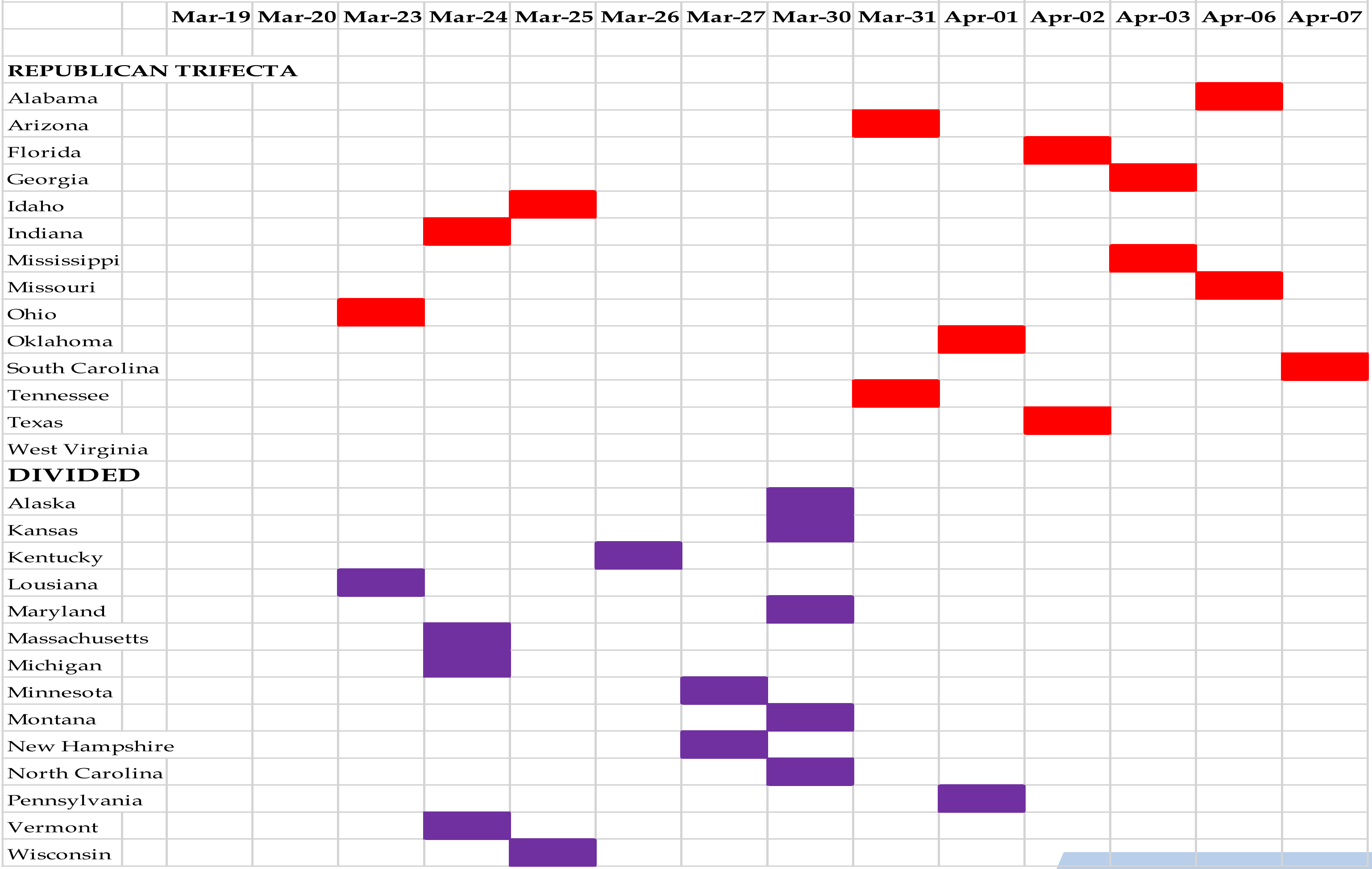
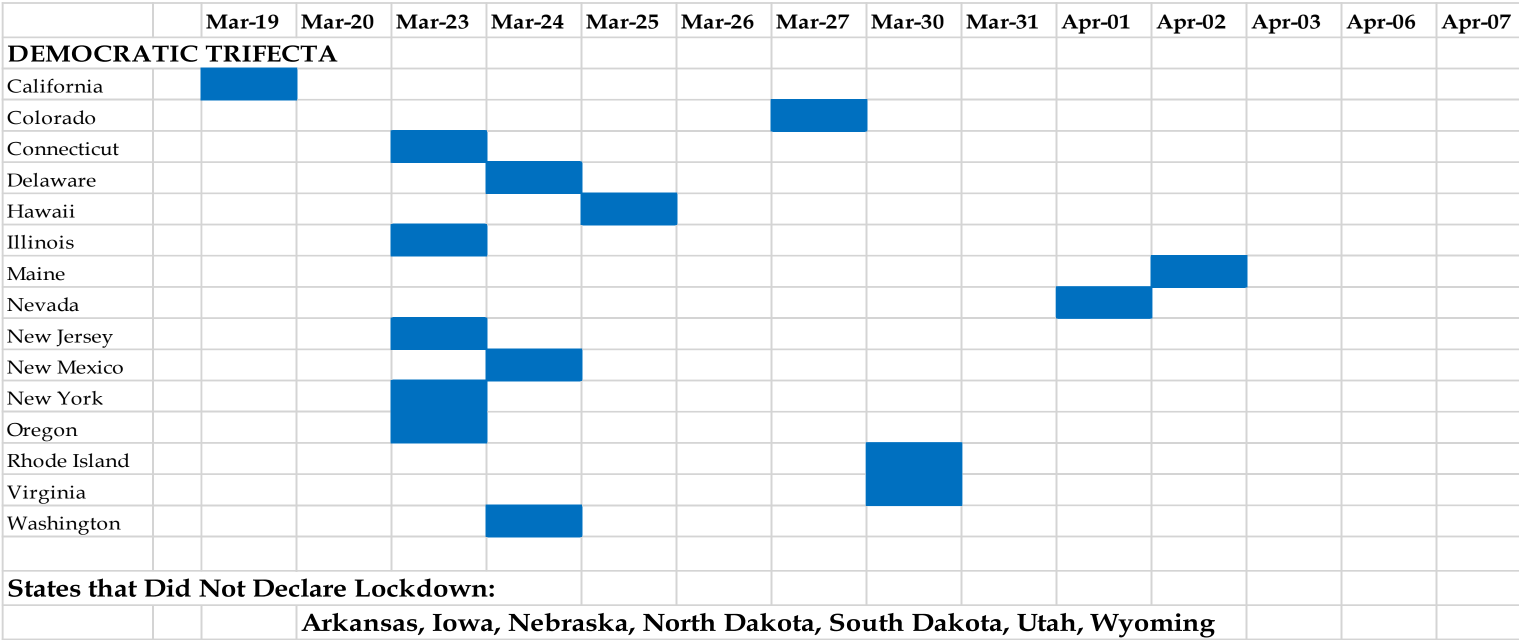
APPENDIX

Figure 1. First Trading Day After Lockdown Became Effective (by Trifecta Status)




Mar-19
Mar-20
Mar-23
Mar-24
Mar-25
Mar-26
Mar-27
Mar-30
Mar-31
Apr-01
Apr-02
Apr-03
Apr-06
Apr-07
DEMOCRATIC TRIFECTA
California
Colorado
Connecticut
Delaware
Hawaii
Illinois
Maine
Nevada
New Jersey
New Mexico
New York
Oregon
Rhode Island
Virginia
Washington
States that Did Not Declare Lockdown:
Arkansas, Iowa, Nebraska, North Dakota, South Dakota, Utah, Wyoming

The role of corporate culture in bad times: Evidence from the COVID-19 pandemic[1]

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After fitting a topic model to 79,597 COVID-19-related paragraphs in 11,183 conference calls over the period January to April 2020, we obtain measures of firm-level exposure and response to COVID-19 for 3,019 U.S. firms. We show that despite many different ways through which COVID-19 affects their operations, firms with a strong corporate culture do better in the midst of a pandemic than their peers without a strong culture. Moreover, firms with a strong culture are more likely to emphasize community engagement and adopt digital technology, and are no more likely to engage in cost cutting than their peers without a strong culture. To explore the channels through which culture makes firms resilient to the pandemic, we show that firms with a strong culture have higher sales per employee and lower cost of goods sold per employee during the first quarter of 2020. Our results provide support for the notion that corporate culture is an intangible asset designed to meet unforeseen contingencies as they arise (Kreps 1990).

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"... We are also in the early stages of understanding if and to what extent we may be temporarily impacted by the coronavirus. At this point, we're expecting a 1- to 1.5-week delay in the ramp of Shanghai-built Model 3 due to a government-required factory shutdown. This may slightly impact profitability for the quarter but is limited as the profit contribution from Model 3 Shanghai remains in the early stages."

Zachary Kirkhorn
Chief Financial Officer, Tesla, Inc., January 29, 2020

"At this point, a broader and more meaningful slowdown in new bookings and an increase in cancellations began to develop for sailings outside of Asia. Since the outbreak began, we have taken several aggressive and proactive measures to assure the safety, security and well-being of our guests and crew by implementing strict embarkation and screening protocols…"

Frank J. Del Rio
President & Chief Executive Officer, Norwegian Cruise Line, February 20, 2020

"... However, as the virus has spread, there has been a sudden sharp decline in demand throughout the rest of the world and RevPAR at our hotels has dropped dramatically. Over the last few days, occupancy rates in North America and Europe were under 25% compared to around 70% a year ago. The crisis outside the Asia Pacific region is much more recent and the trends are still negative. Unfortunately, this situation will likely continue to get worse before it gets better ..."

Arne M. Sorenson
President & Chief Executive Officer, Marriott International, Inc., March 19, 2020

"... We have prioritized the health and safety of our teammates, and we have closed our stores. Over the weekend, we drove a strong digital marketing campaign to engage consumers across Europe and across the U.S. to stay healthy and connected while they're at home. And our digital commerce remains open and in growth mode, supported by our teammates in our distribution centers."

John J. Donahoe
President, Chief Executive Officer & Director, NIKE, Inc., March 24, 2020

1. Introduction

Over the past two decades, the world was hit by a number of outbreaks of epidemic diseases, including the severe acute respiratory syndrome (SARS) outbreak between 2002-2004, the swine flu pandemic between 2009-2010, and the Ebola virus epidemic between 2013-2016. By the end of May 2020, the latest COVID-19 pandemic has infected almost 6 million people and caused over 360 thousand deaths, has kept more than a third of global population under lockdown, and is having a devastating impact on the world economy. Given the extraordinary

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nature of the current public health crisis, it becomes imperative for financial economists to study which firms and industries are expected to gain or lose from an epidemic disease and what makes some firms resilient in the face of great uncertainty as the pandemic spreads. In this paper, we examine how firms with a strong corporate culture fare amid the COVID-19 outbreak and identify the underlying mechanisms.

What is corporate culture? Corporate culture is a system of shared beliefs and values within an organization (Cremer 1993; Lazear 1995; Van den Steen 2010). Different from formal control mechanisms codified in the form of rules and procedures, corporate culture is regulated through peer influence and the social construction of reality (Berger and Luckmann 1967), and results in positive feelings of solidarity and a great sense of autonomy among people within an organization (O'Reilly and Chatman 1996). According to Kreps (1990), corporate culture is an intangible asset designed to meet unforeseen contingencies as they arise. We posit that corporate culture matters (even more) in a challenging operational environment such as the COVID-19 pandemic because a strong culture empowers executives and rank-and-file employees to make consistent decisions and effort based on long-term perspectives.

There are several empirical challenges to test our hypothesis. First, despite the importance of corporate culture, extant literature provides limited large-sample evidence on the relationship between corporate culture and firm policy/value, and mainly employs proxies for corporate culture or relies on survey/interview evidence (e.g., Guiso, Sapienza, and Zingales 2015; Graham, Grennan, Harvey, and Rajgopal 2018, 2019). In this paper, we employ a measure of corporate culture inspired by Guiso, Sapienza, and Zingales (2015) covering five values: innovation, integrity, quality, respect, and teamwork and developed by Li, Mai, Shen, and Yan (2020) using word embedding, a machine learning technique. Their

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method provides more comprehensive coverage of corporate culture than previous approaches.

Second, we need firm-level measure of exposure and response to COVID-19 as firms are hit in very different ways and to different degrees by the pandemic (e.g., their employees, customers, suppliers, and/or financing; see the first three quotes above from executives talking about COVID-19 during conference calls) and also respond differently (e.g., cost cutting and adopting digital technology; see the fourth quote above). We develop a new measure of firm-level exposure and response using conference calls in which senior management discusses business operations and firm performance, and answers questions from market participants about firms' prospects, including comments on COVID-19 and its implications. To do so, we use the word embedding model, the same machine learning technique employed by Li et al. (2020), to create a COVID-19-specific word list (i.e., a list of synonyms) based on 11,183 conference call transcripts over the period January to April 2020. We then tag paragraphs in which any COVID-19-related word shows up as COVID-19-related paragraphs. To capture firm-level exposure/response to COVID-19, we fit a correlated topic model (CTM, Blei and Lafferty 2007) to 79,597 COVID-19-related paragraphs. The CTM uncovers underlying topics in a large set of documents (i.e., paragraphs) based on the statistical correlations among words and topics in these documents. Our first set of measures—firm-level exposure/response to COVID-19—is the proportion of text in its COVID-19-related paragraphs devoted to particular topics. Our second measure—firm-level overall exposure to COVID-19—is simply the sum of firm-level different exposures.

Using over 11,000 calls in the first four months of 2020, we first document the top three exposures to COVID-19 are: 1) negative demand shocks; 2) supply chain disruptions; and 3) employee safety and wellbeing. The remainder are: lockdown, competition, liquidity and financing, and delay to operation. We also identify three major responses to COVID-19

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are: promoting community engagement, cost cutting, and adopting digital technology. At the industry-level, the top three industries with the greatest exposure to COVID-19 are: chemicals and allied products; consumer non-durables; and manufacturing.

Using 2,502 U.S. firms with data on corporate culture, COVID-19 exposure/response, and monthly returns for the period January 2019 to March 2020, we show that firms with a strong culture exhibit better stock market performance during the COVID-19 crisis than their counterparts with a weak culture. A firm is perceived to have a strong culture if its culture score is in the top quartile among all firms (Li et al. 2020). In terms of economic significance, we show that for a firm with a strong culture, a one-standard-deviation increase in a firm's overall exposure to COVID-19 (11.28%) reduces its monthly return drop by 0.9 percentage points (or 2.6 percentage points in quarterly returns).

We further show that despite many different ways through which COVID-19 affects their operations, firms with a strong culture outperform their counterparts with a weak culture. Moreover, we find that firms with a strong culture are more likely to emphasize community engagement and adopt digital technology, and are no more likely to engage in cost cutting than their peers. O'Reilly and Chatman (1996) argue that norms of creativity and innovation may be the most effective mechanisms for promoting organizational adaptability amid a major crisis. Our results provide support for their conjecture.

To explore the channels through which culture makes firms resilient to the pandemic, we find that firms with a strong culture have higher sales per employee and lower cost of goods sold per employee during the first quarter of 2020. Recall that our corporate culture measure is a sum of five cultural value scores in innovation, integrity, quality, respect, and teamwork, that can be grouped into two subcultures: people-oriented culture comprised of integrity, respect, and teamwork, and technology-oriented culture comprised of innovation and quality. We further show that firms strong in either subculture is associated with higher

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sales per employee, and firms strong in people-oriented subculture is associated with lower cost of goods sold per employee. Edmans (2011) and Oswald, Proto, and Sgroi (2015) show that happy employees are better motivated and more productive. Luo and Bhattacharya (2006), Edmans (2011), and Albuquerque, Koskinen, and Zhang (2019) argue and show that customers are drawn to firms that treat their employees well. We show that during the pandemic, happy employees are more productive and incur less cost, and customers are drawn to firms with a strong culture compared to firms without a strong culture. Our results suggest that corporate culture works through the human capital and technology channels to make firm resilient during a pandemic.

Taken together, we conclude that our evidence provides support for the notion that corporate culture is an intangible asset designed to help firms prevail in unforeseen contingencies (Kreps 1990).

Firms with a strong culture are not the only firms that perform better during the first quarter of 2020. Acharya and Steffen (2020) find that firms with access to lines of credit or high cash holdings perform better. Albuquerque, Koskinen, Yang, and Zhang (2020) show that firms with high environmental and social (ES) ratings outperform during the first quarter of 2020 compared to other firms. Ding, Levine, Lin, and Xie (2020) show that firms with stronger balance sheets, less exposure to COVID-19 via global supply chains and customer base, and higher environmental, social, and governance performance, do better. Hassan, Hollander, van Lent, and Tahoun (2020) conclude that firms that have experienced with SARS or H1N1 have more positive expectations about their ability to deal with the COVID-19 outbreak. Pagano, Wagner, and Zechner (2020) and Papanikolaou and Schmidt (2020) show that firms that rely more on technologies and/or have work arrangements that are robust to physical distancing outperform those that rely less on technologies and/or flexible work arrangements during the COVID-19 outbreak. Ramelli and Wagner (2020) find that firms

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with lower financial leverage, higher cash holdings, and lower exposure to China are less affected than other firms. Using survey data on employee satisfaction, Shan and Tang (2020) show that Chinese firms with higher employee satisfaction have better stock market performance than their counterparts with lower employee satisfaction during the COVID-19 outbreak. It is worth noting that our main finding remains after controlling for these other known firm characteristics that make them resilient during the crisis.

Our paper contributes to the existing literature in the following dimensions. First, our paper is among the first in the literature, as far as we are aware, to estimate firm-level measure of exposure and response to COVID-19 for a large sample of firms by employing the word embedding model and correlated topic model. Our paper thus makes an important methodological contribution by highlighting new applications of machine learning tools in finance.[1]

Second, with more granular data on firm-level exposure/response to COVID-19, we are able to delineate the channels through which corporate culture matters amid the pandemic. Our paper hence contributes to a better understanding of the importance of intangibles in general, and whether and how corporate culture in particular, in enhancing firm value.[2]

Third and finally, given that the COVID-19 pandemic is exogenous to a firm's economic fundamentals, the unique setting allows us to establish a causal effect of bad times on the culture-value link.

[1] As such, our paper joins the recent surge in the fields of economics, finance, and accounting with different applications of machine learning tools (see Athey and Imbens (2019) for machine learning applications in general, and Gentzkow, Kelly, and Taddy (2019) for methods involving text data). Earlier papers using the word embedding model are Hanley and Hoberg (2019) and Li et al. (2020); the only earlier paper employing a variation of correlated topic modeling is Dasgupta, Harford, Ma, Wang, and Xie (2020).
[2] The earliest work on the intangible-value link includes Lev and Sougiannis (1996) using capitalized R&D expenses, Chan, Lakonishok, and Sougiannis (2001) using R&D expenses and advertising expenses, and Lev and Radhakrishnan (2005) using capitalized selling, general, and administrative expenses (SGA).

2. Literature Review and Hypothesis Development

2.1 Literature review

Our paper is broadly related to a strand of the literature examining the relation between intangibles and firm value. Edmans (2011) show that firms included in the "100 Best Companies to Work for" as produced by the Great Place to Work Institute tend to have a higher future abnormal stock returns. Servaes and Tamayo (2013) find that corporate social responsibility (CSR) and firm value are positively related for firms with high customer awareness, as proxied by advertising expenditures. Using advertised values via firms' websites, Guiso, Sapienza, and Zingales (2015) show that proclaimed values are not significantly associated with firm performance; instead, values perceived by rank-and-file employees via the Great Place to Work Institute survey have performance implications. Ferrell, Liang, and Renneboog (2016) find a positive relation between CSR and firm value using international data. Lins, Servaes, and Tamayo (2017) find that the trust between a firm and both its stakeholders and investors, built through investments in social capital as measured by CSR, pays off during the 2008-2009 financial crisis. Albuquerque, Koskinen, and Zhang (2019) present a model where firms with credible ES policies have more loyal customer base and face less price-elastic demands for their products, leading to higher firm value. In a recent survey of North American Chief Executive Officers (CEOs) and Chief Financial Officers (CFOs), Graham et al. (2019) note that a majority of senior executives view corporate culture as one of the top three factors that affect their firm's value, and over 90% of them believe that improving corporate culture will increase firm value. Grennan (2019) shows that corporate culture is an important channel through which governance affects firm value. Grennan (2020) finds that a simple mechanism—communicating culture consistently—is linked to value creation. Li et al. (2020) show that corporate culture

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correlates with business outcomes, including operational efficiency, risk-taking, earnings management, executive compensation design, and firm value.

2.2 Hypothesis development

In a seminal paper, Kreps (1990, p.93) takes the view that corporate culture is "how things are done, and how they are meant to be done in the organization." Kreps focuses on situations in which cooperation among employees and their superiors is crucial, and there are two traditional ways to induce cooperation: contracts and repeated interaction. However, Kreps notes that both become too costly and/or infeasible when states or actions are not verifiable or difficult to specify in advance, and that establishing a norm to do things (i.e., corporate culture) addresses those challenges. Kreps concludes that corporate culture, as a coordination mechanism, can sustain desirable outcomes in a world with unforeseen contingencies.

Cremer (1993) defines corporate culture as the knowledge shared by (a sizeable part of the) members of an organization, but not by the general population. Lazear (1995) views corporate culture as shared beliefs or preferences that arise from an evolutionary process. Management can foster culture in two ways: selection and internalization (i.e., actively advocate via training and speeches). Lazear (1995) demonstrates that by changing employees' preferences for behavior, corporate culture acts as an alternative to the price system with costly monitoring as a motivator of employees. Relatedly, O'Reilly and Chatman (1996) note that strong social control systems such as corporate culture often results in positive feelings of solidarity and a great sense of autonomy among people within an organization. Van den Steen (2010) examines the origins of corporate culture, and show that firms develop homogeneous beliefs (i.e., corporate culture) through three mechanisms: screening in the hiring process, employee self-sorting, and joint learning (employees

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experience a firm's behavior and performance together and learn from it). In his model, culture persists despite personnel turnover.

In the business world, corporate executives characterize culture as "a belief system", "a coordination mechanism", and "an invisible hand", and generally believe that a strong culture instills long-term orientation among executives and employees and that there is a positive link between having a strong culture and good firm performance (Graham et al. 2018, 2019).

Based on the above discussion, we expect that the presence of a strong culture whereby a set of norms and values are widely shared and strongly held throughout an organization (O'Reilly 1989), is associated with higher goal alignment among employees, promotes an unusual level of motivation among employees, and provides needed controls without the stifling effects of bureaucracy. The above effects are more salient in a challenging operational environment like the COVID-19 pandemic, when a strong culture empowers executives and rank-and-file employees to make consistent decisions and exert greater effort based on long-term perspectives. Our first hypothesis is thus as follows:

H1: The positive culture-value link is stronger amid the COVID-19 pandemic.

There are large cross-sectional variations in firm-level exposure to COVID-19 (see, for example, the first three quotes above). In addition to the detrimental impact of the virus on employee safety and wellbeing, the lockdown and physical distancing policies reduce revenue and impose additional costs. Pagano, Wagner, and Zechner (2020) and Papanikolaou and Schmidt (2020) show that firms with jobs requiring human contact and difficult to implement work-from-home (WFH) are more exposed to the pandemic. In contrast, firms in technology and communication sectors are less affected and even have the opportunity to expand their businesses. Considering this heterogeneity, we hypothesize that the positive

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association between firms with a strong corporate culture and returns during the pandemic is conditional on firm-level exposure to COVID-19:

H2: The positive culture-value link is stronger for firms with greater exposure to COVID-19.

In today's knowledge economy, increased competition at the worldwide level has increased the demand for process innovation and quality improvement, which are generated by talented employees. Thus, the quest for more innovation and better qualitative products/services increases the importance of human capital in a modern corporation (Zingales 2000). Human relations theories (e.g., Maslow 1943; Hertzberg 1959; McGregor 1960) view employees as key organizational assets, and their satisfaction can improve motivation and retention, leading to better firm performance. Edmans (2011), Oswald, Proto, and Sgroi (2015), and Lins, Servaes, and Tamayo (2017) provide empirical evidence that happy and satisfied employees are more productive. Shan and Tang (2020) document that Chinese firms with greater employee satisfaction appear to endure the COVID-19 stock market downturn better than other firms. A separate benefit of firms treating their employees fairly is that customers may be more willing to patronize these firms (Edmans 2011; Servaes and Tamayo 2013). We thus posit that one potential channel through which firms with a strong culture outperform their peers with a weak culture is the human capital channel, whereby firms investing more in their people during good times will enjoy higher employee productivity in the pandemic because well-treated employees are better motivated and more productive (e.g., Edmans 2011; Oswald, Proto, and Sgroi 2015) and attract more customer patronage (e.g., Edmans 2011; Servaes and Tamayo 2013).

O'Reilly and Chatman (1996) note that norms of creativity and innovation may be the most effective mechanisms for promoting organizational adaptability amid a major crisis. Several contemporaneous papers on COVID-19 show that firms that rely more on technologies and/or have work arrangements that are robust to physical distancing, significantly outperform those that rely less on technologies and/or flexible work arrangements during the COVID-19 outbreak (e.g., Pagano, Wagner, and Zechner 2020; Papanikolaou and Schmidt 2020). Luo and Bhattacharya (2006) establish the link between "corporate ability", as manifested in terms of innovation capability and product quality, and customer satisfaction, leading to higher firm value. Albuquerque, Koskinen, and Zhang (2019) model CSR as an investment to increase product differentiation that allows firms to benefit from higher profit margins. We thus posit that another potential channel through which firms with a strong culture outperform their peers with a weak culture in the pandemic is the technology channel, whereby firms with innovative products and services achieve product differentiation and customer loyalty and/or adopt more digital technology, creating more pricing power.

3. Methodology

In this section, we describe our approach to measure firm-level COVID-19 exposure and response using conference call transcripts.

3.1 Preprocessing the data

We obtain call transcripts from the Standard & Poor's (S&P's) Global Market Intelligence database over the period January 01, 2020, to April 30, 2020. There are a total of 11,183 calls: three-quarters of the calls are earnings calls, about one-tenth are company conference presentations, and the rest are shareholder/analyst calls, special calls, sales/trading statement calls, mergers and acquisitions calls, etc. We include all calls to train the machine learning models because these models benefit from a large corpus.[3] Each call transcript is in

[3] When measuring firm-level exposure and response to COVID-19 through their discussions about COVID-19 in calls, we drop calls without any COVID-19-related discussions. See Section 3.2 for details.

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PDF format, which we convert to a text file using a Python package *pdfminer*.[4] Each file contains the body of a call transcript and the following meta-data that help us match the company to the Compustat database: the ticker symbol header, the company name, the title of the event, and the date of the call.

We use the Stanford CoreNLP package to preprocess and parse the text.[5] We segment text files into sentences and words, and lemmatize words to their base forms. We conduct Named Entity Recognition (NER) to replace named entities such as locations, times, persons, and company names with a predefined tag. Since phrases (collocations) play a crucial role in gathering information from corporate disclosures, we use a two-step approach to extract both general and corpus-specific phrases. In step one, we use the dependency parser in the CoreNLP package to identify fixed multi-word expressions (e.g., *as well as*, *lot of*) and compound words (e.g., *market volatility* and *growth rate*). These phrases are usually part of the general English vocabulary or can be inferred based on the grammatical relationships between words. We remove punctuation marks, stop words, and single-lettered words after identifying and concatenating multi-word expressions (MWEs) and compound words.[6] In the second step, we use the *phraser* module of the *gensim* library to find two- and three-word phrases that are more specific to the corpus (i.e., words that have statistically significant co-occurrences in the collection of call transcripts).[7] For example, the phrases learned in the second step include: *supply_chain_disruption* and *social_distancing_measure*. We concatenate all the phrases using the underscore symbol and treat them as a single word. Our

[4] https://github.com/pdfminer/pdfminer.six.
[5] The CoreNLP package is an open-source Natural Language Processing (NLP) toolkit for a variety of tasks (Manning et al. 2014). We use version 3.9.2, available at https://stanfordnlp.github.io/CoreNLP.
[6] This order is important because some of the stop words are part of MWEs and compound words.
[7] The *gensim* library is an open-sourced NLP Python package that we use for training the *word2vec* model. We use version 3.7.2, available at https://github.com/RaRe-Technologies/gensim.

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results show that phrases constitute an essential part of how a firm's exposure and response to COVID-19 are conveyed in calls.

3.2 The challenge

The conference call examples shown earlier illustrate a number of challenges when using calls to measure firm-level exposure/response. First of all, the goal of conference calls is to talk about industry trends, business operations, and performance. To reduce the number of topics in calls, we need to limit our attention to COVID-19-related paragraphs.

Second, there are many different ways to refer to the COVID-19 pandemic; very often the term COVID-19 or its variations (e.g., coronavirus, and SARS-CoV-2) are not even mentioned, but given the context, the discussion is indeed about COVID-19. For example, earlier in the year, discussions of "virus", "quarantine", "self-isolation" (when the outbreak first took its hold in China) are all about COVID-19, but have no mention of COVID-19 or coronavirus (the two most common terms). We hence need an expanded word list (i.e., a list of synonyms) to tag COVID-19-related paragraphs in calls.

Third, different firms may face different challenges and respond differently amid the pandemic, which could potentially shed light on how strong culture makes firms resilient. For example, in Tesla' January call, it talks about potential disruption to its supply chains, in Norwegian Cruise Line's February call, it talks about the safety of their employees and guests and declines in new bookings and increases in cancellations (demand), and in Marriott's March call, it is all about drastic declines in markets around the world. In contrast, in Nike's March call, it discusses adopting digital marketing campaign as a response to the negative demand shock to its stores. We hence need to develop a measure of firm-level exposure and response to COVID-19.

In this paper, we offer a machine learning alternative to address these challenges, which is different from Hassan et al.'s (2020) simple word count approach.[8] Our approach starts with the word embedding model (specifically, *word2vec* (Mikolov et al. 2013)) to obtain a word list of COVID-19 (the official name for the pandemic from the World Health Organization) based on each word's proximity to it in calls. Using the word list, we can tag COVID-19-related paragraphs in calls. We then fit a topic model to those paragraphs, and the output is our firm-level measure of exposure and response to COVID-19.

3.3 Word-embedding and the COVID-19 word list

The word embedding model is based on a simple, time-tested concept in linguistics: Words that co-occur with the same neighboring words have similar meanings (Harris 1954). The model thus converts the neighboring word counts of a word to a numerical vector, which captures the meaning of the word and supports synonym search using vector arithmetic. While there are different variants of the word embedding model, we use a popular neural network model, *word2vec* (Mikolov et al. 2013), to efficiently learn dense and low-dimensional word vectors. In essence, *word2vec* "learns" the meaning of a specific word via a neural network that "reads" through the textual documents and thereby learns to predict all its neighboring words. The output from the process is a vector representation of the word when learning is completed after a number of iterations through the documents. The vector has a fixed dimension and captures the properties of the original co-occurrence relationship between the word and its neighbors.[9]

We use the *gensim* library in Python to train the *word2vec* model. We set the dimension of word vectors to 300; we define two words as neighbors if they are no farther apart than five words in a sentence, and we omit words that appear fewer than five times in

[8] Hassan et al. (2020) use the following keyword list: sarscov, coronavirus, corona virus, ncov, and covid, and word count to measure firm-level exposure to COVID-19.
[9] See Li et al. (2020) and its Internet Appendix for a more detailed and technical discussion of the word embedding model and *word2vec*.

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the corpus. After training, the model converts each of the 80,173 words in the call corpus to a 300-dimensional vector that represents the meaning of that word, and we can compute the cosine similarity between any two word vectors to quantify their association.

Using this capability, we construct the COVID-19 word list by associating a set of words gleaned from calls to the word COVID-19. We then select the top 1,000 words with the closest associations (i.e., the highest cosine similarity between their word vectors) to the word vector for COVID-19. We do not consider named entities that are recognized automatically by the CoreNLP package. We manually inspect all the words in the auto-generated list and exclude words that do not fit. There are 632 words in the final word list. Most of the excluded words are either too general in meaning (e.g., *threat* and *emergency*), or too specific in terms of industry context (e.g., *oil and gas demand* and *cargo availability*). Table IA1 in the Internet Appendix provides the word list for COVID-19 ordered by descending similarity to the word COVID-19.

With the COVID-19 word list in hand, we tag paragraphs in which any word on the word list shows up (i.e., the COVID-19-related paragraphs) which form the corpus for topic modeling. There are in total 79,597 COVID-19-related paragraphs in 8,859 calls (representing about 80% of calls) over the period January to April 2020. Over time, we see an increase in the fraction of calls with at least one COVID-19-related paragraph: 57% (982/1,728) in January, 70% (3,112/4,415) in February, 91% (2,445/2,673) in March, and 98% (2,320/2,367) in April.

3.4 Topic modeling

To measure firm-level exposure/response to COVID-19, we first need to identify the topics of discussion in relation to COVID-19 and then to quantify the amount of discussion devoted to each topic. We employ the correlated topic model (CTM) developed by Blei and Lafferty (2007) and Roberts, Stewart, and Airoldi (2016) for this task.

The CTM represents a substantial improvement to the plain vanilla topic modeling method, Latent Dirichlet Allocation (LDA), pioneered by Blei, Ng, and Jordan (2003). Topic modeling has gained increasing popularity for quantifying the content of firms' textual disclosures such as earnings calls (Huang, Lehavy, Zhang, Zheng 2018) and 10-K filings (Hanley and Hoberg 2019). LDA uses a statistical generative model to imitate the process of how a human (e.g., a speaker) composes a document (e.g., a paragraph in a call). Specifically, LDA assumes that each word in a document is generated in two steps. First, assuming the speaker decides that document m is about a specific set of topics that can be described by a distribution θ_m, a topic is randomly drawn based on this topic distribution. Next, assuming the drawn topic k has its own word distribution β_k, a word is randomly drawn from this topic's word distribution. Repeating these two steps word by word generates a document. An inference algorithm for LDA discovers the topic distribution for each document and the word distribution for each topic iteratively, by fitting this two-step generative model to the observed words in a collection of documents (i.e., a corpus) until it finds the best set of parameters that describe the topic and word distributions. The fitted model provides (i) the topical proportion (i.e., topic prevalence), which tells us how much of a document is devoted to a topic, and (ii) the word distribution (i.e., topic content), which provides a list of the most probable words given a topic.

The CTM is similar to LDA, except that the former allows correlation among topics.[10] The CTM is thus a more realistic generative model than LDA and provides better model fit (Blei and Lafferty 2007). Conceptually, the interpretation of estimated parameters of interest from the CTM is nearly identical to that of those parameters from LDA. We can decompose a

[10] To generate document m's topic distribution θ_m under the CTM, a vector is first drawn from a multivariate Normal distribution that allows correlations among dimensions, and then the vector is mapped to the parameters of a Dirichlet distribution, which produces θ_m. Under LDA, the topic distribution θ_m is drawn from a Dirichlet distribution directly and correlations among topics are not modeled (and hence not allowed).

document into a mixture of topics with their proportions sum to one, and we can also label those topics by inspecting the word distribution of each topic. There are different estimation methods for the CTM that are superior to those for LDA. We fit a CLM using the *stm* package in R based on the variational expectation-maximization algorithm developed by Roberts, Stewart, and Airoldi (2016).[11]

Choosing the number of topics remains a challenge in topic modeling as no "ground truth" is available. Chang, Gerrish, Wang, Boyd-Graber, and Blei (2009) note a trade-off between the interpretability of model outcomes and statistical goodness-of-fit. While interpretability usually favors fewer topics, statistical fitness in general favors more. Give that the purpose of our application is to use the CTM to generate interpretable topic clusters (rather than as a predictive model), we choose the number of topics based on the most meaningful topic clustering. We vary the number of topics from 5 to 40 and inspect the results, and find that 30 topics perform the best in terms of interpretability.[12] As pointed out by Blei (2012), interpretability is a key objective for selecting the best topic model, and careful human inspection is the most common approach.

3.5 Capturing firm-level exposure and response to COVID-19

Our goal is to capture firm-level exposure/response to COVID-19, so we would like to reduce the number of topics unrelated to our goal. As discussed earlier, we exclude general discussions of earnings and performance and fit the topic model using only a set of COVID-19-related paragraphs. We further remove common English stop words since these words are usually noise or meaningless.[13] As noted earlier, based on human judgment of topic quality, we choose a CTM model with 30 topics.

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[11] The *stm* package in R is written for structural topic models (STM), another improvement to LDA that allows correlations among topics and covariates that can explain the prevalence of topics. In the case of no covariates, the *stm* package reduces to a (fast) implementation of the CTM, which is what we employ in this paper.
[12] We find that interpretable topics remain relatively stable when the number of topics is around 30.
[13] We adopt the *stopwords-iso* list available at: https://github.com/quanteda/stopwords because this stop word list captures a broad range of meaningless words and provides the best specific topics. It is worth noting that

We take a two-pronged approach to interpret the 30 topics and assign them with meaningful labels. First, we rely on the topic-word distributions (i.e., the topic content) from the model output. We look at not only the high probability words in the vocabulary under a given topic, but also the important keywords indicated by three alternative measures: FREX, Lift, and Score.[14] All these three measures facilitate interpretation because they highlight keywords that are more exclusive to each topic and discount common words that appear across all topics. Second, for each topic, we inspect representative paragraphs by selecting ten paragraphs with the highest proportions of discussion about that topic.

To label the economic meanings of those identified topics hence different exposures/responses to COVID-19, we make two adjustments in the labeling/interpretation process. First, we drop 17 of the 30 topics because they are either boilerplate comments (e.g., greetings and concluding remarks), or not about a specific aspect of COVID-19 (e.g., uncertainty and performance). Second, we find that some identified topics share a common theme and can be naturally consolidated (such as supply chain disruptions). This is expected as the CTM allows topics to be correlated. We consolidate the remaining 13 topics to ten broad topics, seven of which are about firms' exposures to COVID-19 including competition, demand, employees, liquidity, lockdown, operation, and supply chains, and three of which are about firms' responses including community, cost cutting, and digital technology.[15]

Our measure of firm-level exposure/response is the average proportion of a firm's discussion in its COVID-19-related paragraphs over the period January to March 2020 devoted to a particular topic. For a specific firm, we first sum up the product of the

using other stop word lists or/and using different thresholds to remove noise words produce similar number of and similar topics.

[14] We refer readers to Roberts, Stewart, and Tingley (2019) for formal definitions of these measures.

[15] It is worth pointing out that our list of topics largely overlaps with the seven topics (negative demand shock, increased uncertainties, supply chain disruption, production capacity reductions/retail store closure, concerns about employee welfare and labor market, financial markets/financing concerns, and market opportunities) identified in Hassan et al. (2020) from manually reading 367 calls over the period January to April 2020.

proportion of a topic at the paragraph level and the paragraph length, then standardize (divide) by the total length of all COVID-19-related paragraphs, and finally, we take an average of the above ratio across calls if a firm has multiple calls over the three-month period. Thus, the measure is computed as:

$$Topic_{i,k} = \frac{1}{I_i}\sum_{n=1}^{I_i} \frac{\sum_{m=1}^{J_{i,n}}(P_{i,n,m,k} \times L_{i,n,m})}{\sum_{m=1}^{J_{i,n}} L_{i,n,m}} \quad (1)$$

where $Topic_{i,k}$ is the intensity of topic k for firm i. $P_{i,n,m,k}$ is the proportion of topic k in COVID-related paragraph m call n of firm i. $L_{i,n,m}$ is the paragraph length, i.e., the total number of words (a phrase is treated as a single word) in COVID-19-related paragraph m call n of firm i, $J_{i,n}$ is the number of COVID-19-related paragraphs in call n of firm i, and I_i is the number of calls of firm i in the first quarter of 2020. This measure satisfies the constraint that $\sum_{k=1}^{30} Topic_{i,k} = 1$. Throughout the paper, we multiply our measure of COVID-19 exposure/response by 100, thus the unit of measure is percentage points.

Our measure of overall exposure to COVID-19 is the sum of the proportions of discussion devoted to the seven exposure-related topics. Different from prior literature that employs a count of COVID-19-related words divided by the call length as COVID-19 exposure (e.g., Hassan et al. 2020), our measure has two advantages in terms of accuracy and cross-sectional comparability. First, as we note from topic modeling, not all topics in COVID-19-related discussion are about types of exposure, instead, some are different responses and some are simply meaningless boilerplate statements (e.g., opening greetings and concluding remarks). Using word count overstates COVID-19 exposure if firms mainly discuss topics unrelated to exposure. Our measure addresses this concern by only scoring exposure-related discussion. Second, we use the length of COVID-19-related paragraphs to normalize exposure-related discussion, which is cleaner than using the call length since a conference call can cover many issues unrelated to COVID-19.

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Figure 1
Word clouds for different topics

Panel A: Word clouds for different exposures to COVID-19

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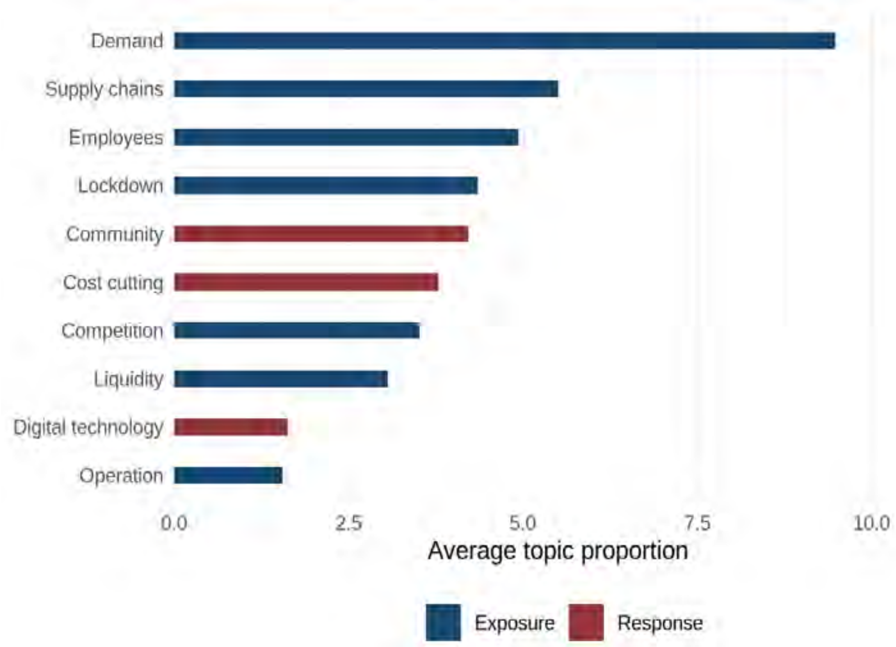
Panel B: Word clouds for different responses to COVID-19

Note: This figure plots the word cloud for each of the ten topics, seven of which are about firms' different exposures to COVID-19 including competition, demand, employees, liquidity, lockdown, operation, and supply chains, and three of which are about their responses to COVID-19 including community, cost cutting, and digital technology. For each topic, we generate a word cloud that shows top words with the highest probabilities. Panel A presents word clouds for the seven different exposures to COVID-19. Panel B presents word clouds for the three different responses to COVID-19.

Figure 2. An overview of COVID-19 exposure and response



Note: This figure plots the average proportion (in percentage points) of each topic across 79,597 COVID-19-relevant paragraphs in conference calls made over the period January to April 2020. The blue bars represent the seven different exposures to COVID-19, including competition, demand, employees, liquidity, lockdown, operation, and supply chains. The red bars represent the three different responses to COVID-19, including community, cost cutting, and digital technology. The *x* axis is the average proportion of each topic. Topics on the *y* axis are ranked by the average proportion in descending order.

Table IA2 in the Internet Appendix presents representative paragraphs for each topic, and Figure 1 presents the word cloud for each topic. Figure 2 presents an overview of COVID-19 exposure/response based on 79,597 COVID-19-related paragraphs over the period January to April 2020. The top three exposures are demand, supply chains, and employees. The importance of responses (in descending order) is community engagement, cost cutting, and adopting digital technology.

4. Sample Overview

4.1 Sample formation

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We obtain 11,183 conference calls from the S&P's Global Market Intelligence database over the period January 1, 2020 to April 30, 2020. We limit calls to U.S. firms listed on NYSE, NASDAQ, or NYSE American (formerly AMEX) and matched with GVEKY. We end up with 5,569 calls made by 3,019 firms. Table 1 Panel A provides the steps taken and filters applied to form our sample of calls so that we could generate firm-level COVID-19 exposure and response, as well as overall exposure.

Table 1. Sample formation

Panel A: Match company names in conference call transcripts to GVKEY

	# calls
Initial sample (conference calls from January 1 to April 30, 2020)	11,183
Remove calls by firms not listed on NYSE, NASDQ, or NYSE American (formerly AMEX)	4,943
Calls available for GVKEY matching	6,240
Matched by	
Perfect match using ticker	6,110
Perfect match with Compustat company name	19
Manual matching if no perfect match	31
Remove calls by non-U.S. firms	591
Final sample	**5,569**
	(3,019 firms)

Panel B: Sample formation for regression analysis

	# firms
Culture values available from Li et al. (2020)	5,427
Return data available	2,738
Control variables available	2,733
COVID-19 measures available from conference calls	**2,502**

Note: Panel A reports our steps to match company names in conference call transcripts to GVKEY. We obtain conference call transcripts from the S&P's Global Market Intelligence database for the period January 1 to April 30, 2020. Panel B reports our data filters to form the sample for regression analysis.

Our measure of corporate culture comes from Li et al. (2020) that compute scores of the five top cultural values proposed by Guiso, Sapienza, and Zingales (2015): innovation, integrity, quality, respect, and teamwork. Following Li et al. (2020), for each firm-year, we average all culture values over a three-year window and the year 2017 is the most recent year

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with available cultural value data. A firm is perceived to have a strong culture if the sum of its five cultural value scores is in the top quartile among all firms (Li et al. 2020).

We obtain monthly stock returns from the Compustat Security Monthly Database and accounting information from the Compustat Fundamentals Annual/Quarterly Database. We require a firm's monthly return data to be available from January through March 2020. One goal of our paper is to assess the stock market performance of firms with a strong culture and hence we do not want stock returns contaminated by government interventions. Specifically, on March 23, 2020, the Federal Reserve Board (Fed) announced two new facilities to support credit to large corporations, and on March 27 the US government approved a US$ 2 trillion relief bill into law (The Coronavirus Aid, Relief, and Economic Security Act (CARES Act)). *A priori*, it is not clear whether firms with a strong culture benefit more or less from the government bailout. As a result, our monthly return measure for March 2020 will end on March 20 (Friday). After merging with firms in the culture data set, we obtain a final sample of 2,502 firms for our baseline regressions. Table 1 Panel B provides the steps taken and filters applied to form the final sample for regression analysis.

4.2 Sample overview

Table 2 provides the summary statistics of stock and operating performance variables, key firm control variables, strong culture, and measures of COVID-19 exposure and response. Figure IA1 plots average firm-level exposure/response to COVID-19 by Fama-French 12 industries for our final sample of 2,502 firms.

In Panel A, we show that in terms of overall exposure, the top three industries are: chemicals and allied products; consumer non-durables; and manufacturing. In Panel B, we present different responses across industries. In terms of community engagement, the top three industries are: wholesale, retail, and some services (laundries, repair shops); healthcare, medical equipment, and drugs; and chemicals and allied products. In terms of cost cutting, the top three industries are: oil, gas, and coal extraction and products; manufacturing; and consumer non-durables. In terms of digital technology, the top three industries are: telephone and television transmission; business equipment; and consumer non-durables.

Table 2. Summary statistics

Panel A: Summary statistics

	N	Mean	SD	25th percentile	Median	75th percentile
Baseline cross-sectional regression						
Quarterly return	2,502	-40.787	20.480	-54.735	-41.306	-28.226
Strong culture	2,502	0.251	0.434	0.000	0.000	1.000
ln(Market cap)	2,502	7.434	2.012	6.069	7.517	8.772
Leverage	2,502	0.323	0.240	0.118	0.310	0.463
Cash holdings	2,502	0.167	0.214	0.025	0.074	0.213
Profitability	2,502	-0.030	0.212	-0.019	0.021	0.059
B/M	2,502	0.534	0.579	0.192	0.415	0.746
Momentum	2,502	20.844	44.240	-3.761	19.574	40.453
Overall exposure	2,502	23.197	14.292	13.347	26.119	33.672
Competition	2,502	2.893	2.799	1.351	2.477	3.803
Demand	2,502	7.040	6.242	2.469	6.071	10.059
Employees	2,502	2.785	3.413	0.850	1.832	3.541
Liquidity	2,502	1.782	2.692	0.652	1.173	1.872
Lockdown	2,502	2.662	2.559	1.097	2.237	3.621
Operation	2,502	1.123	1.556	0.446	0.831	1.249
Supply chains	2,502	4.913	4.993	1.618	3.637	6.789
Community	2,502	2.362	2.563	0.834	1.776	3.145
Cost cutting	2,502	3.004	3.640	0.984	1.965	3.717
Digital technology	2,502	1.076	1.202	0.505	0.871	1.298
Panel data regression						
Monthly return	37,095	-1.463	15.523	-8.065	0.330	6.689
Overall exposure	37,095	4.644	11.280	0.000	0.000	0.000
Competition	37,095	0.579	1.709	0.000	0.000	0.000
Demand	37,095	1.410	3.968	0.000	0.000	0.000
Employees	37,095	0.556	1.885	0.000	0.000	0.000
Liquidity	37,095	0.358	1.405	0.000	0.000	0.000
Lockdown	37,095	0.533	1.567	0.000	0.000	0.000
Operation	37,095	0.225	0.830	0.000	0.000	0.000
Supply chains	37,095	0.984	2.979	0.000	0.000	0.000
Sales per employee	9,453	174.139	291.104	56.529	87.982	161.541
COGS per employee	9,453	112.373	215.922	24.310	47.415	107.418
Overall exposure	9,453	4.358	10.973	0.000	0.000	0.000

Panel B: Correlation matrix for variables in the baseline regression

	Quarterly return	Strong culture	ln(Market cap)	Leverage	Cash holdings	Profitability	B/M	Momentum
Quarterly return	1.000							
Strong culture	0.153***	1.000						
ln(Market cap)	0.132***	-0.062***	1.000					
Leverage	-0.190***	-0.124***	0.062***	1.000				
Cash holdings	0.220***	0.267***	-0.208***	-0.267***	1.000			
Profitability	0.006	-0.117***	0.461***	0.018	-0.496***	1.000		
B/M	-0.206***	-0.176***	-0.289***	-0.138***	-0.228***	-0.004	1.000	
Momentum	0.100***	-0.017	0.255***	-0.017	0.017	0.200***	-0.309***	1.000

Panel C: Cross-sectional correlations among strong culture and firm exposure to COVID-19

	Strong culture	Overall exposure	Competition	Demand	Employees	Liquidity	Lockdown	Operation	Supply chains
Strong culture	1.000								
Overall exposure	-0.051**	1.000							
Competition	0.023	0.559***	1.000						
Demand	-0.090***	0.728***	0.299***	1.000					
Employees	0.041**	0.465***	0.112***	0.092***	1.000				
Liquidity	-0.073***	0.370***	0.200***	0.136***	0.099***	1.000			
Lockdown	-0.007	0.607***	0.336***	0.249***	0.307***	0.128***	1.000		
Operation	-0.002	0.380***	0.146***	0.196***	0.151***	0.241***	0.163***	1.000	
Supply chains	-0.030	0.692***	0.262***	0.342***	0.211***	0.031	0.397***	0.132***	1.000

Panel D: Cross-sectional correlations among strong culture and firm response to COVID-19

	Strong culture	Community	Cost cutting	Digital technology
Strong culture	1.000			
Community	0.120***	1.000		
Cost cutting	-0.032	0.203***	1.000	
Digital technology	0.140***	0.370***	0.190***	1.000

Note: The sample consists of 2,502 firms in the baseline cross-sectional quarterly return regression in the first quarter of 2020 and 37,095 firm-month observations in the panel data monthly return regression over the period January 2019 to March 2020. Panel A provides summary statistics. Panel B presents the correlation matrix for variables in the baseline regression. Panel C presents cross-sectional correlations among *Strong culture* and firm exposure to COVID-19. Panel D presents cross-sectional correlations among *Strong culture* and firm response to COVID-19. Definitions of variables are provided in Appendix. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

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Table 3. Top ten firms by their exposure/response to COVID-19

Panel A: Top ten firms by their exposure to COVID-19

Overall exposure	Competition	Demand	Employees
Simply Good Foods Co	BP Midstream Partners LP	Simply Good Foods Co	Simpson Manufacturing Co Inc
WD-40 Co	Pinnacle Financial Partners Inc	Northern Technologies International Corp	PNM Resources Inc
Simpson Manufacturing Co Inc	Cohen & Steers Inc	Hain Celestial Group Inc	Encore Capital Group In
Park Aerospace Corp	DSP Group Inc	Duke Energy Corp	Frequency Electronics Inc
Northern Technologies International Corp	Tuesday Morning Corp	Flowers Foods Inc	Vista Gold Corp
Duke Energy Corp	ProAssurance Corp	Knoll Inc	Era Group Inc
Laredo Petroleum Inc	SeaSpine Holdings Corp	Insteel Industries Inc	Optical Cable Corp
Wayfair Inc	SmartFinancial Inc	NCS Multistage Holdings Inc	Plains All American Pipeline LP
Matthews International Corp	Taylor Morrison Home Corp	Globus Medical Inc	EMCOR Group Inc
CorVel Corp	American Homes 4 Rent	TimkenSteel Corp	ExlService Holdings Inc

Liquidity	Lockdown	Operation	Supply chains
HCI Group Inc	Watsco Inc	Ambac Financial Group Inc	SiteOne Landscape Supply Inc
CenterPoint Energy Inc	SP Plus Corp	Avangrid Inc	Lawson Products Inc
Prospect Capital Corp	Franklin Covey Co	Ekso Bionics Holdings Inc	Wayfair Inc
Armada Hoffler Properties Inc	Franklin Street Properties Corp	Tetra Tech Inc	Laredo Petroleum Inc
Granite Point Mortgage Trust Inc	Crown Crafts Inc	Omega Healthcare Investors Inc	WD-40 Co
Great Elm Capital Corp	Capital Southwest Corp	Independent Bank Group Inc	Park Aerospace Corp
FedNat Holding Co	Weyco Group Inc	Lantheus Holdings Inc	Drive Shack Inc
Streamline Health Solutions	Full House Resorts Inc	Berkshire Hills Bancorp Inc	Sturm Ruger & Co Inc
Chimera Investment Corp	Park Aerospace Corp	On Deck Capital Inc	Power Integrations Inc
OneMain Holdings Inc	Camden Property Trust	Boyd Gaming Corp	Modine Manufacturing Co

Panel B: Top ten firms by their response to COVID-19

Community	Cost cutting	Digital technology
Installed Building Products Inc	RPC Inc	Electronic Arts Inc
Plus Therapeutics Inc	California Resources Corp	Invacare Corp
Green Dot Corp	Red Lion Hotels Corp	Ribbon Communications Inc
Exterran Corp	Chaparral Energy Inc	American Public Education Inc
TESSCO Technologies Inc	Superior Energy Services Inc	Rollins Inc
HealthStream Inc	Owens Corning	Synacor Inc
Richardson Electronics Ltd	Entercom Communications Corp	2U Inc
Blackbaud Inc	A10 Networks Inc	Sutter Rock Capital Corp
Regional Management Corp	Intrepid Potash Inc	DSP Group Inc
Edison International	First Midwest Bancorp Inc	Tecogen Inc

Note: Panel A lists the top ten firms by their exposure to COVID-19 in the first quarter of 2020, including overall exposure and seven different exposures (competition, demand, employees, liquidity, lockdown, operation, and supply chains). Panel B lists the top ten firms by their response to COVID-19 in the first quarter of 2020, including community, cost cutting, and digital technology.

Table 3 Panel A lists the top ten firms by their overall and different exposures to COVID-19. In terms of overall exposure, the top ten firms are: Simply Good Foods Co., WD-40 Co., Simpson Manufacturing Co Inc., Park Aerospace Corp., Northern Technologies International Corp., Duke Energy Corp., Laredo Petroleum Inc., Wayfair Inc., Matthews International Corp., and CorVel Corp., spanning industries from oil and gas to consumer non-durables. Panel B lists the top ten firms by their different responses to COVID-19.

In summary, Tables 2-3 and Figure IA1 show that there is a wide variation across firms in their exposure and response to COVID-19.

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5. Main Results

5.1 Baseline results

We estimate regression models of stock returns during the first quarter of 2020 as a function of firms' pre-COVID-19 cultural ratings and a number of control variables. Table 4 presents our baseline regression results. The dependent variable is quarterly returns (in percentage points) computed as the buy-and-hold return from January 1 to March 20, 2020. Our variable of interest is the indicator variable, *Strong culture*, that takes a value of one if the sum of a firm's five cultural value scores is in the top quartile among all firms with available cultural values, and zero otherwise. The raw cultural scores are available till 2017. In all models, we include industry dummies (defined at the Fama-French 48 industry-level) because different industries may promote organizational culture with different focuses (Li et al. 2020).

Column (1) presents the return regression without other control except industry dummies. We show that firms with a strong culture performed significantly better during the first quarter of 2020. In terms of economic significance, firms with a strong culture were associated with a 4.7 percentage point increase in returns during the first quarter of 2020. In column (2), we also control for a firm's factor loadings based on the Fama and French three-factor model plus the momentum factor (Fama and French 1993; Carhart 1997). We find that the coefficient on *Strong culture* remains positive and significant.

Table 4. Corporate culture and stock returns in the first quarter of 2020

	Quarterly return			
	(1)	(2)	(3)	(4)
Strong culture	4.700***	4.762***	3.394***	3.443***
	[1.070]	[1.051]	[1.068]	[1.070]
ln(Market cap)			1.148***	0.765***
			[0.230]	[0.245]
Leverage			-13.580***	-11.550***
			[2.029]	[2.043]
Cash holdings			9.052***	9.586***
			[3.084]	[3.090]
Profitability			7.751**	5.467*
			[3.193]	[3.087]
B/M			-3.102***	-1.798*
			[0.955]	[0.966]
Momentum			-0.002	-0.003
			[0.011]	[0.012]
Constant	-41.974***	-33.695***	-45.385***	-36.738***
	[0.455]	[1.042]	[2.284]	[2.583]
Four-factor loadings	No	Yes	No	Yes
Industry dummies	Yes	Yes	Yes	Yes
N	2,502	2,502	2,502	2,502
Adj. R^2	0.153	0.218	0.210	0.247

Note: This table presents baseline cross-sectional regression estimates of the relation between strong culture and stock returns in the first quarter of 2020. *Quarterly return* is buy-and-hold return (in percentage points) from January to March 2020, where the return for March ends on March 20, 2020. Industry dummies are based on Fama-French 48-industry classification. Definitions of variables are provided in Appendix. Heteroskedasticity-consistent standard errors are presented in brackets. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

One concern with the specifications in columns (1) and (2) is that the better performance of firms with a strong culture during the period may be due to omitted variables that are correlated with corporate culture, rather than due to corporate culture itself. To address this concern, in columns (3) and (4), we control for firm accounting performance in the year before the pandemic and for other characteristics known to affect stock returns (e.g., Daniel and Titman 1997; Asness, Moskowitz, and Pedersen 2013). We again show that firms with a strong culture had higher stock returns during the first quarter of 2020. The magnitude of the outperformance by firms with a strong culture is somewhat attenuated after we include

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additional control variables, but the effect is still economically important. In column (4), we show that firms with a strong culture were associated with a 3.4 percentage point increase in returns during the first quarter of 2020.

In terms of the control variables, we show that firms that entered the pandemic with higher market capitalization, lower leverage, higher cash holdings, higher profitability, and lower B/M ratios are associated with higher first-quarter stock returns. In terms of economic significance, a one-standard-deviation increase in market capitalization (2.012), leverage (0.240), cash holdings (0.214), profitability (0.212), and B/M ratios (0.579) is associated with a change in quarterly returns of 1.5, 2.8, 2.1, 1.2, and 1.0 percentage points, respectively. Thus, the economic impact of culture during the first quarter of 2020 is 97% of the impact of market capitalization, 56% of the impact of leverage, 73% of the impact of cash holdings, 129% of the impact of profitability, and 144% of the impact of B/M ratios, indicating that corporate culture is important in explaining returns in the first quarter of 2020.

The above findings provide some direct evidence of our first hypothesis, i.e., there is a positive association between firms with a strong culture and stock returns during the first quarter of 2020. Next, we employ time-series of returns to directly test our first hypothesis that the culture-value link is stronger during the pandemic.

5.2 Corporate culture, COVID-19 exposure, and returns

So far, we show that firms with a strong culture are associated with higher returns during the first quarter of 2020. Next, we investigate whether this positive association is unique to bad times or is common to most periods, perhaps due to some unobservable risk factors that are correlated with culture. Following Lins, Servaes, and Tamayo (2017), we utilize monthly return data before and during the onset of COVID-19 pandemic. More importantly, the topic model we employ allows us to explore whether this positive association is contingent on firms' differential exposure to COVID-19. To do so, we estimate a panel data regression model interacting culture with a continuous COVID-19 exposure variable – *Overall exposure* – and include firm and month fixed effects:

$$Return_{i,t} = \alpha + \beta_1 Overall\ expoure_{i,t} + \beta_2 Overall\ exposure_{i,t} \times Strong\ culture_i + \beta_3 Firm\ characteristics_{i,t} + \beta_4 Factor\ loadings_{i,t} + Firm\ FE + Month\ FE + \varepsilon_{i,t} \quad (2)$$

where $Return_{i,t}$ is the monthly return over the period January 2019 to March 20, 2020. We end our sample period on March 20, before major government bailout packages were announced starting March 23, 2020. *Overall exposure* is the sum of proportions of discussion on the seven different exposures to COVID-19 from the output of a correlated topic model for the first quarter in 2020, and zero for the entire year of 2019. Corporate culture is measured at the end of 2017, two years before the onset of the pandemic to eliminate any concern that firms changed their culture in anticipation of a public health crisis. Firm fixed effects control for time-invariant omitted risk factors, and month fixed effects control for return seasonality. The standalone indicator, *Strong culture,* is absorbed by firm fixed effects. All standard errors are clustered at the firm level. The coefficient on the interaction term *Overall exposure × Strong culture* captures the differential impact of corporate culture on monthly stock returns during the three-month period from January 2020 to March 20, 2020, for a given level of overall exposure to COVID-19.

Table 5. Corporate culture, COVID-19 exposure, and stock returns

Panel A: Strong culture, overall exposure, and stock returns

	Monthly return			
	(1)	(2)	(3)	(4)
Overall exposure	-0.084***	-0.090***	-0.079***	-0.083***
	[0.012]	[0.013]	[0.012]	[0.013]
Overall exposure × Strong culture	0.098***	0.101***	0.074***	0.077***
	[0.016]	[0.017]	[0.015]	[0.016]
Firm characteristics	No	No	Yes	Yes
Four-factor loadings	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
N	37,095	37,095	37,095	37,095
Adj. R^2	0.423	0.430	0.438	0.444

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Panel B: Strong culture, different exposure, and stock returns

	Monthly return						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Competition	-0.277***						
	[0.064]						
Competition × Strong culture	0.484***						
	[0.086]						
Demand		-0.231***					
		[0.030]					
Demand × Strong culture		0.184***					
		[0.051]					
Employees			-0.140**				
			[0.056]				
Employees × Strong culture			0.456***				
			[0.102]				
Liquidity				-0.333***			
				[0.065]			
Liquidity × Strong culture				0.602***			
				[0.194]			
Lockdown					-0.211***		
					[0.075]		
Lockdown × Strong culture					0.463***		
					[0.122]		
Operation						-0.296**	
						[0.140]	
Operation × Strong culture						0.876***	
						[0.272]	
Supply chains							-0.111***
							[0.039]
Supply chains × Strong culture							0.183***
							[0.069]
Firm characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Four-factor loadings	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	37,095	37,095	37,095	37,095	37,095	37,095	37,095
Adj. R^2	0.443	0.444	0.443	0.443	0.443	0.443	0.443

Note: This table presents panel data regression estimates of the relation between strong culture and stock returns contingent on firms' exposure to COVID-19. *Monthly return* (in percentage points) is over the period January 2019 to March 2020, where the return for March ends on March 20, 2020. Overall exposure and seven different exposures (in percentage points) are from the output of fitting a correlated topic model to a corpus of COVID-19-relevant paragraphs in conference calls in the first three months in 2020, and zero for the entire year of 2019. Panel A presents results using overall exposure. Panel B presents results using seven different exposures. Control variables are the same as those in Table 4. Firm fixed effects and month fixed effects are included. Definitions of variables are provided in Appendix. Heteroskedasticity-consistent standard errors in brackets are clustered at the firm level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

Table 5 Panel A presents the results. We first show that the coefficient on *Overall exposure* is negative and significant. In terms of economic significance, based on column (4) specification, a one-standard-deviation increase in *Overall exposure* (11.3%) is associated with a drop in monthly returns of 0.94 percentage points. We further show that the coefficient on the interaction term *Overall exposure × Strong culture* is positive and significant, suggesting that firms with a strong culture are associated with a smaller drop in returns. In terms of economic significance, the coefficient of 0.077 on the interaction term indicates that a one-standard-deviation increase in *Overall exposure* (11.3%) of firms with a strong culture is associated with reducing the monthly return drop by 0.87 percentage points during the crisis compared to firms without a strong culture. In combination with the economic effect from the standalone term *Overall exposure*, we show that in net, firms with a strong culture are associated with only a monthly return drop of 0.07 percentage points compared to 0.94 percentage points for firms without when their exposure to COVID-19 is increased by one-standard-deviation. These results suggest that in the face of a major pandemic, firms with a strong culture experienced a significantly smaller drop in returns than their peers without a strong culture.

Table 5 Panel A presents the results. We first show that the coefficient on *Overall exposure* is negative and significant. In terms of economic significance, based on column (4) specification, a one-standard-deviation increase in *Overall exposure* (11.3%) is associated with a drop in monthly returns of 0.94 percentage points. We further show that the coefficient on the interaction term *Overall exposure* × *Strong culture* is positive and significant, suggesting that firms with a strong culture are associated with a smaller drop in returns. In terms of economic significance, the coefficient of 0.077 on the interaction term indicates that a one-standard-deviation increase in *Overall exposure* (11.3%) of firms with a strong culture is associated with reducing the monthly return drop by 0.87 percentage points during the crisis compared to firms without a strong culture. In combination with the economic effect from the standalone term *Overall exposure*, we show that in net, firms with a strong culture are associated with only a monthly return drop of 0.07 percentage points compared to 0.94 percentage points for firms without when their exposure to COVID-19 is increased by one-standard-deviation. These results suggest that in the face of a major pandemic, firms with a

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strong culture experienced a significantly smaller drop in returns than their peers without a strong culture.

Panel B presents the results when we decompose the overall exposure measure into seven components coming out of topic modeling. We show large heterogeneity in terms of how a strong culture help firms with different exposures to outperform their peers without a strong culture. *Demand* has the largest standalone effect on returns among different types of exposure. A one-standard-deviation increase in *Demand* is associated with a drop in monthly returns by 0.92 percentage points. Corporate culture is most effective in alleviating the negative impact of *Employees*. A one-standard-deviation increase in *Employees* of firms with a strong culture is associated with reducing the return drop by 0.86 percentage points compared to firms without. Similarly, a one-standard-deviation increase in *Liquidity* of firms with a strong culture is associated with reducing the return drop by 0.85 percentage points than firms without a strong culture. In contrast, corporate culture is least effective in alleviating the negative impact of *Supply chains*. A one-standard-deviation increase in *Supply chains* of firms with a strong culture is associated with reducing the return drop by 0.55 percentage points than firms without.

5.3 Channels

As discussed earlier, the topic model we employ not only identifies firms' exposure to COVID-19, but also their response/strategy to deal with the pandemic. Table 6 provides the first investigation into the relation between firms with a strong culture and their different responses as discussed in conference calls.

We first show that firms with a strong culture are more likely to promote community/stakeholder engagement and adopt digital technology (columns (1) and (5)). Moreover, firms with greater exposure to COVID-19 are more likely to promote community/stakeholder engagement, cut costs, and adopt digital technology (columns (2), (4), and (6)). Finally, we show that in the midst of a pandemic, firms with a strong culture are more likely to promote community/stakeholder engagement, no more likely to engage in cost cutting, and more likely to adopt digital technology, than their peers without a strong culture (as shown via the three interaction terms in columns (2), (4), and (6)).

Table 6. Corporate culture and firm response in the first quarter of 2020

	Community		Cost cutting		Digital technology	
	(1)	(2)	(3)	(4)	(5)	(6)
Strong culture	0.679***	0.123	0.079	-0.035	0.249***	-0.041
	[0.147]	[0.181]	[0.180]	[0.217]	[0.077]	[0.105]
Overall exposure		0.066***		0.087***		0.031***
		[0.003]		[0.004]		[0.001]
Overall exposure × Strong culture		0.026***		0.007		0.013***
		[0.008]		[0.009]		[0.004]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	2,502	2,502	2,502	2,502	2,502	2,502
Adj. R^2	0.033	0.173	0.052	0.158	0.042	0.184

Note: This table presents cross-sectional regression estimates of the relation between strong culture and firm response in the first three months of 2020. Overall exposure and three firm responses (in percentage points) are from the output of fitting a correlated topic model to a corpus of COVID-19-relevant paragraphs in conference calls in the first three months in 2020. We control for the natural logarithm of total assets, leverage, cash holdings, profitability, and B/M. Industry dummies are based on Fama-French 48-industry classification. Definitions of variables are provided in Appendix. Heteroskedasticity-consistent standard errors are presented in brackets. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

Grennan (2020) argues that consistent communication of cultural values is a necessary condition for culture to have a positive association with performance. Our finding that firms with a strong culture are more likely to promote community/stakeholder engagement is consistent with her proposition that a simple mechanism for culture to matter is to communicate culture consistently.

According to the human capital channel discussed earlier, firms with a strong culture invest more in their employees during calm times, and well-treated employees are better motivated and more productive. Our finding suggests that firms that have regularly treated their employees well can weather negative economic shocks better, hence there is no need to engage in aggressive cost-cutting. Our finding on cost-cutting is consistent with this channel.

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According to the technology channel discussed earlier, highly innovative firms are more adaptable to changing environment. Our finding that firms with a strong culture, part of which is about innovation, are more likely to pivot towards digital technology amid a pandemic, supports this channel.

We next study firms' operating performance to shed light on the excess returns earned by firms with a strong culture during the first quarter of 2020. The model specification is similar to Equation (2) with the dependent variables being quarterly accounting measures covering one quarter in 2020 and four quarters prior.[16]

To gain a better understanding of how a strong culture helps firms in the midst of a pandemic, we group the five cultural values underlying a strong culture into two subcultures: people-oriented culture comprised of integrity, respect, and teamwork, and technology-oriented culture comprised of innovation and quality.

Table 7 Panel A presents the results of strong culture and strong people/technology culture. We first show that the coefficient on the standalone term *Overall exposure* is negative but not significant when the dependent variable is *Sales per employee* (column (1)). We further show that the coefficient on the interaction term *Overall exposure* × *Strong culture* is positive and significant, indicating that firms with a strong culture exhibit higher employee productivity relative to their peers with a weak culture in the first quarter after the onset of the pandemic. In terms of economic significance, a one-standard-deviation increase in *Overall exposure* of firms with a strong culture is associated with a higher quarterly sales of about $3,961 per employee compared to firms without a strong culture. For an average-sized firm in our sample (15,280 employees), this translates into an extra increase in quarterly sales of about $61 million, which is 4% of the average quarterly sales ($1,659 million) over

[16] As such, firms included in this analysis have their fiscal year-end month in January (39), March (54), April (3), June (95), July (6), September (107), October (14) or December (1,732).

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the estimation period. The size of these effects appears to be economically meaningful. In columns (2) and (3), we show that both *Strong people culture* and *Strong technology culture* help foster higher employee productivity.

We next examine cost of goods sold per employee (*GOGS per employee*). We first show that the coefficient on the standalone term *Overall exposure* is negative and significant across all columns, indicating that firms with greater exposure to COVID-19 exhibit lower cost of production in the first quarter after the onset of the pandemic. We then show that the coefficient on the interaction term *Overall exposure* × *Strong culture* is negative and significant, indicating that firms with a strong culture do cut their cost of production more than their peers with a weak culture. In terms of economic significance, a one-standard-deviation increase in *Overall exposure* is associated with a drop in *GOGS per employee* by \$4,631, and an additional drop in *GOGS per employee* by \$3,029 for firms with a strong people culture. For an average-sized firm in our sample (15,280 employees), this translates into an extra reduction of quarterly COGS of about \$46 million, which is 4% of the average quarterly COGS (\$1,062 million) over the estimation period. In columns (5)-(6), we show that such effect mainly comes from *Strong people culture*. This effect of *Strong people culture* on COGS could be due to well-treated employees being more productive thereby spreading fixed cost of production across more units of output.

Panel B presents the results using strong culture indicators based on the five cultural values: innovation, integrity, respect, teamwork, and quality. We first show that among the three components of people-oriented culture, *Strong respect culture* is the primary driver of employee productivity; between the two components of technology-oriented culture, the effect mainly comes from *Strong innovation culture*. Our findings are consistent with both the human capital and technology channels.

We further show that among the three components of people-oriented culture, *Strong respect culture* is the primary driver of lower COGS, supporting the human capital channel.

In summary, the results in Table 7 provide supporting evidence for the human capital and technology channels through which corporate culture makes firms resilient to pandemics.

Table 7. Corporate culture, COVID-19 exposure, and operating performance

Panel A: Strong culture, strong people/technology culture, overall exposure, and operating performance

	Sales per employee			COGS per employee		
	(1)	(2)	(3)	(4)	(5)	(6)
Overall exposure	-0.047	-0.037	-0.039	-0.415*	-0.422*	-0.437*
	[0.138]	[0.137]	[0.141]	[0.245]	[0.243]	[0.242]
Overall exposure × Strong culture	0.361***			-0.262*		
	[0.121]			[0.137]		
Overall exposure × Strong people culture		0.381***			-0.276**	
		[0.137]			[0.140]	
Overall exposure × Strong technology culture			0.266***			-0.119
			[0.099]			[0.159]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	9,453	9,453	9,453	9,453	9,453	9,453
Adj. R^2	0.065	0.065	0.065	0.067	0.067	0.067

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Panel B: Five cultural values, overall exposure, and operating performance

	Sales per employee					COGS per employee				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Overall exposure	-0.001	-0.051	0.001	-0.077	-0.016	-0.442*	-0.413*	-0.438*	-0.424*	-0.420*
	[0.136]	[0.139]	[0.141]	[0.138]	[0.143]	[0.243]	[0.248]	[0.243]	[0.242]	[0.250]
Overall exposure × Strong integrity culture	0.136					-0.140				
	[0.169]					[0.140]				
Overall exposure × Strong respect culture		0.334***					-0.235*			
		[0.120]					[0.130]			
Overall exposure × Strong teamwork culture			0.140					-0.191		
			[0.180]					[0.140]		
Overall exposure × Strong innovation culture				0.422***					-0.167	
				[0.120]					[0.163]	
Overall exposure × Strong quality culture					0.152*					-0.181
					[0.089]					[0.122]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	9,453	9,453	9,453	9,453	9,453	9,453	9,453	9,453	9,453	9,453
Adj. R^2	0.065	0.065	0.065	0.066	0.065	0.067	0.067	0.067	0.067	0.067

Note: This table presents panel data regression estimates of the relation between strong culture, its components, and operating performance contingent on firms' exposure to COVID-19. The sample consists of 2,050 firms from Table 6 whose latest earnings quarter ends either in March or April 2020 and whose earnings data is available from Compustat. In the panel regression, we include one quarter in 2020 and four quarters prior. Overall exposure (in percentage points) is from the output of fitting a correlated topic model to a corpus of COVID-19-relevant paragraphs in conference calls in the first quarter in 2020, and zero for all the four previous quarters. For firms whose latest quarter ends in March, we measure overall exposure from conference calls over the period January to March 2020. For firms whose latest quarter ends in April, we measure overall exposure from conference calls over the period February to April 2020. Panel A presents panel data regression estimates of the relation between strong culture, its two components – strong people culture and strong technology culture, and operating performance contingent on firms' exposure to COVID-19. Panel B presents panel data regression estimates of the relation between five cultural values (the three components of strong people culture—integrity, respect, and teamwork, the two components of strong technology culture—innovation and quality) and operating performance contingent on firms' exposure to COVID-19. We control for the natural logarithm of total assets, leverage, cash holdings, profitability, and B/M. Firm fixed effects and quarter fixed effects are included. Definitions of variables are provided in Appendix. Heteroskedasticity-consistent standard errors in brackets are clustered at the firm level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% level, respectively.

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5.4 Robustness checks

In this section, we conduct a number of robustness checks by controlling for other known characteristics that make firms resilient during the pandemic and using an alternative window to measure returns in March 2020.

Table IA3 presents panel data regression estimates of the relation between strong culture, overall exposure to COVID-19, and stock returns after controlling for other characteristics that make firms resilient during the COVID-19 pandemic.

Lins, Servaes, and Tamayo (2017) show that during the 2008–2009 financial crisis, firms with high social capital, as measured by CSR intensity, had stock returns that were four to seven percentage points higher than firms with low social capital. Albuquerque, Koskinen, Yang, and Zhang (2020) show that firms with high ES ratings outperform during the first quarter of 2020 compared to other firms. We obtain firms' CSR ratings from the MSCI ESG Stats Database, covering community, diversity, employee relations, environment, and human rights. The indicator variable, *High CSR*, takes the value of one if a firm's CSR score is in the top quartile among all firms, and zero otherwise. In column (1), we control for firms with high social capital and show that, indeed, firms with high social capital are associated with a reduced drop in returns. Nonetheless, after controlling for social capital, our main findings remain.

Pagano, Wagner, and Zechner (2020) and Papanikolaou and Schmidt (2020) show that firms that have flexible work-from-home arrangements significantly outperform those that do not have such arrangements during the COVID-19 outbreak. The indicator variable, *Top WFH*, takes the value of one if a firm is in the top five two-digit NAICS industry in terms of the share of jobs that can be done from home, and zero otherwise. The data is from Dingel and Neiman (2020). In column (2), we control for the feasibility of working from home and show that our main findings remain.

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Hassan et al. (2020) show that firms that have experienced SARS or H1N1 are better at dealing with the COVID-19 outbreak. The indicator variable, *Prior epidemic experience*, takes the value of one if a firm has prior experience with SARS or H1N1, and zero otherwise. The data is from Hassan et al. (2020). In column (3), we control for firms' prior experience with other pandemics and show that our main findings remain, and indeed that firms with prior pandemic experiences are better able to weather COVID-19.

Ramelli and Wagner (2020) find that firms with lower exposure to China are less affected than other firms. The indicator variable, *China*, takes the value of one if a firm mentions China in its 10-K in relation to importing or exporting activities, and zero otherwise. The data is from Hoberg and Moon (2017). In column (4), we control for firms' business association with Chinese firms and show that our main findings remain, while the coefficient on *China* is insignificant. One possible explanation is that by March 2020, China emerged from the pandemic and any business connection to China becomes an asset.

Table IA4 presents both cross-sectional and panel data regression estimates where the return for March ends on March 31, 2020. We show that our main findings remain.

In summary, we conclude that firms with a strong culture are associated with a smaller drop in returns than their peers without a strong culture, controlling for social capital/trust, ability to work-from-home, prior pandemic experience, and connection to Chinese businesses.

6. Conclusions

After fitting a topic model to 79,597 COVID-19-related paragraphs in 11,183 conference calls over the period January to April 2020, we obtain measures of firm-level exposure and response to COVID-19 for 3,019 U.S. firms. We show that despite many different ways through which COVID-19 affects their operations, firms with a strong corporate culture do better in the midst of a pandemic than their peers without a strong culture. Moreover, firms with a strong culture are more likely to emphasize community engagement and adopt digital technology, and are no more likely to engage in cost cutting than their peers without a strong culture.

To explore the channels through which culture makes firms resilient to the pandemic, we show that firms with a strong culture have higher sales per employee and lower cost of goods sold per employee during the first quarter of 2020. Our results provide support for the notion that corporate culture is an intangible asset designed to meet unforeseen contingencies as they arise (Kreps 1990).

Appendix: Variable definitions

Variable	Definition
COVID-19 Exposure	
Competition	The proportion of discussion on competition and market opportunities (in percentage points) from the output of fitting a correlated topic model to a corpus of COVID-19-relevant paragraphs in conference calls. For each firm, we take the average of call-level proportions across all calls over the period January to March 2020.
Demand	The proportion of discussion on demand shocks (in percentage points) from the output of fitting a correlated topic model to a corpus of COVID-19-relevant paragraphs in conference calls. For each firm, we take the average of call-level proportions across all calls over the period January to March 2020.
Employees	The proportion of discussion on employee safety and wellbeing (in percentage points) from the output of fitting a correlated topic model to a corpus of COVID-19-relevant paragraphs in conference calls. For each firm, we take the average of call-level proportions across all calls over the period January to March 2020.
Liquidity	The proportion of discussion on liquidity and financing (in percentage points) from the output of fitting a correlated topic model to a corpus of COVID-19-relevant paragraphs in conference calls. For each firm, we take the average of call-level proportions across all calls over the period January to March 2020.
Lockdown	The proportion of discussion on lockdown and its implications for business operations (in percentage points) from the output of fitting a correlated topic model to a corpus of COVID-19-relevant paragraphs in conference calls. For each firm, we take the average of call-level proportions across all calls over the period January to March 2020.
Operation	The proportion of discussion on delay to operation (in percentage points) from the output of fitting a correlated topic model to a corpus of COVID-19-relevant paragraphs in conference calls. For each firm, we take the average of call-level proportions across all calls over the period January to March 2020.

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Supply chains	The proportion of discussion on supply chain disruptions (in percentage points) from the output of fitting a correlated topic model to a corpus of COVID-19-relevant paragraphs in conference calls. For each firm, we take the average of call-level proportions across all calls over the period January to March 2020.
Overall exposure	The sum of proportions of discussion (in percentage points) on the seven different exposures to COVID-19 (competition, demand, employees, liquidity, lockdown, operation, and supply chains) over the period January to March 2020.
COVID-19 Response	
Community	The proportion of discussion on community engagement (in percentage points) from the output of fitting a correlated topic model to a corpus of COVID-19-relevant paragraphs in conference calls. For each firm, we take the average of call-level proportions across all calls over the period January to March 2020.
Cost cutting	The proportion of discussion on cost cutting (in percentage points) from the output of fitting a correlated topic model to a corpus of COVID-19-relevant paragraphs in conference calls. For each firm, we take the average of call-level proportions across all calls over the period January to March 2020.
Digital technology	The proportion of discussion on adopting digital technology (in percentage points) from the output of fitting a correlated topic model to a corpus of COVID-19-relevant paragraphs in conference calls. For each firm, we take the average of call-level proportions across all calls over the period January to March 2020.
Firm-level Variables	
Quarterly return	Buy-and-hold return (in percentage points) from January to March 2020, where the return for March ends on March 20, 2020.
Monthly return	Monthly return (in percentage points) from January 2019 to March 2020, where the return for March ends on March 20, 2020.
Strong culture	An indicator variable that takes the value of one if the sum of a firm's five cultural value scores is in the top quartile across all firms in a year, and zero otherwise. Corporate culture data is from Li et al. (2020) who compute scores of the five top cultural values proposed by Guiso, Sapienza, and Zingales (2015): innovation, integrity, quality, respect, and teamwork. Following Li et al. (2020), for each firm-year, we average cultural values over a three-year window ending in 2017 which is the most recent year with available cultural value data.
Strong innovation culture	An indicator variable that takes the value of one if the cultural value score of innovation is in the top quartile across all firms in a year, and zero otherwise.
Strong integrity culture	An indicator variable that takes the value of one if the cultural value score of integrity is in the top quartile across all firms in a year, and zero otherwise.
Strong quality culture	An indicator variable that takes the value of one if the cultural value score of quality is in the top quartile across all firms in a year, and zero otherwise.
Strong respect culture	An indicator variable that takes the value of one if the cultural value score of respect is in the top quartile across all firms in a year, and zero otherwise.
Strong teamwork culture	An indicator variable that takes the value of one if the cultural value score of teamwork is in the top quartile across all firms in a year, and zero otherwise.
Strong people culture	An indicator variable that takes the value of one if the sum of a firm's three people-oriented cultural value scores (integrity, respect, and teamwork) is in the top quartile across all firms in a year, and zero otherwise.
Strong technology culture	An indicator variable that takes the value of one if the sum of a firm's two technology-oriented cultural value scores (innovation and quality) is in the top quartile across all firms in a year, and zero otherwise.
Sales per employee	Sales per employee, in thousands.
COGS per employee	Cost of goods sold (COGS) per employee, in thousands.
ln(Market cap)	Natural logarithm of market capitalization.

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ln(Total assets)	Natural logarithm of total assets.
Leverage	Total liabilities divided by total assets.
Cash holdings	Cash and marketable securities divided by total assets.
Profitability	Operating income divided by total assets.
B/M	Book value of equity divided by market value of equity.
Momentum	Buy-and-hold return (in percentage points) over months (−12, −2) before the focal month. In Table 4, we use buy-and-hold return over the period January to November 2019.
Four-factor loadings	Factor loadings based on the Fama-French three-factor model plus the momentum factor, which are estimated over the previous 60 months period. Firms are excluded from the analysis if fewer than 12 months of data are available to estimate factor loadings. For Table 4, factor loadings are estimated over the previous 60 months period ending in December 2019.
High CSR	An indicator variable that takes the value of one if a firm's CSR score is in the top quartile across all firms in a year, and zero otherwise. CSR data is from the MSCI ESG Stats Database ending in 2016. We construct a firm's CSR score covering community, diversity, employee relations, environment, and human rights following Lins et al. (2017).
Top WFH	An indicator variable that takes the value of one if a firm is in the top five two-digit NAICS industry in terms of the share of jobs that can be done from home, and zero otherwise. Data on industry-level measure of feasibility of working from home is from Dingel and Neiman (2020).
Prior epidemic experience	An indicator variable that takes the value of one if a firm mentions SARS- and/or H1N1-related words in its earnings calls in 2003 and/or 2009, and zero otherwise. The data is from Hassan et al. (2020).
China	An indicator variable that takes the value of one if a firm mentions China in its annual report in relation to importing and/or exporting activities, and zero otherwise. The data is from Hoberg and Moon (2017) ending in 2017.

Note: Continuous variables with the exception of COVID-19 exposure/response variables are winsorized at the 1^{st} and 99^{th} percentiles.

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Community-level social capital and COVID-19 infections and fatality in the United States[1]

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The literature has long documented social capital as a key social determinant of health. However, because personal social interactions are implicated in the spread of viral infections, areas with high levels of social capital may have been especially at risk during the early phases of the COVID-19 pandemic when spread could not be halted by behavioral changes. We analyzed data from US counties on laboratory-confirmed COVID-19 cases and COVID-19 deaths and relate county level social capital with the number of days it took a county to reach 10 or 15 cases (from January 22) and with case fatality rate in the county between January 22 and May 8 2020. From January 22 on average it took 68 days for a county to reach at least 10 COVID-19 cases. Disease spread was faster the higher the social capital in a community. In counties with average levels of social capital 10 cases were identified by March 29, but in counties with social capital one SD above the average 10 cases were identified by March 26. The difference is equivalent to the difference estimated across two counties that differ in population density by 12,000 people per square mile. Other things being equal we estimate lower case fatality in higher social capital counties, with a reduction of between 0.2% and 0.4% points per SD difference in social capital. As governments lift mandatory social distancing, social capital may play a key role as a social determinant of health.

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Introduction

Social interactions foster the spread of infectious diseases (Mossong et al., 2008; Béraud, et al., 2015; Leung et al., 2017; Zhang et al., 2019; Fumanelli et al., 2013). The fact that East Asia and Southern Europe were particularly hard hit by the COVID-19 pandemic has been related to the fact that countries in these regions have particularly high levels of social mixing across age groups within extended family units (Dowd et al., 2020). Strong family ties might become a risk factor in the presence of a disease that has a marked age-related fatality profile such as the SARS-CoV-2 virus (Dowd et al., 2020; Li et al., 2020; Zhou et al., 2020; Chen et al., 2020; Jordan, Adab & Cheng, 2020). While patterns of family interactions are important, we argue that a closer examination of the social bonds that exist within a community is crucial. These bonds determine how much individual households can be considered as isolated clusters or have extensive connections with other households, thus facilitating the spread of diseases.

Social capital reflects the resources and benefits that individuals and groups acquire through connections with others and involves both shared norms and values that promote cooperation as well as, and crucially for disease spread, actual social relationships (Kawachi, Subramanian & Kim, 2008; Fukuyama, 2000; Putnam, 1993). Social capital is therefore different from civic capital, conceived as 'the set of values and beliefs that help a group overcome the free-rider problem in the pursuit of socially valuable activities' (Guiso et al., 2011). Social capital comprises not only a cognitive component, reflecting attitudes and dispositions that promote interpersonal cooperation but also a relational component, reflecting social connections within a community. We argue that this is underappreciated distinction in the current literature on the role of social/civic capital during the pandemic (see Ding et al., 2020 for an important exception) and that the two components played a different role in shaping variations across communities in the evolution of the COVID-19 pandemic.

Communities with high levels of social capital tend to have a dense web of interpersonal relations and may therefore be especially vulnerable to disease spread (Bai, et al., 2020). Especially in the early days of the COVID-19 pandemic, the fact that many individuals suffering from COVID-19 are asymptomatic or have only light symptoms (Bai, et al., 2020). As a result, most people did not know that physical contacts with individuals who did not display any symptoms and with no known contact with affected areas in China could lead to viral transmission. Therefore, in such early phase, individuals living in communities with high levels of social capital may have been more exposed to the SARS-CoV-2 virus because of their higher than average physical contacts without the adoption of personal protective behaviours.

Community level social capital could be related with COVID-19 fatality as well as transmission. Social capital is generally associated with a lower incidence of chronic conditions (Rodgers et al., 2019) and because COVID-19 fatality is particularly high among individuals with prior health conditions (Li, et al., 2020; Zhou et al., 2020; Chen et al., 2020; Jordan, Adab & Cheng, 2020), fatality among those infected could be lower in high social capital communities. A second important feature of COVID-19 is that many of those infected require hospitalisation and intensive care. Therefore, social capital could influence fatality through an indirect effect on health care capacity. Communities with high levels of social capital appear better at lobbying decision makers and key providers to obtain adequate resources to support those who need medical care.

Social capital may also facilitate the diffusion of information on the health consequences of COVID-19 and the risks individuals face of suffering severe outcomes if infected, on individuals who are at an especially high risk of dying because of COVID-19 and on behaviours that reduce transmission. In communities with high levels of horizontal social capital transaction costs are typically lower and access to material resources and to health-related information is higher (Stephens, Rimal & Flora, 2004; Viswanath, Steele & Finnegan, 2006). This is important as a way to facilitate the adoption of behaviours that protect the individual and the community in the second phase (Lin et al., 2014; Savoia, Lin & Viswanath, 2013). Social capital may also importantly shape a community's overall sense of mutual responsibility and support (Coleman, 1998; Putnam, 1993) and willingness to follow advice to reduce transmission among the most vulnerable (Szreter & Woolcock, 2004).

Evidence on the role social capital on information acquisition and mobility changes during the Covid-19 pandemic, both voluntary and in response to regulations, is emerging (Bargain & Aminjonov, 2020; Durante, Guiso, & Gulino, 2020; Borgonovi & Andrieu, 2020; Bartscher et al., 2020; Barrios et al., 2020). Social capital has been identified as an important asset for individuals and communities during previous pandemics such as the H1N1 pandemic. In that context social capital led to greater awareness and adoption of health protective behaviors beyond mobility, such as wearing face masks and vaccinating (Chuang, Huang & Tseng, 2015; Rönnerstrand, 2013; 2014; 2016).

By contrast, if the initial surge of infections due to extensive social relations in high social capital areas were to overwhelm the system, social capital could indirectly lead to a

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higher indirect fatality in an area, by reducing the capacity of the health care system to cater to COVID-19 patients.

In this work we evaluate the association between social capital and speed of COVID-19 infections and fatality in the United States and hypothesize that higher community level social capital is associated with a faster spread of the virus in the initial phase but lower fatality in a longer timeframe. The United States witnessed a very rapid spread of the covid-19 pandemic and is currently the country with the largest number of identified cases (WHO, 2020) and deaths. It is also a country with large geographical disparities in socio-economic and demographic characteristics and social capital (Putnam, 2000). We examine data from US counties to identify: the speed of COVID-19 spread across local communities with different levels of social capital in the initial phase of the pandemic (January 22 to April 6); and differences in COVID-19 fatality across counties with differed levels of social capital over a longer timeframe (January 22 to May 8). The early phase of the pandemic paints the picture of the role communities' relations have when they cannot organise and change their behaviour in response to a threat. The longer timeframe details the outcomes communities experience when they have time to react. Moreover, the fatality measure reflects community level differences in levels of susceptibility (such as, for example, level of pre-existing conditions).

Methods

Data

Outcome variables:

Speed of infection: the number of days elapsed between the 22nd of January (the first day from when county level information on infection and mortality due to covid-19 was first released and that precedes contagion in virtually all US counties) and the day when at least 10 cases of covid-19 (or 15 depending on model) were diagnosed in the county.
Case fatality: the cumulative number of deaths due to covid-19 divided by the cumulative number of covid-19 diagnoses at the county level.

Control variables:
Social capital: county level social capital was acquired through "The geography of social capital" project. Data are available for 2,992 counties and cover 99.7 percent of the American population ($\mu=0$; $\sigma=1$).

Economic orientation: refers to the 2015 classification into one of the following six mutually exclusive categories of primary economic activity characterising the county: category 0 refers to non-specialized counties; category 1 comprises farming; category 2 comprises mining; category 3 comprises manufacturing; category 4 comprises federal/state government, and category 5 comprises recreation (for definitions of the county typology codes, visit: https://www.ers.usda.gov/data-products/county-typology-codes/documentation/).

Population density: the total population within a county divided by the land area of that county measured in square miles (US Census methodology). The density is expressed as "population per square mile". The population data are estimates from 2018 that come from the June 2019 release of the Annual County Resident Population Estimates by Age, Sex, Race, and Hispanic Origin by the U.S. Census Bureau, Population Division and land area from the U.S. Census Bureau, Census of Population and Housing (2010). We express the variable in 1,000 individuals per square mile.

Share of population above 65: the total number of people above 65 divided by the total population at the county level.

Number of intensive care (ICU) beds: healthcare capacity data are provided at the hospital level; therefore, we aggregated hospital figures to obtain county level estimates. The data come from Definitive Healthcare, which contains information on the typical bed capacity of hospitals. The number of ICU beds refers to the number of qualified ICU based on definitions by Centers for Medicare and Medicaid Services (section 2202.7, 22-8.2) and include ICU beds, psychiatric ICU beds, and Detox ICU beds. We express the variable as number of beds per 100,000 individuals.

Mobility patterns: the change in the weekly mobility index between weeks starting in March 16 and week starting on April 20 using Cuebiq's Mobility Index (CMI). The CMI is a publicly accessible resource made available by Cuebiq and provides the level of movement for each week and in each county in the United States. The index is based on de-identified, geo-located information on smartphone users. The CMI for each county is the median of the aggregated movements of all users within a county. A detailed description of the Cuebiq dataset can be found at https://help.cuebiq.com/hc/en-us/articles/360041285051-Reading-Cuebiq-s-COVID-19-Mobility-Insights.

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Table 1: Variable description and sources where data can be accessed

Data	Unit	Resource/website
Outcome variables:		
- Number of cases and deaths	Counts	https://usafacts.org/visualizations/coronavirus-covid-19-spread-map/
Control variables:		
- Social capital	Std (mean 0 and SD of 1)	https://www.jec.senate.gov/public/index.cfm/republicans/2018/4/the-geography-of-social-capital-in-america#toc-007-backlink
- Population • Share of people 65+ • Total population	 Share Counts	https://www2.census.gov/programs-surveys/popest/technical-documentation/file-layouts/2010-2018/cc-est2018-alldata.pdf
- Capacity for intensive care (ICU)	Number of ICU beds per 100,000 individuals	https://opendata.arcgis.com/datasets/1044bb19da8d4dbfb6a96eb1b4ebf629_0.csv
- Cuebiq's Mobility Index (CMI)	Weekly index	https://help.cuebiq.com/hc/en-us/articles/360041285051-Reading-Cuebiq-s-COVID-19-Mobility-Insights
- Economic dependence of counties	Factor	https://www.ers.usda.gov/data-products/county-typology-codes/
- Density	Population per square mile	U.S. Census Bureau, Census of Population and Housing (https://www.census.gov/library/publications/2011/compendia/usa-counties-2011.html#LND)

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Table 2: List of variables and descriptives

Variables	Mean	SD	Notes
Outcome variables:			
- Number of days elapsed before a county reaches 10 confirmed cases of Covid-19	65	7	*January 22 to April 6*
- Deaths (covid-19)	24	199	*On May 8 2020*
- Cases (covid-19)	403	2496	*On May 8 2020*
Control variables:			
- Social capital	0	1	*Standardised*
- Demographics (share of people >65)	0,26	0,06	*Mean centered in analysis*
- Capacity for intensive care (ICU)	36 37	36 114	*Per 100, 000 individuals and in counts. Mean centered in analysis*
- Cuebiq's Mobility Index (CMI)	0,03	0,10	*Mean change in mobility (March 16 and April 20) & centered*
- Density	277	1804	*Mean centered in analysis*

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Table 3 Data sources used to calculate the social capital indicator at the county level

Share of births in past year to women who were unmarried	American Community Survey, 2012-2016, 5-year estimates	American FactFinder Table S1301
Share of women ages 35-44 who are currently married (and not separated)	American Community Survey, 2012-2016, 5-year estimates	American FactFinder Table B12002
Share of own children living in a single-parent family	American Community Survey, 2012-2016, 5-year estimates	American FactFinder Table B09002
Registered non-religious non-profits per 1,000	IRS, Business Master File, 12/2015; ACS population estimates, 7/2015 (2015 vintage)	via National Center for Charitable Statistics & American FactFinder Table PEPANNRES
Religious congregations per 1,000	U.S. Religion Census: Religious Congregations and Membership Study, 2010	via Association of Religious Data Archives, census conducted 2009-11
Share of adults who report having volunteered for a group in the past year	Volunteer Supplement to the September 2015 Current Population Survey	
Share who report having attended a public meeting re. community affairs in past year	Volunteer Supplement to the September 2015 Current Population Survey	
Share who report having worked with neighbors to fix/improve something in past year	Volunteer Supplement to the September 2015 Current Population Survey	
Share of adults who served on a committee or as an officer of a group	Volunteer Supplement to the November 2013 Current Population Survey	
Share who attended a meeting where political issues were discussed in past year	Civic Engagement Supplement to the November 2008 Current Population Survey	
Share who took part in march/rally/protest/demonstration in past year	Civic Engagement Supplement to the November 2008 Current Population Survey	
Average (over 2012 and 2016) of votes in the presidential election per citizen age 18+	Election Administration and Voting Survey; ACS, 2012-2016, 5-year estimates	U.S. Election Assistance Commission; EAVS voting combined with American FactFinder Table B05003 estimates of citizens 18+; votes unavailable for Alaska counties, which we assign the statewide voting rate
Mail-back response rates for 2010 census	Census Bureau	via University of Michigan Population Studies Center, Institute for Social Research
Confidence in Institutions Sub-Index	Volunteer Supplement to the November 2013 Current Population Survey	combination of share reporting at least some confidence in corporations, in the media, and in public schools

Source: Table 2. available online at https://www.jec.senate.gov/public/index.cfm/republicans/2018/4/the-geography-of-social-capital-in-america#toc-005-backlink accessed on May 3rd 2020.

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Statistical analysis

We identify the number of days elapsed between January 22 (the first day from when county level information on infection and mortality due to COVID-19 was first released and that precedes contagion in virtually all US counties) and the day when at least 10 cases of COVID-19 (or 15 depending on model) were diagnosed in the county up to April 6, a period in which communities did not have time to react by modifying their behaviour and see such changes reflected in changes in case detection. We then estimate the association between social capital and this measure, which indicates how fast the SARS-Cov-2 virus spread in a community. Results are presented without state fixed effects as well as for specifications with state fixed effects and that control for the economic sector of the county, the share of population in the county above 65, population density (1,000 per square mile) and the number of beds in intensive care unit (expressed in number of beds per 100,000 individuals). These factors could determine the intensity of close physical contacts in a community and, as a result, how fast transmission occurred. Models with state fixed effects exploit within state but between county variations in infections and social capital and therefore account for measurement error potentially due to differences in reporting standards across states.

Next, we present results on the association between social capital and COVID-19 case fatality between January 22 and May 8. Case fatality was calculated as the cumulative number of deaths in a county due to COVID-19 divided by the cumulative number of COVID-19 diagnoses that were made in a county. We present results for a model with social capital and controls for the number of beds in intensive care available in the county expressed as the number of beds per 100 000 individuals (because lack of potential treatment may lead to death), the share of the population who is above the age of 65 (because of evidence that COVID-19 is more fatal among the elderly) and changes in levels of mobility between the week starting on March 16 and the week starting on April 20 (as a proxy for the willingness of the population to adopt health protective behaviours). Results are presented without and with state fixed effects.

All specifications are weighted using population estimates for 2018 from the June 2019 release of the Annual County Resident Population Estimates by Age, Sex, Race, and Hispanic Origin by the U.S. Census Bureau, Population Division. Introducing population weights allows us to derive estimates that are representative at the population level and that are not overly sensitive to disease spread and fatality observed in scarcely populated counties. All statistical analyses were conducted using R version 3.5.3.

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Results

Relationship between social capital and infection

Results presented in Table 4 suggest that on average in the United States it took a county 67 days from January 22 to have at least 10 COVID-19 cases (or 68 days to reach 15 cases). In counties with a higher level of social capital the propagation of COVID-19 was faster than in counties with lower levels of social capital: a change of one standard deviation in the social capital index was associated with a reduction of around 3 days in the number of days elapsed until the county reached 10 (or 15) cases. These results are from the specifications including controls for the economic dependency indicators of the county, share of old, number of intensive care unit beds, population density and state fixed effects. In specifications not including state fixed effects, results are in the expected direction but are imprecisely estimated and very small, suggesting large differences across states. Our models suggest that the virus spread faster in communities that were more densely populated and that had a lower share of residents aged 65 or over. The magnitude of the association between social capital and the speed of infection in specifications that account for all controls and state fixed effects is equivalent to the difference observed between two counties that differ in population density by 12,000 (13,000) people per square mile.

Table 4. *COVID-19 spread and county level social capital in the United States*

	Dependent variable:			
	Days until 10th case	Days until 15th case	Days until 10th case	Days until 15th case
	Controls (weighted)	Controls (weighted)	Controls + FE (weighted)	Controls + FE (weighted)
	(1)	(2)	(3)	(4)
Constant	59.594***	60.562***	67.862***	66.793***
	(0.368)	(0.390)	(4.148)	(4.796)
Social capital	-0.225	-0.260	-2.550***	-2.571***
	(0.273)	(0.288)	(0.374)	(0.391)
Population density (1000 people per sqmile)	-0.283***	-0.275***	-0.214***	-0.196***
	(0.030)	(0.031)	(0.030)	(0.031)
% of people above 65	45.836***	41.117***	57.528***	53.483***
	(4.971)	(5.243)	(5.114)	(5.450)
ICU beds (number of beds per 100,000 people)	0.003	0.0004	-0.055***	-0.056***
	(0.011)	(0.011)	(0.010)	(0.011)
Economic dependency	yes	yes	yes	yes
State FE	no	no	yes	yes
Observations	1,091	900	1,091	900
R^2	0.185	0.177	0.469	0.472
Adjusted R^2	0.179	0.168	0.439	0.435
Residual Std. Error	3,468.980 (df = 1081)	3,574.106 (df = 890)	2,867.935 (df = 1031)	2,944.658 (df = 840)
F Statistic	27.345*** (df = 9; 1081)	21.199*** (df = 9; 890)	15.435*** (df = 59; 1031)	12.750*** (df = 59; 840)

Notes: *p<0 .1; **p<0.05; ***p<0.01. (SE) refers to standard errors. All specifications are weighted by the population. Data: number of observations varies due to missing data at the county level. Dependent variable is computed as the number of days from the January 22 2020 until the county reaches its 10th case (Models 1 and 3) or 15th case (Models 2 and 4). All models include controls for the economic dependence of the county (reference category undifferentiated economic activity), population density (per 1000 people and mean centered), percentage of people above 65 (mean centered) and the number of ICU beds per 100,000 people (mean centered). Models (3) and (4) include state fixed effects.

Table 5 presents results on the association between social capital and case fatality. We estimate a cumulative case fatality rate of around 3.7-5% in the period between 22 January and 8 May 2020, on average, in the counties in our sample: i.e. for every 100 cases with a positive diagnosis of COVID-19 up to May 8, 3.5-5 COVID-19 related deaths were recorded. In models that do not control for state fixed effects a difference of one standard deviation in social capital is associated with a difference of 2 per 1,000 in the case fatality rate observed in the county, when we include controls for the economic dependency indicators of the county, the number of intensive care beds, the share of the population who is especially susceptible to

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COVID-19 because of age and the change in mobility. Moreover, specifications that include state fixed effects and therefore reflect within state, between country variability, suggest that a difference of one standard deviation in social capital is associated with a larger difference in the case fatality rate of around 4 per 1,000. Results indicate that the disease is more fatal for elderly populations: fatality is higher the higher the share of older residents.

Table 5. *COVID-19 fatality rate and county level social capital in the United States*

	Dependent variable:	
	Case fatality rate (January 22- May 8)	
	Controls (weighted)	Controls + FE (weighted)
	(1)	(2)
Constant	0.050***	0.037***
	(0.001)	(0.005)
Social capital	-0.002***	-0.004***
	(0.001)	(0.001)
ICU beds (number of beds per 100,000 people)	0.00003	0.00002
	(0.00003)	(0.00003)
% of people above 65	0.124***	0.097***
	(0.015)	(0.017)
Change in mobility (week March 16 and week April 20)	-0.057***	-0.044***
	(0.003)	(0.005)
Economic dependency	yes	yes
State FE	no	yes
Observations	2,264	2,264
R^2	0.159	0.271
Adjusted R^2	0.156	0.252
Residual Std. Error	11.791 (df = 2254)	11.103 (df = 2206)
F Statistic	47.512*** (df = 9; 2254)	14.352*** (df = 57; 2206)

Notes: *p<0 .1; **p<0.05; ***p<0.01. (SE) refers to standard errors. All specifications are weighted by the population. Data: number of observations is lower than number of counties due to missing data at the county level. Dependent variable is the mortality rate computed on May 8 2020. All models include controls for the economic dependence of the county (reference category undifferentiated economic activity), percentage of people above 65 (mean centered), the number of ICU beds per 100,000 people (mean centered) and the change in mobility (mean centered) computed on the Cuebiq data between the week beginning March 16 and week beginning on April 20 (controls for the behaviour of people which we suspect to have an effect on the mortality rates). Model (2) includes state fixed effects.

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Strengths and Limitations

Most of the analyses conducted refer to events that occurred in the very early phases of the COVID-19 pandemic. Data quality remains unknown at this point. In particular, county level data on COVID-19 infections and deaths may reflect differences in reporting standards across counties and reporting standards may differ depending on social capital. The introduction of state fixed effects eliminates differences in reporting across states but if counties with a higher level of social capital have higher than average infection rates and see infections rise faster, estimates presented would be upwardly biased during the propagation phase (leading to an even more negative association between social capital and how fast infections spread) and a downwardly bias results for case fatality (because a higher number of cases would be identified). However, if social capital also led to a higher recognition of COVID-19 as a cause of death, the overall bias (both in terms of size and sign) on case fatality would remain undetermined.

Our results are descriptive and illustrate associations between the stocks of social capital in different US communities prior to the unfolding of the COVID-19 pandemic and how fast COVID-19 infections and how fatal COVID-19 was in the initial phases of the pandemic. No causal claims can be made.

Discussion and Conclusion

Until a vaccine or effective treatments become available, the impact of the pandemic on the health of communities in the United States will crucially depend on the willingness and ability of such communities to change their behaviours to reduce infections and to protect the most vulnerable (van Bavel et al., 2020). Now that national and local leaders across the world are considering relaxing limitations to freedom of movements, lifting shelter in place regulations, and reopening schools, social capital could play a role in protecting the health of community members. Personal behaviours such as washing hands frequently and adequately, wearing face masks when encountering others, avoiding close physical contact with others, isolating if one develops any symptoms can effectively reduce infections and transmission (Cowling, et al., 2020).

Adopting such behaviours can be difficult and costly for individuals (van Bavel et al., 2020). Individuals living in communities with high levels of social capital might be more motivated and prepared to adopt such behaviours: in such communities members may be less likely to adopt free-riding behaviours and may be more willing to sustain personal costs for the benefit of the community. Moreover, one important reason as to why individuals do not adopt health protective behaviours is that they severely underestimate the risk they face if infected with COVID-19 (Niepl, Kranz, Borgonovi, Valentin & Greiff, 2020; Sheeran, Harris & Epton, 2014; Bish & Michie, 2010). Social capital can facilitate the transmission of information on health risks (Kim, Subramanian & Kawachi, 2008). Moreover, in communities with high levels of social capital, community level monitoring and social sanctioning can ensure that even when individuals do not have accurate risk perceptions, they still act to minimize community level transmission. Finally, communities with high levels of social capital may be better at ensuring that critical workers are supported, that necessary equipment and devices are sources and made available in the most efficient way for the entire community, for example, giving priorities to those who are most at risk of being infected or of suffering severe health consequences if they become infected.

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COVID, on-premise retail format, and product-market concentration[1]

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The COVID-19 pandemic has led to considerable changes in retail shopping. There has been a significant increase in online shopping compared to on-premise, but due to social distancing and other safety regulations, there have also been significant changes in how on-premise retail is conducted. Prior studies have demonstrated significant effects on product-market concentration from the move to more online shopping, but here we focus on the effects on concentration due to the common change of moving from self-service stores to counter-service. Using a pre-COVID field experiment of a move in the opposite direction, our results suggest that an increase in counter-service shopping is likely to increase product-market concentration, potentially overwhelming the opposite change from the move to online shopping.

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1. Introduction

The COVID-19 pandemic has led to dramatic shifts in retail commerce: both a shift from on-premise to on-line, and a shift in the operations of on-premise outlets that restrict the number of customers in store. Although popular press accounts have tended to focus on the former (e.g., Robertson 2020), the latter in fact accounts for the majority of change. On-premise grocery retail sales remain more than five times larger than on-line grocery retail even after a substantial shift to on-line purchasing due to COVID (Relihan et al. 2020: 17 [Figure 12]), and brick-and-mortar retail sales remained substantially larger than online sales in early March (Alexander & Karger 2020: 20-21; Census 2020). Notably, the shift within on-premise operations frequently entails customers asking for items that shopkeepers then retrieve from inside the store, thus reverting to a formerly common "behind-the-counter" format as opposed to a self-service format.

Although scholars have tended to focus on the impact of COVID on retailers themselves (e.g., Carvalho et al. 2020; Benzell et al. 2020), there is reason to expect that these changes will also affect upstream manufacturing sectors (Alstadsæter et al. 2020). Recent research has explored the effect on overall product sectors, such as clothing (Coibion et al. 2020). Yet such retail format changes can also differentially affect specific products or brands within a sector (Goldfarb et al. 2015). In this paper we ask: How should we expect the COVID-impelled changes in on-premise retail practices to affect product manufacturers? Although it is too soon to use COVID-era data to explore this, we draw prospective lessons by using a field experiment that isolated a change in distribution-channel activities to test how different retail distribution formats affect product-market concentration.

Specifically, in the 1990s the Swedish state alcohol retail monopoly randomly moved seven stores from behind-the-counter to self-service sales format, in which shelves were stocked with

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products and customers could walk through the aisles, select what they wished, and proceed to a cashier. In other words, these stores experienced the *reverse* of the current COVID-driven shift. Pairs of stores were matched by demographics and by alcohol sales; one was chosen randomly to move to self-service and the other retained the behind-the-counter format. Each of the fourteen stores was the only store in its town. We find that the Hirschmann-Herfindahl Index (hereafter Herfindahl) measure of sales concentration fell 16% in the stores that switched to self-service, even though prices and products offered were the same in the self-service stores and the stores that stayed in counter-service. The timing of these changes is coincident with the change in store format and the results are robust across product categories. This increase in the diversity of products sold when going from counter-service to self-service is similar in magnitude to moving from print catalog to online (Brynjolfsson et al. 2011). This is consistent with the findings of Pozzi (2012) and gives further evidence that the format of the retail channel is significant for exploration of unfamiliar brands. Since the effect sizes of the two changes --- from on-premise to online and from self-service to counter-service --- are similar and the on-premise retail is currently much larger than online retail, the net effect suggested by these findings is that the COVID pandemic may lead to increased concentration of product segments due to the consequent shift from self-service to back-of-counter service at on-premise retailers.

Why is concentration lower in self-service stores than in back-of-counter stores? Although determining the precise mechanism is beyond the reach of our data, the most likely explanation relates to information costs. Indeed, Demsetz (1982: 50) describes the buyer's cost of obtaining information as a fundamental "barrier" that makes a reputable history a valuable asset. Relatedly, Schmalensee's (1982) model of pioneering advantages under imperfect information suggests that cost of getting information by the consumer (rather than advertising per se) slows consumer

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adoption and thus can deter exploration of alternative brands. The self-service format allows consumers easy access to information about products, particularly on non-price attributes. In this way, our finding that retail format affects concentration is consistent with Brynjolfsson et al.'s (2011) evidence that reduced search costs online lead to more variety sold. Another possible source of concentration in our setting relates to the change in the interaction between customers and staff. Self-service stores allow customers to peruse the aisles self-guided at their leisure and then carry selected products to the cashier. In the behind-the-counter stores one searches through a catalog and then requests a product from the salesperson – with possibly several other customers waiting in line and a chance that the salesperson will return from the back to announce that the requested item is not in stock. Evidence from psychology suggests that this social interaction with the sales staff, and the possibly associated time pressure, is likely to result in selection of familiar rather than new products (Ben-Zur and Breznitz, 1981; Goldfarb et al., 2015), making it harder for less popular products to gain or retain share.

Our study's finding of a link between retail format and market concentration is important not only due to the size of the effect but also due to the ubiquity of the behind-the-counter format. In numerous jurisdictions in North America and Europe, many goods are sold behind the counter by law including pharmaceuticals, alcohol, and cigarettes. And, as public health officials strive to devise modes of interaction that reduce the spread of COVID, such retail practices may be increasingly mandated or encouraged. Understanding how the format affects competition is important to the regulators who develop the rules and to the firms who develop strategies under the regulations.

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2. Empirical Setting and Data

Our data come from a field experiment conducted by the Swedish national alcohol retail monopoly, Systembolaget, in the early 1990s.[1] In 1990, Systembolaget operated roughly 400 stores throughout Sweden to serve a population of 8.5 million. Sales of wine, distilled spirits, and "strong beer" (above 3.5% alcohol) by any other retailers were prohibited. Many other retailers sell beer with up to 3.5% alcohol.

Systembolaget conducted a field experiment to explore the effect of a self-service retail format on aggregate alcohol sales.[2] Although we are not interested in the effect on alcohol sales per se, the experiment provides a convenient way to explore how a change in retail format affects the concentration of sales. To identify the effects and reduce the chances of simply cannibalizing sales across stores, Systembolaget chose 14 towns that each had a single retail store for alcohol sales. Thus Stockholm and other large cities in Sweden are not in the data. According to Skog (2000, p. 96), Systembolaget used data from 1984 through 1989 to match the towns into seven pairs "in such a way as to make the members of each pair as similar as possible in terms of population size, economic bases and sales of alcoholic beverages; the latter both in terms of volume per capita and pattern of variation over time." The pairs were also chosen to be sufficiently far apart geographically to prevent spillover effects. The member of the pair chosen for the treatment was decided by randomization. Table 1a lists the pairs and their characteristics.

[1] Many of the details that follow come from Skog's (2000) assessment of the impact of this experiment on alcohol consumption and repeat information in another paper on the same dataset (citation suppressed for anonymity). Specifically, many of the motivating results resemble the motivating results of that paper which focused on social interaction and hard-to-pronounce products (with slightly different data samples related to the need in (citation suppressed for anonymity) to identify difficulty of pronunciation). Furthermore, we used this data in a paper on the impact of potentially embarrassing social interaction on product choice in Goldfarb et al (2015). The key new results in this paper focus on the distribution of products sold: Table 5 and Figures 3 and 4.

[2] Sweden has a history of using experiments to understand how changes in retail policy affect alcohol consumption. For example, a 1967 experiment allowed beer with over 3.5% alcohol to be sold in some grocery stores. Nilsson (2008) uses this experiment to examine how alcohol exposure in utero affects lifetime earnings and education.

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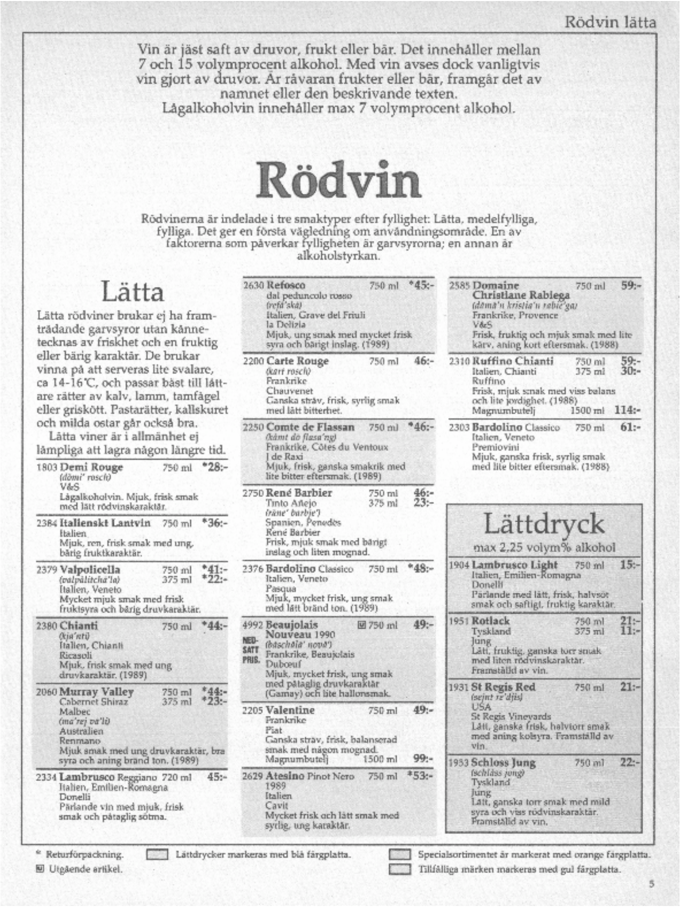
Table 1a: Treatment and control stores and characteristics (as of January 1991)

Towns	Treatment or control	Date of change	Town Population	Sales (units)	Herfindahl (products, units sold)	Sales (Liters)	Revenue in million Krona
Filipstad	Treatment	June 1991	13296	58413	0.1309	28404	234.7
Nybro	Control	None	20997	53542	0.1270	27764	281.0
Köping	Treatment	July 1991	26345	97701	0.1126	50513	418.0
Säffle	Control	None	17960	46807	0.1082	23581	223.2
Vänersborg	Treatment	Nov. 1991	36734	99028	0.0925	51084	449.0
Lidköping	Control	None	36097	84143	0.0959	43611	374.4
Motala	Treatment	May 1992	42223	92758	0.1184	48069	441.3
Falun	Control	None	54364	123305	0.0779	69196	614.2
Karlshamn	Treatment	Sept. 1993	31407	82538	0.1220	43830	425.8
Lerum	Control	None	33548	88043	0.0846	46687	345.5
Ludvika	Treatment	Sept. 1994	29144	78178	0.1252	41441	371.6
Vetlanda	Control	None	28170	65646	0.1098	33069	307.0
Mariestad	Treatment	Jan. 1995	24847	92972	0.1044	47584	427.6
Värnamo	Control	None	31314	88514	0.1069	45906	424.1

Table 1b: Store-category-level descriptive statistics (unit of observation is month-store-category)

	Mean	Std. Dev.	Minimum	Maximum	# obs.
Herfindahl (products, units sold)	0.1096	0.0806	0.0045	0.7929	10570
Herfindahl (products, mL sold)	0.1085	0.0827	0.0043	0.7979	10570
Herfindahl (SKUs, units sold)	0.0767	0.0670	0.0038	0.7929	10570
C4 (products, units sold)	0.5014	0.2126	0.0543	1	10570
C1 (products, units sold)	0.2137	0.1213	0.0141	0.8896	10570
Units sold	14831.8	18331.9	23	159917	10570
Liters sold	7487.0	8621.1	15.1	6.32e+04	10570
Revenue in million Krona	61.2	57.9	0.0335	400	10570
Price per mL	10.91	9.57	1.27	93.72	10570

Figure 1a: Sample page from a typical menu, covering red wines (from January 1991)



Rödvin lätta

Vin är jäst saft av druvor, frukt eller bär. Det innehåller mellan 7 och 15 volymprocent alkohol. Med vin avses dock vanligtvis vin gjort av druvor. Är råvaran frukter eller bär, framgår det av namnet eller den beskrivande texten.
Lågalkoholvin innehåller max 7 volymprocent alkohol.

Rödvin

Rödvinerna är indelade i tre smaktyper efter fyllighet: Lätta, medelfylliga, fylliga. Det ger en första vägledning om användningsområde. En av faktorerna som påverkar fylligheten är garvsyrorna; en annan är alkoholstyrkan.

Lätta

Lätta rödviner brukar ej ha framträdande garvsyror utan kännetecknas av friskhet och en fruktig eller bärig karaktär. De brukar vinna på att serveras lite svalare, ca 14-16°C, och passar bäst till lättare rätter av kalv, lamm, tamfågel eller griskött. Pastarätter, kallskuret och milda ostar går också bra.

Lätta viner är i allmänhet ej lämpliga att lagra någon längre tid.

1803 **Demi Rouge** 750 ml *28:-
(dõmi' rosch)
V&S
Lågalkoholvin. Mjuk, frisk smak med lätt rödvinskaraktär.

2384 **Italienskt Lantvin** 750 ml *36:-
Italien
Mjuk, ren, frisk smak med ung, bärig fruktkaraktär.

2379 **Valpolicella** 750 ml *41:- / 375 ml *22:-
(valpålitchä'la)
Italien, Veneto
Mycket mjuk smak med frisk fruktsyra och bärig druvkaraktär.

2380 **Chianti** 750 ml *44:-
(kja'nti)
Italien, Chianti
Ricasoli
Mjuk, frisk smak med ung druvkaraktär. (1989)

2060 **Murray Valley** 750 ml *44:- / 375 ml *23:-
Cabernet Shiraz
Malbec
(ma'rej va'li)
Australien
Renmano
Mjuk smak med ung druvkaraktär, bra syra och aning bränd ton. (1989)

2334 **Lambrusco** Reggiano 720 ml 45:-
Italien, Emilien-Romagna
Donelli
Pärlande vin med mjuk, frisk smak och påtaglig sötma.

2630 **Refosco** 750 ml *45:-
dal peduncolo rosso
(refå'skå)
Italien, Grave del Friuli
la Delizia
Mjuk, ung smak med mycket frisk syra och bärigt inslag. (1989)

2200 **Carte Rouge** 750 ml 46:-
(kart rosch)
Frankrike
Chauvenet
Ganska sträv, frisk, syrlig smak med lätt bitterhet.

2250 **Comte de Flassan** 750 ml *46:-
(kåmt do flasa'ng)
Frankrike, Côtes du Ventoux
J de Raxi
Mjuk, frisk, ganska smakrik med lite bitter eftersmak. (1989)

2750 **René Barbier** 750 ml 46:- / 375 ml 23:-
Tinto Añejo
(räne' barbje')
Spanien, Penedès
René Barbier
Frisk, mjuk smak med bärigt inslag och liten mognad.

2376 **Bardolino** Classico 750 ml *48:-
Italien, Veneto
Pasqua
Mjuk, mycket frisk, ung smak med lätt bränd ton. (1989)

4992 **Beaujolais Nouveau** 1990 ⊠ 750 ml 49:-
NEDSATT PRIS.
(båschålä' novå')
Frankrike, Beaujolais
Duboeuf
Mjuk, mycket frisk, ung smak med påtaglig druvkaraktär (Gamay) och lite hallonsmak.

2205 **Valentine** 750 ml 49:-
Frankrike
Piat
Ganska sträv, frisk, balanserad smak med någon mognad.
Magnumbutelj 1500 ml 99:-

2629 **Atesino** Pinot Nero 750 ml *53:-
1989
Italien
Cavit
Mycket frisk och lätt smak med syrlig, ung karaktär.

2585 **Domaine Christiane Rablega** 750 ml 59:-
(dåmä'n kristia'n rabie'ga)
Frankrike, Provence
V&S
Frisk, fruktig och mjuk smak med lite kärv, aning kort eftersmak. (1988)

2310 **Ruffino Chianti** 750 ml 59:- / 375 ml 30:-
Italien, Chianti
Ruffino
Frisk, mjuk smak med viss balans och lite jordighet. (1988)
Magnumbutelj 1500 ml 114:-

2303 **Bardolino** Classico 750 ml 61:-
Italien, Veneto
Premiovini
Mjuk, ganska frisk, syrlig smak med lite bitter eftersmak. (1988)

Lättdryck

max 2,25 volym% alkohol

1904 **Lambrusco Light** 750 ml 15:-
Italien, Emilien-Romagna
Donelli
Pärlande med lätt, frisk, halvsöt smak och saftigt, fruktig karaktär.

1951 **Rotlack** 750 ml 21:- / 375 ml 11:-
Tyskland
Jung
Lätt, fruktig, ganska torr smak med liten rödvinskaraktär.
Framställd av vin.

1931 **St Regis Red** 750 ml 21:-
(sejnt re'djis)
USA
St Regis Vineyards
Lätt, ganska frisk, halvtorr smak med aning kolsyra. Framställd av vin.

1953 **Schloss Jung** 750 ml 22:-
(schlåss jong)
Tyskland
Jung
Lätt, ganska torr smak med mild syra och viss rödvinskaraktär.
Framställd av vin.

* Returförpackning.
⊠ Utgående artikel.
Lättdrycker markeras med blå färgplatta.
Specialsortimentet är markerat med orange färgplatta.
Tillfälliga märken markeras med gul färgplatta.

5

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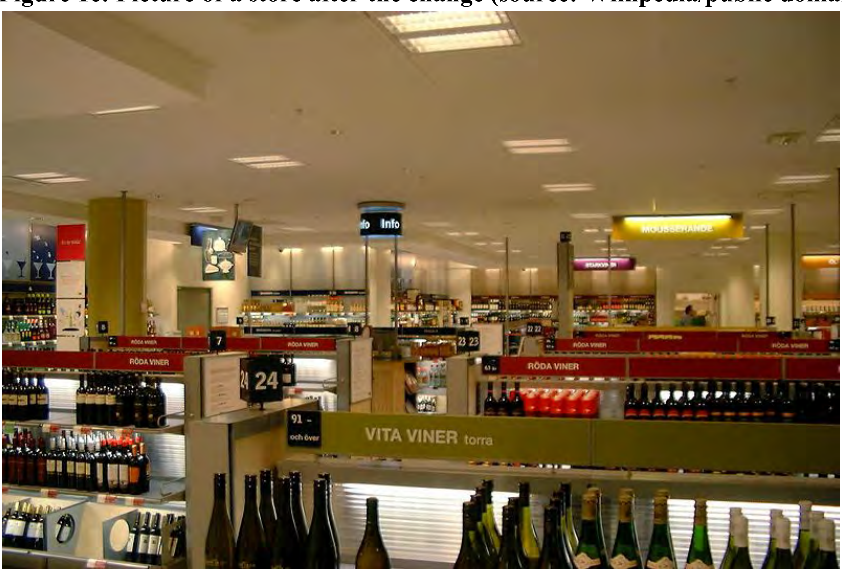
Figure 1b: Picture of a store with behind-the-counter service

(source: Wikipedia/copyright Christan Koehn 2006, used under GNU Free Documentation License)

Figure 1c: Picture of a store after the change (source: Wikipedia/public domain)



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Three aspects of Systembolaget and Sweden make the experimental setting especially clean.[3] First, during the experiment, prices (which are based on a fixed, legislated per-unit markup) and products offered did not change in the treatment stores relative to the control stores. All that changed was the format of the store. Thus we can focus on the consumer response without worrying about controlling for endogenous changes in price and product offerings. Second, Systembolaget is a monopoly seller of alcohol (above 3.5%-vol.) within Sweden and therefore competitor responses to the change in format are unlikely to be relevant outside of weak beer and non-alcoholic drinks. Third, advertising and promotions are banned for alcohol above 2.25% (although foreign magazines sold in Sweden were allowed to carry alcohol advertisements), thus removing concerns about endogenous changes in marketing expenditures by alcohol manufacturers in response to the format change.

All items sold in Systembolaget stores are listed in a catalog, or menu. Every store provides the same menu, although not every store stocks every item. Figure 1a shows a sample page from a 1991 menu covering red wines. It lists the product names (sorted by category) and their prices. Figure 1b shows a picture of a typical behind-the-counter store. Customers approach the counter and order verbally. A clerk then retreats to the back of the store to retrieve the items. Figure 1c shows a typical self-service store. This is the familiar retail environment where customers roam the aisles, pick up items, and bring the items to the cashier in order to pay.

Our data contain monthly sales and prices for each product at each of the 14 stores in the experiment from January 1988 through December 1996. Systembolaget divides its products into

[3] Our research fits in a long line of literature that leverages the rich data and regulatory variation available on alcohol sales and marketing (e.g. Seim and Waldfogel 2009; Clements and Selvanathan 1988; Milyo and Waldfogel 1999; Tremblay and Tremblay 2006).

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seven main categories: Vodka, other spirits, wine, fortified wine, Swedish beer, imported beer, and non-alcoholic drinks.

We examine the data at the month-store-category level and examine the concentration of sales by category for each store and each month. We construct six different measures of sales concentration. Our primary measure is a Herfindahl index of units sold by product. In this measure, we consider different stock-keeping units (SKUs) of the same product to be the same (e.g. the 500 mL and 1000 mL bottles of Absolut vodka). We calculate the sum of the squared market shares in each store-category-month. Our second measure is also a Herfindahl index, but we use volume sold rather than units sold as our measure of quantity. Third, we calculate a unit-level Herfindahl but treat each SKU as a different product. Fourth, we generate a four-product concentration ratio (C4). Fifth, we use the market share of the top product (C1). And sixth, we explore percentage sales by product quintile. In addition to measuring the effect on sales concentration, we also explore what happens to aggregate units sold, volume sold, revenue, and price. Table 1b provides descriptive statistics.

3. Effects of the Format Change on Total Sales and Purchase Concentration

In order to estimate the effect of the retail format change on total sales (defined in units, liters, and revenue) and purchase concentration, we use a straightforward difference-in-difference identification strategy. For store *s*, product category *j*, and month *t*, our estimating equation for each of the four outcomes listed above is:

$$(1) \qquad Outcome_{sjt} = \beta TreatmentGroup_{sj} * AfterTreatment_{sjt} + \mu_{sj} + \nu_t + \ + \varepsilon_{sjt}$$

The analysis then controls for store-product category fixed effects (μ_{sj}) and month fixed effects (ν_t). Thus, the regression controls for differences across stores at the category level and for

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changes over time. The coefficient β will therefore show how outcomes in the treatment group of stores change after conversion to self-service compared to how outcomes change in the control group of stores over the same period of time. We cluster the standard errors by store in order to reduce the potential to overstate significance due to the fact that a given location is observed several times (Bertrand, Duflo, and Mullainathan 2004). With a small number of clusters, we check that standard errors are larger than without clustering. Because our data come from a true randomized field experiment, the typical challenges of endogeneity and omitted variables bias in difference-in-difference studies should not be a cause for concern; the differences between the treatment and control groups should be random. Nevertheless, we check that the timing of the change in sales concentration is coincident with the format change.

Columns 1 through 3 of Table 2 show that the retail format change results in an increase in sales, whether measured by units, volume, or revenue. This is consistent with the findings of Skog (2000).[4] Interestingly, Column 4 shows that the average price paid did not change. Thus, there does not appear to be a sharp change in the use of price information between the two retail formats and customers appear to substitute between similarly priced products.

Table 2: Format change increases sales, but does not affect average price.

Dependent variable →	(1) Log sales in units	(2) Log sales in volume (mL)	(3) Log sales in Krona	(4) Log price per mL sold
Self serve stores after change	0.2283 (0.0230)**	0.2092 (0.0245)**	0.2125 (0.0218)**	0.0032 (0.0066)
R^2	0.39	0.43	0.44	0.44
Avg. Value in Jan. 1991	11760	6123940	5.44e+07	10.567

Regressions include store-category fixed effects (differenced out) and 107 monthly fixed effects.
Robust standard errors clustered by store in parentheses; * significant at 5%; ** significant at 1%
Each regression has 10570 observations and 98 store-category groups.

[4] Despite the increase in alcohol purchases, Systembolaget decided to convert all stores to self-service because of high customer satisfaction with the new format.

Table 3: Format change reduces the concentration of sales.

	(1)	(2)	(3)	(4)	(5)
Dependent variable →	Herfindahl (products, units sold)	Herfindahl (products, volume sold)	Herfindahl (SKUs, units sold)	C4 (products, units sold)	C1 (products, units sold)
Self serve stores after change	-0.0180 (0.0030)**	-0.0170 (0.0037)**	-0.0168 (0.0029)**	-0.0443 (0.0038)**	-0.0250 (0.0067)**
R^2	0.18	0.18	0.21	0.32	0.15
Avg. Value in Jan. 1991	0.1083	0.1063	0.0750	0.5217	0.2073

Regressions include store-category fixed effects (differenced out) and 107 monthly fixed effects.
Robust standard errors clustered by store in parentheses; * significant at 5%; ** significant at 1%
Each regression has 10570 observations and 98 store-category groups.

Table 3 shows how the concentration of sales changes after the format change, for our various measures of sales concentration. Column 1 shows the main result, an estimated marginal effect of 0.0180 percentage points on the Herfindahl measured with product-level shares of units sold. This represents a substantial 16.6% drop from the average Herfindahl in January 1991 of 0.1083. The remaining columns show robustness to alternative measures of the concentration of sales, explained above: two different ways to calculate the Herfindahl, the four-product concentration ratio, and the one-product concentration ratio. The results across the range of measures are highly consistent.

We next extend the analysis to encompass changes in concentration over time. Rather than a simple discrete variable identifying the time a store changes format, we replace the *Self-serve stores after change* variable with a sequence of dummy variables for the quarters before and after the format change. As Figure 2 shows, prior to the change of format stores in the treatment group (i.e. stores that change format) exhibit no trend towards decreased product concentration. The timing of the change in the estimated coefficients is coincident with the timing of the change in format.

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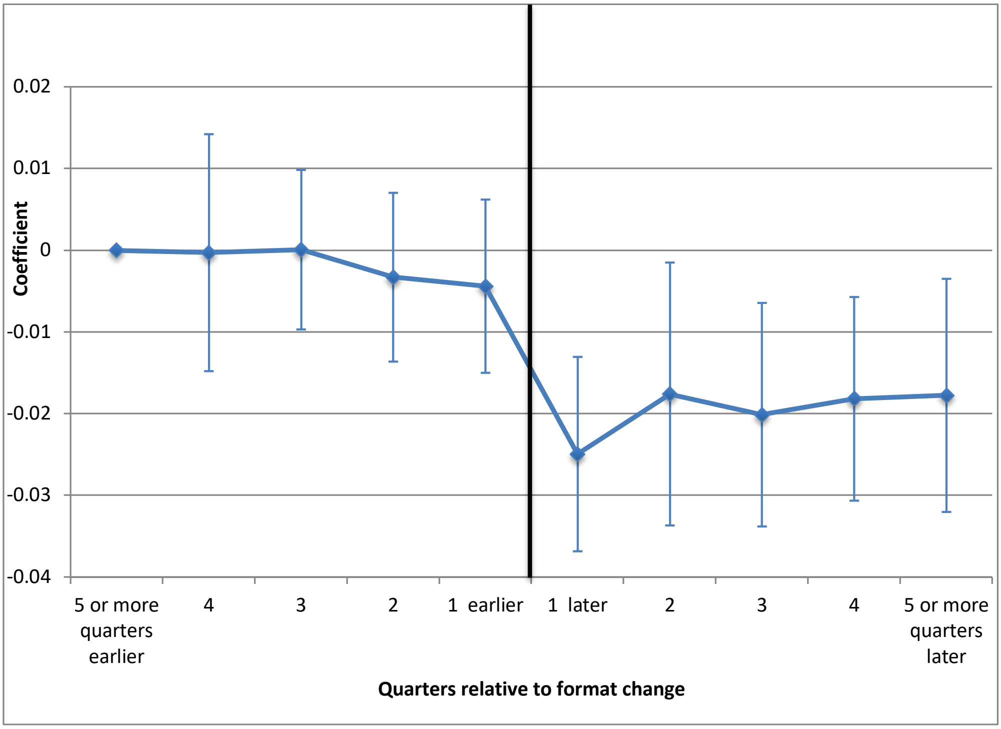
Figure 2: The decline in the concentration of sales is coincident with the format change.



Regression of Herfindahl on quarter x treatment group, with five or more quarters before as the base. Plot shows coefficients and 95% confidence intervals. Regressions include store-category fixed effects (differenced out) and 107 monthly fixed effects. Unit of observation is the store-category-month for 10570 observations and 98 store-category groups.

As a further robustness check, Table 4 shows that the results are consistent across product categories across a range of concentration measures. The coefficients for domestic and foreign beer have the same sign as all other categories, but fail to reach significance. As the coefficients of the beer categories are of a similar magnitude than the other coefficients, this difference seems to be due primarily to the larger standard errors compared to other categories. This does not seem to be driven by the prior concentration figures in the beer categories, nor by the available number of beer SKUs, as both beer categories fall in the middle range of the other product categories on these measures. It also does not appear to be driven by informational spillovers from retail channels that sell 3.5%-or-less alcohol – although beer is likely more affected by such channels than wine or spirits, non-alcoholic beverages should be affected most of all; however, the non-alcoholic drink category experiences a significant decrease in concentration.

Table 4: Decline in concentration is robust across most product categories

	(1) Vodka	(2) Spirits	(3) Wine	(4) Fortified Wine	(5) Domestic Beer	(6) Foreign Beer	(7) Non-alcoholic
HERFINDAHL (PRODUCTS, UNITS SOLD)							
Self serve stores	-0.0373	-0.0173	-0.0032	-0.0165	-0.0061	-0.0004	-0.0386
after change	(0.0056)**	(0.0031)**	(0.0011)*	(0.0049)**	(0.0126)	(0.0133)	(0.0107)**
R^2	0.92	0.77	0.85	0.87	0.74	0.35	0.77
Avg. in Jan. 1991	0.2246	0.0714	0.0141	0.1142	0.0946	0.1168	0.1225
HERFINDAHL (ML, UNITS SOLD)							
Self serve stores	-0.0380	-0.0194	-0.0031	-0.0147	-0.0077	-0.0057	-0.0373
after change	(0.0053)**	(0.0033)**	(0.0011)*	(0.0045)**	(0.0098)	(0.0120)	(0.0168)*
R^2	0.92	0.76	0.85	0.85	0.79	0.42	0.71
Avg. in Jan. 1991	0.2209	0.0725	0.0141	0.1125	0.0992	0.1169	0.1077
FOUR-PRODUCT CONCENTRATION RATIO (C4)							
Self serve stores	-0.0532	-0.0873	-0.0126	-0.0254	-0.0251	-0.0392	-0.0672
after change	(0.0075)**	(0.0135)**	(0.0050)*	(0.0109)*	(0.0255)	(0.0250)	(0.0195)**
R^2	0.93	0.85	0.93	0.83	0.87	0.71	0.60
Avg. in Jan. 1991	0.8210	0.4466	0.1393	0.5614	0.5249	0.5778	0.5807

Dependent variable is Herfindahl (products, units sold).
Regressions include store-category fixed effects (differenced out) and 107 monthly fixed effects.
Robust standard errors clustered by store in parentheses; * significant at 5%; ** significant at 1%
Each regression includes 1510 observations and 14 store-category groups.

Table 5 and figure 3 provide the core results. Table 5 examines how the format change correlates with the distribution of sales, defined by quintile. The dependent variable in each column is the percentage of total sales by month-store-category represented by that quintile. Column (1) examines the top 20% of products and reiterates the earlier result that the fraction of sales going

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to the top-selling products falls after the format change. The remaining columns show that the entire lower 80% of the distribution experiences a relative gain in sales after the format change Especially striking is the relative increase in market share as one moves towards the bottom quintile. Indeed, the market share of the bottom quintile increases over 50% from prior levels. This leads to a "fattening" of the tail of the distribution, as is evident in comparing Figures 3a and 3b. This change is comparable in magnitude to what Brynjolfsson et al. (2011, Figure 2) observed when transitioning from catalog sales to Internet sales.

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Table 5: Format change and percentage of sales by quintile

Dependent variable →	(1) Percentage of sales in top quintile	(2) Percentage of sales in second highest quintile	(3) Percentage of sales in middle quintile	(4) Percentage of sales in second lowest quintile	(5) Percentage of sales in bottom quintile
Self serve stores after change	-0.0373 (0.0048)**	0.0124 (0.0021)**	0.0134 (0.0020)**	0.0093 (0.0019)**	0.0023 (0.0007)**
R^2	0.07	0.05	0.06	0.07	0.07
Avg. Value in Jan. 1991	0.746	0.155	0.070	0.025	0.004

Regressions include store-category fixed effects (differenced out) and 107 monthly fixed effects.
Robust standard errors clustered by store in parentheses; * significant at 5%; ** significant at 1%
Each regression has 10570 observations and 98 store-category groups.

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Figure 3a: Change in Distribution of Products Sold in Control Group

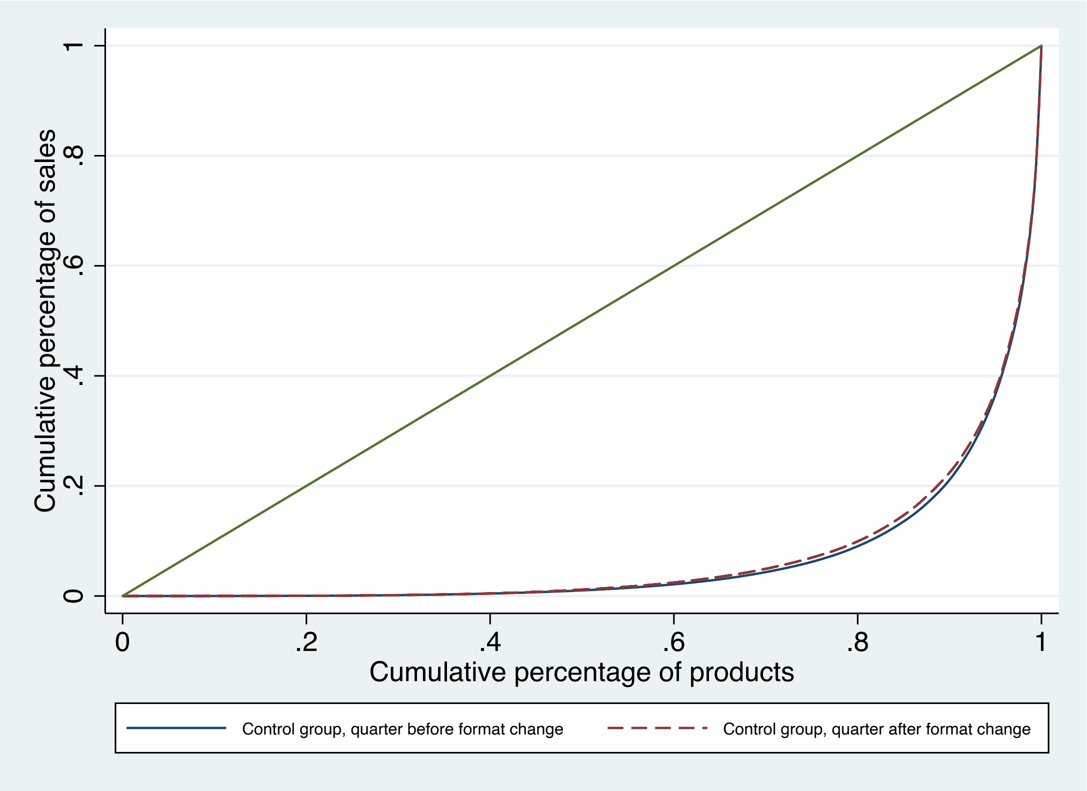

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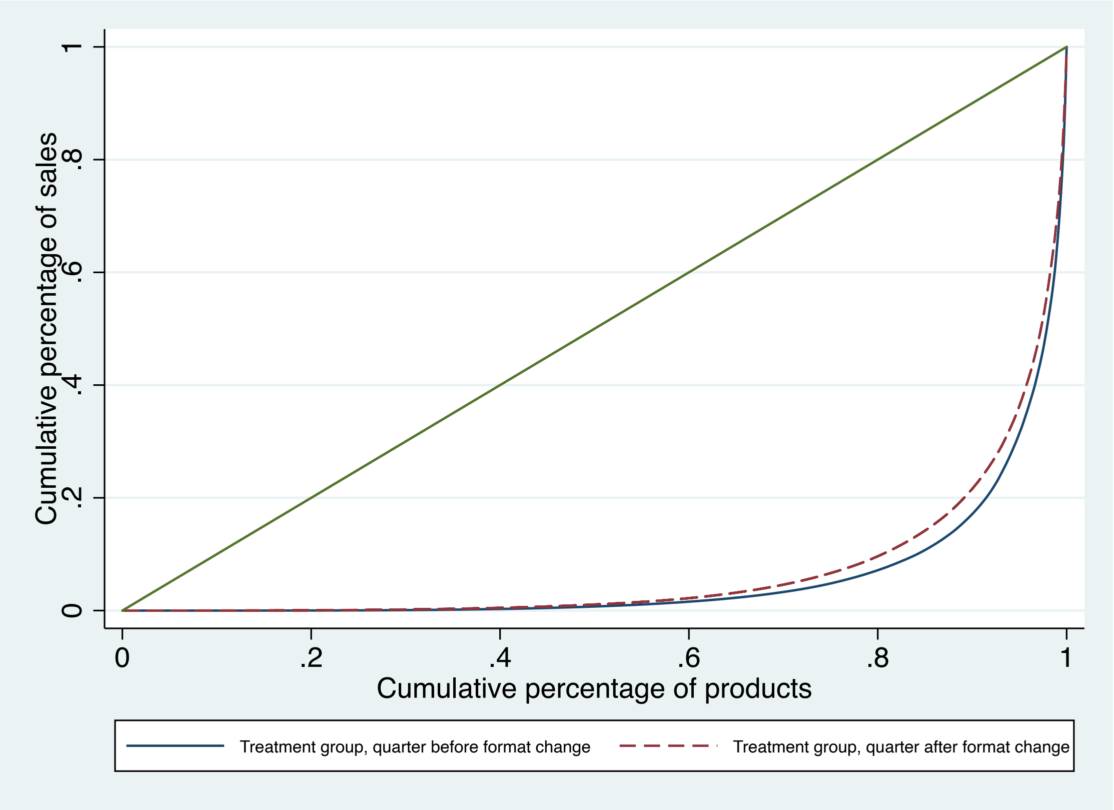
Figure 3b: Change in Distribution of Products Sold in Treatment Group



4 Conclusion

We have shown that retail format has a substantial impact on sales concentration. Specifically, the adoption of self-service rather than behind-the-counter retail format is associated with substantial reductions in the concentration of sales, as measured by the Herfindahl index. To the extent that retailers replace self-service with behind-the-counter operations in response to COVID, we speculate that the concentration of sales in these stores will rise, thus differentially affecting product manufacturers. The size of this effect is similar though opposite in direction to moving from on-premise to online and thus in the net could lead to more concentrated sales.

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More broadly, our results suggest that the nature of interactions downstream can have considerable impact upstream in terms of perpetuating the dominance of popular products. By enforcing a behind-the-counter format in regulated industries such as alcohol, tobacco, and pharmaceuticals, governments may inadvertently be increasing the profitability of the incumbent firms. Our analysis also helps understand the consequences from, and perhaps the reasons behind, this format. For example, in Ontario, Canada, the main distribution channel for beer is through "The Beer Store." This retailer is owned by the three largest Canadian breweries: Labatt (a subsidiary of Interbrew), Molson (part of Molson-Coors), and Sleeman. The majority of the Beer Stores in Ontario have behind-the-counter service. Our results suggest that this helps the main brewers maintain their dominant share. Although the Beer Store's operational report (2007, p. 3) emphasizes that "Any brewer in the world can sell their beer through the beer store" and that the brewers set their own prices, the behind-the-counter format itself may restrict the ability of new entrants to gain share. The vertical integration of the industry, combined with regulation, generates incentives for the behind-the-counter format.

In developing countries, the behind-the-counter format is common even in unregulated industries. For example, in India, the dominant retail format is the kirana, a type of general store where the vast majority of items are behind the counter (*The Economist* 2008). Although supermarkets and other forms of organized retail are growing in India and elsewhere in the developing world, sales in kirana stores continue to grow in absolute, if not relative, terms (Reardon and Gulati 2008). Humphrey (2007) notes that behind-the-counter stores still have substantial shares in Brazil, Mexico, and Kenya, although much of this share is in fresh (not packaged) food. Assuming that our results from Sweden carry over to the diverse contexts of developing countries, the ubiquity of the behind-the-counter format may have substantial effects on market structure and even on development outcomes.

The COVID-19 crisis has made these retail formats relatively common, even at well-established private retailers in developed countries. By examining what happened when Systembolaget moved from behind-the-counter to self-service retail, we provide suggestive evidence of how the concentration of retail sales will change as long as this type of social distance measure remains in place in retail.

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Epidemics: A tale of two workers[1]

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This paper shows that the labour market opportunities available to an agent has a significant bearing on how that agent experiences the outbreak of an epidemic. I consider two types of labour (i) market labour that can only produce output in close physical proximity, and (ii) remote labour that can produce output at a distance. This paper develops a Two Agent New Keynesian model extended to include an epidemic bloc and dual feedback between economic decisions and the evolution of the epidemic. I show that an agent restricted to only supply market labour experiences higher death rates vis-à-vis their share of the population, and suffers larger declines in labour and consumption over the course of the epidemic. Post-epidemic, these agents are significantly worse off than their counterparts who can work from home and hence a more unequal society emerges. I then show that simple containment policies, while leading to larger losses in economic prosperity as measured by output loss, can significantly reduce death rates across the population, bring the death rates of the two groups closer together, and reduce the inequality that emerges post epidemic.

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1 I would like to thank Judy Goh, Srijita Ghosh, Suraj Shekhar and Swagata Bhattacharjee for their useful discussions, feedback and comments. This version: June 22, 2020. Download the latest version from my website www.rahulnath.co.uk.

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A common refrain during the current Covid-19 pandemic is that it is a great leveller since the disease does not discriminate among those who contract the disease. From a purely scientific point of view it is true that the Covid-19 virus does not discriminate at the point of infection, i.e. anyone is capable of getting the disease. However, contracting the disease is a whole different ballgame since contracting the disease requires interaction, often in a social setting, and here the playing field is much less level. Over the course of the current pandemic there has been mounting evidence that some groups are over-represented among those that contract the disease. Doctors, nurses, other healthcare workers, those working in services deemed essential, minority groups and migrant workers are among the groups that make up a disproportionately higher proportion of total infected cases.

As various containment measures were initially introduced around the world, work has shifted to remote models where possible. There are many occupations, however, that cannot be easily moved to remote work. Consider a nurse in a hospital or care facility, or a fire fighter, these workers are far less likely to be able to work remotely than a lawyer, a teacher, or an economist. Many occupations have characteristics that make them difficult to carry out except in close proximity to other people. In a pandemic where disease spreads by proximity of social contact this exposes workers in such occupations to much higher risk of ultimately contracting the disease. The present paper seeks to understand why some groups are more likely to contract a given disease based on the economic opportunities available to them. Specifically, this paper focuses on whether agents may have differing experiences of a pandemic depending on the labour market opportunities available to them, i.e. whether the opportunity to work remotely is a possibility. Through the study of labour market opportunities the paper seeks to shed light on a more general question of how entrenched differences between groups that impact their economic opportunities affect the experience of the epidemic within these groups, and how such pre-epidemic differences may help to predict the level of inequality that materialises post-epidemic.

I find that when agents are restricted in their labour market opportunities, they experience the epidemic differently. Correspondingly, there is an increase in economic inequality between the two groups. Agents who can only work in market labour are worse off both in terms of death rates and economic outcomes. They experience significantly higher death rates in excess of their share of the population arising from a higher exposure to infection risk from only being able to engage in market labour. These agents also face worse economic outcomes via larger declines in labour supply and consequently lower consumption. I find that containment measures aimed at reducing the spread of the disease can reduce this inequality. All of the containment measures studied significantly reduce the death rates of all agents at the cost of slightly higher decline in output. I find that even containment measures with early exit, i.e. not reducing the infected populations to zero, can still have significant impact albeit even though they see a second wave of the epidemic. In particular I find that non-symmetric containment policies, i.e. those that treat

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the two groups differently, is the most preferred option from a purely economic standpoint as it leads to minimal output decline vis-à-vis the laissez-faire policy scenario. There are three key contributions of this paper to the literature. First is the study of how groups differing in their economic opportunities before the epidemic begins have different experiences of an epidemic. Second, I develop a simple New Keynesian framework that allows for mutual feedback between epidemics and economic behaviour. And finally, I explore how pre-epidemic group characteristics can be used to better understand the evolution of an epidemic and the design of containment measures.

I study the central question of this paper by developing a simple Two Agent New Keynesian DSGE model. The model is populated with two types of households who are identical in all respects except the labour market opportunities available to them. Both households can engage in market labour (i.e. labour requiring social proximity to others), but one household has the opportunity to also supply their labour remotely. This model is augmented with an epidemic bloc using an extension of the Susceptible-Infected-Recovered (SIR) epidemiological framework of Kermack and McKendrick (1927) that allows for dual feedback between the evolution of the epidemic and macroeconomic decisions. That is, the evolution of the epidemic affects how agents make their optimal decisions and agent decisions affect the evolution of the epidemic by altering the amount of social contact they have through the supply of market labour. This dual feedback is introduced by altering the utility function to allow agents to incorporate the current state of the epidemic into their decisions, and by altering the transmission rate of the disease to take into account social interactions.

During an epidemic, household behaviour changes to reduce engagement in economic activities that involve social proximity, out of fear of infection. The only form of social economic activity considered in this paper is market labour. The undesirability of working in market labour during the pandemic is captured via an additional epidemic factor that increases the disutility agents experience from engaging in market labour. The epidemic introduces tension into the model as some agents can substitute market labour for remote labour while others may not. All other things equal, those agents that can only supply market labour end up being more exposed to the disease if they seek to maintain their labour supply at the pre-epidemic level.

The standard SIR framework of Kermack and McKendrick (1927) does not consider how the evolution of an epidemic may respond to changing social behaviour during the epidemic. During an epidemic, as agents choose to spend less time in social economic activity they effectively reduce the transmission of the disease. The basic SIR model is extended to include this behavioural response by introducing an aggregate exposure variable that depends on how agents change their supply of market labour during the pandemic. This allows labour market decisions to impact the spread of the epidemic. The introduction of behavioural responses is not new and has been

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explored in various economic models that deal with disease spread. An early example of this approach is Kremer (1996) in studying the spread of AIDS, and more recently from the countless current papers studying the Covid-19 epidemic.

Since the onset of the Coivd-19 crisis there has been a very quickly growing body of work looking at the economics of epidemics. Before moving on to the main body of the paper I briefly survey the papers most relevant to this work below.

This paper is most closely related to the excellent work by Eichenbaum et al. (2020). Eichenbaum et al. (2020) consider how economic decisions affect the evolution of an epidemic, they show that there is an inevitable trade-off between controlling the evolution of an epidemic and the severity of the economic decline. The households in Eichenbaum et al. (2020) are identical pre-epidemic and are then differentiated during the epidemic by health status. This paper departs from Eichenbaum et al. (2020) by considering groups differentiated by economic opportunities that exist regardless of the presence of an epidemic. That is, I focus on entrenched differences due to the nature of the agents occupation rather than those that arise from the epidemic in order to study group differences.

Preliminary work presented by Kaplan et al. (2020) studies the macroeconomic impact of epidemics in a fully Heterogeneous Agent New Keynesian framework. They allow for remote labour within the model in a more elaborate multi-sector setting where occupations are differentiated along various dimensions. As of the date of writing no results had been circulated. This paper differs from Kaplan et al. (2020) by studying a much simplified heterogeneous agent model to allow for a clearer understanding of how epidemics evolve and the macroeconomic consequences when labour can only vary between two types. The results of Kaplan et al. (2020), when available, would provide useful insight into how differing labour along other dimensions might play a role in modifying the results of this paper.

Multiple agent types differentiated by economic opportunities are also a feature of both Bodenstein et al. (2020) and Glover et al. (2020). Glover et al. (2020) differentiate agents along age (old and young), health status and employment sector (basic and luxury), while in Bodenstein et al. (2020) agents supply labour inelastically either in a labour intensive production sector or a production sector that uses capital in production. Critically, in both papers, labour can only be supplied inelastically and in the market. In this paper I abstract away from all of these important dimensions to focus on the impact of the epidemic on the supply of labour which is differentiated in whether it can produce output without the need for close social contact necessitated by being present on-site.

The remainder of this paper is structured as follows. Section 1 describes the model, Section

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2 discusses calibration and simulation methods used to solve the model, Section 3 analyses the results of the benchmark model, Section 4 considers how containment measures affect the results and Section 5 concludes.

1 The Model

The model studied in this paper is a Two Agent New Keynesian (TANK) model where the households differ in the types of labour that they may supply. The two types of labour in the economy are 'market' labour and 'remote' labour which differ in how they produce output: 'market' labour must be physically present on-site to produce output while 'remote' labour can produce output without being physically present. There is clearly a lot of heterogeneity within these two broad classes and the 'remotability' of labour is a continuous variable rather than a discrete binary variable. This paper abstracts from both of these dimensions by considering a single type of labour that can be supplied by agents that differ in how they supply this labour.

The set-up of firms in the economy follows the standard practice in the New Keynesian literature. Namely there are two types of firms in the economy - a final goods firm and a continuum of intermediate goods firms. The intermediate goods firms each produce a differentiated good which endues them with some degree of market power. These intermediate firms use both types of labour in the production of their output and face costs to their adjustment of nominal price in the spirit of Rotemberg costs. The final goods firm aggregates the output of intermediate firms and sells this aggregate output to households.

The model is closed with a central bank that controls the nominal interest rate and sets monetary policy according to a simple Taylor Rule.

There are three exogenous shocks that hit the economy - technology shocks, monetary policy shocks and epidemic shocks. The first two shocks are standard shocks in the NK literature, while the epidemic shock is introduced to study how the presence of an epidemic affects the dynamics of the economy. Epidemic shocks have a two-way impact whereby the epidemic impacts economic activity and economic activity affects the spread of the disease. The epidemic shock affects economic activity by altering household disutility from providing 'market' labour hence impacting their desire to supply 'market' labour. This then impacts the dynamics of epidemic by altering the exposure of agents to the disease.

The remainder of this section discusses the model set-up in detail and is divided into 5 sections. The first two sections describe the core macroeconomic bloc, i.e. households and firms. The third section describes the epidemic bloc of the economy. The final two sections describe the Central Bank policy rule, and aggregation and equilibrium in the model.

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1.1 Households

There exist a continuum of households indexed on the unit interval $j \in [0,1]$ and make all of their decisions at the beginning of the period. These households are split into two groups depending on where on the unit interval they are indexed and they differ only in the labour supply opportunities available to them. Type-1 households fall in the interval $j = (\theta_t, 1]$ and supply both market and remote labour, i.e. they can decide whether or not to be physically present during the production of output. Type-2 households fall in the interval $j = [0, \theta_t)$ and supply only market labour, i.e. they must be physically present in the firm to produce output.

The utility of the household household of Type-j is defined over the consumption of aggregate good $(c_{t,j})$, supply of market labour $\left(n^M_{t,j}\right)$, and supply of remote labour $\left(n^R_{t,j}\right)$.[1]. Specifically I use the GHH form of Greenwood et al. (1988) which removes the presence of any Type-j level wealth effect from the labour supply decision so that labour supply only depends on the wage rate. The utility function takes general form,

$$u\left(c_{t,j}; n^M_{t,j}; n^R_{t,j}\right) = \frac{\left[c_{t,j} - \chi^M_j \Gamma_t \frac{\left(n^M_{t,j}\right)^{1+\psi}}{1+\psi} - \chi^R_j \frac{\left(n^R_{t,j}\right)^{1+\psi}}{1+\psi}\right]^{1-\sigma}}{1-\sigma} \tag{1.1}$$

where σ captures the degree of risk aversion, ψ is the inverse of the Frisch Elasticity of Labour, χ^M_j measures the disutility of providing market labour for the Type-j household and χ^R_j measures the disutility of providing remote labour for the Type-j household. The parameter, Γ_t captures the impact of the epidemic shock on the supply of market labour and it defined as,

$$\Gamma_t = 1 + \widetilde{\beta}_{t,j} \mathcal{S}_t \frac{\mathcal{I}_t}{\mathcal{N}_t} \tag{1.2}$$

where $\widetilde{\beta}_{t,j}$ is the belief of Type-j agents about the 'effective' transmission rate of the disease.[2] In this paper I assume that the belief is symmetric, i.e. both agents have the same $\widetilde{\beta}_{t,j}$. Further to the symmetric belief assumption, I also assume that $\widetilde{\beta}_{t,j} \mathcal{S}_t \frac{\mathcal{I}_t}{\mathcal{N}_t} = \beta^-_t \mathcal{S}^-_t \frac{\mathcal{I}^-_t}{\mathcal{N}^-_t}$, i.e. the agent forms a belief based on the information available to them at the beginning of the period.[3]

The general budget constraint for households is given by,

$$c_{t,j} + \frac{B_{t+1,j}}{R^n_t P_t} = \frac{W^M_t}{P_t} n^M_{t,j} + \kappa \frac{W^R_t}{P_t} n^R_{t,j} + \frac{B_{t,j}}{P_t} + D_{t,j} \tag{1.3}$$

where $B_{t,j}$ is holdings of nominal bonds, R^n_t is the nominal interest rate set by the central bank, $\frac{W^M_t}{P_t}$ is the real wage for market labour, $\frac{W^R_t}{P_t}$ is the real wage for remote labour, and $D_{t,j}$ is the

[1] Note that for Type-2 household $n^R_{t,j} = 0$

[2] The 'effective' transmission rate is defined in the section on the epidemic bloc of the model.

[3] The study of more complex belief structures is beyond the scope of the present paper and left for future work.

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dividend received by virtue of household ownership of firms. Wages are determined in perfectly competitive labour markets and both households and firms take wages as given. The parameter $\kappa \leq 1$ captures the idea that working from home entails a cost in terms of lost wages. This parameter captures all aspects of the cost of working remotely (e.g. lost productivity, set-up costs, etc.) and introduces a wedge that makes market labour more desirable all other things equal.

The Type-j household therefore solves the following optimisation problem,

$$\max E_t\left[\sum_{h=0}^{\infty}\beta^h u\left(c_{t+h,j};n^M_{t+h,j};n^R_{t+h,j}\right)\right]$$
$$\text{s.t.}$$
$$c_{t+h,j}+\frac{B_{t+h+1,j}}{R^n_{t+h}P_{t+h}}=\frac{W^M_{t+h}}{P_{t+h}}n^M_{t+h,j}+\kappa\frac{W^R_{t+h}}{P_{t+h}}n^R_{t+h,j}+\frac{B_{t+h,j}}{P_{t+h}}+D_{t+h}$$

This yields the following conditions,

$$\frac{W^M_t}{P_t}=\chi^M_j\Gamma_t\left(n^M_{t,j}\right)^{\psi} \tag{1.4}$$
$$\frac{W^R_t}{P_t}=\frac{\chi^R_j}{\kappa}\left(n^R_{t,j}\right)^{\psi} \tag{1.5}$$
$$1=E_t\left[\beta\frac{u_{c,t+1,j}}{u_{c,t,j}}\frac{R^n_t}{\pi_{t+1}}\right] \tag{1.6}$$

which have the standard interpretations as labour supply conditions and consumption Euler Equations.

1.2 Firms

1.2.1 Final Goods Firms

The output of intermediate goods firms, $y_t(i)$, is bought by perfectly competitive final goods firms which costlessly aggregate the output. This aggregate output is sold to households as an aggregate consumption good.

The final goods firms aggregate output using the Dixit-Stiglitz aggregator,

$$y_t=\left[\int_0^1 y_t(i)^{\frac{\varepsilon^p-1}{\varepsilon^p}}di\right]^{\frac{\varepsilon^p}{\varepsilon^p-1}}, \tag{1.7}$$

where $\varepsilon^p>0$ measures the degree of substitutability between different goods. The final goods firms maximise their profits leading to the standard demand function for the intermediate goods

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firms,

$$y_t(i) = \left[\frac{P_t(i)}{P_t}\right]^{-\varepsilon^p} y_t, \tag{1.8}$$

where y_t is the aggregate demand and P_t is the aggregate price level defined as,

$$P_t = \left[\int_0^1 P_t(j)^{1-\varepsilon^p} di\right]^{\frac{1}{1-\varepsilon^p}}. \tag{1.9}$$

1.2.2 Intermediate Goods Firms

There exist a continuum of monopolistically competitive intermediate goods firms indexed on the unit interval $i \in [0,1]$ each of whom produce a differentiated good determined by their index. The intermediate goods firm produces output by employing both market and remote worker types, for which it pays market determined wages, and are subject to nominal rigidities in changing prices *à la* Rotemberg (1982). I assume that the cost of adjusting prices is an intangible cost that enters the firms optimisation problem as a form of 'disutility', i.e. it doesn't affect cash flow. The profit of the firm is given by,

$$\frac{P_{t+h,i}y_{t+h,i}}{P_{t+h}} - \frac{W^M_{t+h}}{P_{t+h}}n^M_{t+h,i} - \frac{W^R_{t+h}}{P_{t+h}}n^R_{t+h,i} - \frac{\chi^P}{2}\left(\frac{P_{t+h,i}}{P_{t+h-1,i}} - 1\right)^2 y_{t+h} \tag{1.10}$$

where $n^M_{t,i}$ and $n^R_{t,i}$ are the aggregate market and remote labour employed by the firm. The parameter χ^P determines the strength of the disutility arising from adjusting prices, and hence the degree of price stickiness.

The production function of the firm is given by a Cobb-Douglas production function defined over labour input only,

$$y_{t,i} = z_t\left(n^M_{t,i}\right)^{\alpha_M}\left(n^R_{t,i}\right)^{\alpha_R}; \qquad \alpha_M + \alpha_R = \alpha \tag{1.11}$$

where α_M is the income share of market labour in the production of output, and α_R is the income share of remote labour in the production of output. In order to be consistent with aggregate data the restriction $\alpha_M + \alpha_R = \alpha$ is imposed, where α is the income share of labour in the production of output.

This technology is assumed to be subject to non-idiosyncratic shocks to productivity, z_t. Productivity follows an AR(1) process in logs, i.e.

$$\ln z_{t+1} = \rho \ln z_t + v^y_t \tag{1.12}$$

where ρ measures the persistence of the shock and $v^y_t \sim N\left(0, \sigma^2_z\right)$ is a random shock. The firm is owned by both households and so uses an aggregate discount factor to discount profits given by,

$$m_{t,t+1} = (1-\theta_t)\frac{\beta\Lambda_{t+1,1}}{\Lambda_{t,1}} + \theta_t\frac{\beta\Lambda_{t+1,2}}{\Lambda_{t,2}} \tag{1.13}$$

The firm maximises profit subject to production function and demand, i.e.

$$\max E_t\left\{\sum_h^\infty m_{t,t+h}\left[\frac{P_{t+h,i}y_{t+h,i}}{P_{t+h}} - \frac{W^M_{t+h}}{P_{t+h}}n^M_{t+h,i} - \frac{W^R_{t+h}}{P_{t+h}}n^R_{t+h,i} - \frac{\chi^P}{2}\left(\frac{P_{t+h,i}}{P_{t+h-1,i}}-1\right)^2 y_{t+h}\right]\right\}$$

s.t.

$$y_{t+h,i} = \left[\frac{P_{t+h,i}}{P_{t+h}}\right]^{-\varepsilon_P} y_{t+h}$$

$$y_{t+h,i} = z_{t+h}\left(n^M_{t+h,i}\right)^{\alpha_M}\left(n^R_{t+h,i}\right)^{\alpha_R}$$

Noting that firms are ex-post identical in under Rotemberg pricing, the firms problem leads to the following two equilibrium conditions,

$$E_t\left[m_{t,t+1}\chi^P\pi_{t+1}\left(\pi_{t+1}-1\right)y_{t+1}\right] - \chi^P\pi_t\left(\pi_t-1\right)y_t = \left(\varepsilon_P-1\right)y_t - \frac{W^M_t}{P_t}\frac{\varepsilon_P y_t}{f_{M,t}} \tag{1.14}$$

$$\frac{W^M_t}{f_{M,t}} = \frac{W^R_t}{f_{R,t}} \Rightarrow \frac{W^M_t}{W^R_t} = \frac{\alpha_M}{\alpha_R}\frac{n^R_t}{n^M_t} \tag{1.15}$$

where the first is the Phillips Curve, and the second requires that firms hire each labour type until their effective marginal costs are equalised.

1.3 The Epidemic Bloc

The epidemic bloc of the model is an extension of the standard SIR epidemic model that allows for aggregate exposure to respond endogenously to economic activity, and so modify disease transmission. At any point in time an agent can be in one of five states: Susceptible ($\mathcal{S}_t$), Exposed ($\mathcal{E}_t$), Infectious ($\mathcal{I}_t$), Recovered ($\mathcal{R}_t$), and Dead ($\mathcal{D}_t$). The spread of the epidemic is described by the following system of equations,

$$\mathcal{S}_{t+1} = \mathcal{S}_t - \beta_0\mathcal{S}_t\frac{\mathcal{I}_t}{\mathcal{N}_t}\mathcal{X}_t \tag{1.16}$$

$$\mathcal{E}_{t+1} = \mathcal{E}_t - \lambda_{\mathcal{E}}\mathcal{E}_t + \beta_0\mathcal{S}_t\frac{\mathcal{I}_t}{\mathcal{N}_t}\mathcal{X}_t \tag{1.17}$$

$$\mathcal{I}_{t+1} = \mathcal{I}_t - \lambda_{\mathcal{I}}\mathcal{I}_t + \lambda_{\mathcal{E}}\mathcal{E}_t \tag{1.18}$$

$$\mathcal{R}_{t+1} = \mathcal{R}_t + (1-\gamma)\lambda_{\mathcal{I}}\mathcal{I}_t \tag{1.19}$$

$$\mathcal{D}_{t+1} = \mathcal{D}_t + \gamma\lambda_{\mathcal{I}}\mathcal{I}_t \tag{1.20}$$

$$\mathcal{N}_{t+1} = \mathcal{S}_{t+1} + \mathcal{E}_{t+1} + \mathcal{I}_{t+1} + \mathcal{R}_{t+1} \tag{1.21}$$

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where β_0 is the transmission rate for the disease, $\mathcal{X}_t$ is aggregate exposure, γ is the death rate, and λ_j $j = \{E, I\}$ is the transition rate out of the respective states. The parameter β_0 is referred to as the 'basic' transmission rate, i.e. the rate of transmission were agents not to respond endogenously. Our focus is on aggregate exposure, $\mathcal{X}_t$, as this modifies the rate at which agents enter the disease states, and $\beta_t = \beta_0 \mathcal{X}_t$ is referred to as the 'effective' transmission rate. Once an agent enters the Exposed state they move mechanically, as defined by the transmission rates, through the states until they exit as either Recovered or Dead. Agents can only infect other agents while in the Infectious state.

Labour supply in market labour is the only activity that requires interacting with other agents in close proximity. Hence, the aggregate level of exposure is defined using the time spent in market labour by agents relative to their steady states, i.e.

$$\mathcal{X}_t = \sum_{j \in \mathcal{J}} w_{t,j} \frac{n^M_{t,j}}{\overline{n}^M_j}; \sum_{j \in \mathcal{J}} w_{t,j} = 1 \tag{1.22}$$

where $\mathcal{J}$ is the set of agent types, and $w_{t,j}$ is the weight of Type-j in the economy. In the simple two agent set-up in this paper $w_{t,1} = 1 - \theta_t$ and $w_{t,2} = \theta_t$, however this measure can be extended to any arbitrary set of agent types.

This measure of aggregate exposure captures two salient features of how economic actions affect disease spread. The first, that individual group level actions can modify overall exposure can easily be seen from (1.22). For example, either type of agent can reduce aggregate exposure by reducing their individual supply of market labour. The second feature is that these individual group level decisions have broader aggregate consequences, i.e. there are exposure externalities. To see this clearly, define group level exposure [4] as,

$$\mathcal{X}_{t,j} = \frac{w_{t,j} n^M_{t,j}}{n^M_t} \mathcal{X}_t \tag{1.23}$$

So that equilibrium labour supply decision of the other agent affects the group level exposure by changing both aggregate supply of market labour, n^M_t, and the aggregate exposure level. In the two agent case the following relationship holds for the cross partial derivative of exposure,

$$\frac{\partial \mathcal{X}_{t,j}}{\partial n^M_{t,k}} > 0 \iff \frac{\overline{n}^M_k}{\overline{n}^M_j} < 1 \tag{1.24}$$

[4]This definition of group level exposure is consistent with aggregate exposure and the aggregation of market labour

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such that the group level exposure will increase for the group with higher steady state market labour.[5] The calibration of the model fixes the sign of these cross-partial effects in the two-agent case.

1.4 Central Bank

The economy is closed by specifying how the central bank sets the nominal interest rate. The central bank sets the gross nominal interest rate $\mathcal{R}_t^n$ according to the Taylor Rule,

$$\frac{\mathcal{R}_t^n}{\overline{\mathcal{R}}^n} = (\pi_t)^{\rho_\pi} \eta_t, \tag{1.25}$$

where the parameter ρ_π controls the degree to which the central bank responds to price inflation in setting the nominal rate. The Taylor Rule rule is subject to uncertainty via the nominal interest rate shock η_t which follows an AR(1) process,

$$\ln \eta_{t+1} = \iota \ln \eta_t + \upsilon_t^{\mathcal{R}^n} \tag{1.26}$$

where ι is the degree of persistence of the shock and $\upsilon_t^{\mathcal{R}^n} \sim N\left(0, \sigma^2_{R^n}\right)$ is a random shock.

1.5 Aggregation and Equilibrium

Aggregate variables are given by the population weighted averages, i.e.

$$\begin{aligned}
c_t &= (1-\theta_t)\, c_{t,1} + \theta_t c_{t,2} \\
n_t &= (1-\theta_t)\left(n_{t,1}^M + n_{t,1}^R\right) + \theta_t n_{t,2}^M \\
n_t^M &= (1-\theta_t)\, n_{t,1}^M + \theta_t n_{t,2}^M \\
n_t^R &= (1-\theta_t)\, n_{t,1}^R \\
B_t &= (1-\theta_t)\, B_{t,1} + \theta_t B_{t,2}
\end{aligned}$$

In equilibrium the aggregate labour markets clear for each type of labour and hence the aggregate labour market is in equilibrium. In equilibrium $B_t = 0$, i.e. bonds are in zero net supply.

The aggregate resource constraint is derived by noting that the firm pays all profits to the households so that it makes no profit post-dividend and that the cost of adjusting prices doesn't

[5]This result is unique to the case of two agents, for more than two agents the following condition determines the sign of the externality,

$$\frac{\partial \mathcal{X}_{t,j}}{\partial n_{t,k}^M} > 0 \Longleftrightarrow \sum_{i \neq k} \left(1 - \frac{\overline{n}_k^M}{\overline{n}_i^M}\right) > 0$$

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affect cash flow. Hence the dividend paid by the firm is given by,

$$D_t = \frac{P_{t,i} y_{t,i}}{P_t} - \frac{W_t^M}{P_t} n_{t,i}^M - \frac{W_t^R}{P_t} n_{t,i}^R \tag{1.27}$$

Combining with the aggregate budget constraint, and labour market clearing conditions yields the following aggregate resource constraint in equilibrium,

$$c_t + (1-\kappa) \frac{W_t^R}{P_t} n_t^R = y_t \tag{1.28}$$

this is also the goods market clearing condition for this economy. This is an intuitive relationship that requires that output be used either for aggregate consumption or to pay for the costs incurred by Type-1 households working remotely. So the inefficiency of working remotely introduces a wedge between consumption and output.

2 Calibration and Simulation

The calibration of the model uses relatively standard values from the New Keynesian DSGE literature and the model is calibrated to daily frequency as epidemics occur over days and weeks rather than quarters. The values of all calibrated parameters in the benchmark model can be found in Table: 1.

The model is solved using non-linear methods. In particular I use the Generalised Stochastic Simulation Algorithm (GSSA) of Judd et al. (2011) and Maliar and Maliar (2014). GSSA is an extension of the standard Parameterised Expectations Algorithm of den Haan and Marcet (1990) that replaces simple polynomials with more general basis functions, and replaces non-linear least squares estimation with quadrature techniques to estimate conditional expectations. In the simulation solution I employ Hermite Polynomials as basis functions and use 5 nodes in the quadrature calculations.

2.1 Calibrating Market and Remote Worker Parameters

The parameters $\left(\alpha_R, \alpha_M, \theta, \chi_1^M, \chi_1^R, \chi_2^M, \kappa\right)$ relate to the presence of market and remote workers.

Labour shares, (α_R, α_M) are calibrated using the fact that capital share of output is a well estimated parameter in the literature with a value of 0.36. So in order to be consistent with aggregate data one must have $\alpha_R + \alpha_M = 0.64$. Simple rearrangement of the first order conditions

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for intermediate firms requires that in steady state the following relationships hold

$$\alpha_R = \frac{\varepsilon_P}{\varepsilon_P - 1}\frac{W^R}{P}\frac{n^R}{y}$$
$$\alpha_M = \frac{\varepsilon_P}{\varepsilon_P - 1}\frac{W^R}{P}\frac{n^M}{y}$$

In order to be consistent with the aggregate data it is known that the total labour share of income equals 0.64, i.e. $\frac{\frac{W}{P}n}{y} = 0.64$. Combining these gives,

$$\alpha_R = 0.64\frac{\frac{W^R}{P}n^R}{\frac{W^R}{P}n^R + \frac{W^M}{P}n^M} \tag{2.1}$$

where the denominator comes from realising that the total wage bill can be decomposed as $\frac{W}{P}n = \frac{W^R}{P}n^R + \frac{W^M}{P}n^M$.

I use the Occupational Estimate Statistics from the Bureau of Labour Statistics (BLS) from 2009 - 2019 to estimate the wage bills. The BLS Occupational Estimate Statistics an annual statistical release that classifies employment by occupation with data on employment numbers, proportion of workforce and average annual salary estimates. The classification by occupation is crucial to the calibration as the objective is to determine the share of workers that can feasibly engage in remote work from home. I proceed by manually classifying each 6 digit Standard Occupational Classification (SOC) codes as either being able to work remotely or not. The classification of occupations is very similar to Dingel and Neiman (2020). Using this classification α_R can be calculated as follows. Let $\mathcal{O}$ be the set of occupations, and further $\mathcal{O}_R$ denote the subset of occupations that are classified as being remote-able work. Then α_R is calculated as,

$$\alpha_R = 0.64\frac{\sum_{h\in\mathcal{O}_R}\frac{W_h}{P}n_h^R}{\sum_{h\in\mathcal{O}}\frac{W_h}{P}n_h} \tag{2.2}$$

This was done for each of the surveys from 2009-2019 yielding an average value of $\alpha_R = 0.3313$, which is robust to alternative SOC classifications.

A similar approach is used to work out the share of the population in 'remote-able' occupations, this share is given by $1-\theta$. Using the BLS Occupational Estimate Statistics and the same set of 'remote-able' occupations $\mathcal{O}_R$ the $1-\theta$ share of 'remote-able' occupation households is estimated as,

$$1-\theta = \frac{\sum_{h\in\mathcal{O}_R} n_h}{\sum_{h\in\mathcal{O}} n_h} \tag{2.3}$$

This calculation yields an average value of $\theta = 0.6144$, which again is robust to alternative SOC classifications.

The preference parameters $\left(\chi_1^M, \chi_1^R, \chi_2^M\right)$ are calibrated to ensure that workers spend a third of their time in working in steady state. Given the two labour types the 2018 BLS American Time Use Survey is used to pin down the ratio of time spent in market labour versus remote labour. The 2018 survey finds that 23.7% workers worked from home at the aggregate level, which implies that

$$\frac{n_M}{n_R} = \frac{1-0.237}{0.237}$$

Having pinned this ratio down one can easily find the steady state labour supply for each agent and labour type from the aggregate labour relationships. The labour supply first order conditions are then used to find the values of $\left(\chi_1^M, \chi_1^R, \chi_2^M\right)$ that ensure workers spend a third of their time working in steady state.

The final parameter to be calibrated is κ. To my knowledge there is no study that estimates this parameter so I use a benchmark value of $\kappa = 0.9$ in the analysis.

2.2 Calibrating Epidemiology Parameters

The parameters $\beta_0, \lambda_E, \lambda_I, \gamma$ are chosen to replicate the Covid-19 pandemic. The Covid-19 pandemic is a rapidly evolving real-time pandemic at the time of writing and there are large variations in the parameter estimates for the epidemiological parameters. The calibration used here attempts to use the best available estimates of these parameters.

Most epidemiological studies assume an average of 5.2 days spent in the exposed state. (Adhikari et al., 2020; Guan et al., 2020; He et al., 2020; Wang et al., 2020). There is a high degree of uncertainty surrounding the time spent in the infectious state. In this paper I assume that agents spend on average of 7 days in the infectious state. This seems a reasonable as it implies an average duration of the disease at 12 days which is roughly in accordance with the 14 day isolation/quarantine regime in most countries for those who have tested postive for Covid-19. This leads to calibration of the transition rates as $\lambda_E = \frac{1}{5.2}$ and $\lambda_I = \frac{1}{7}$. The current estimate for the case mortality rate is $\gamma = 0.02$.

In order to calibrate β_0 the concept of the basic reproduction rate, R_0, is used. The basic reproduction rate is the average number of people that an infected agent can infect before recovering and is given by the expected duration in the infected state multiplied by the transmission rate. The expected duration in the infectious state is 7 days so a single agent can infect on $R_0 = 7\beta_0$. Most studies use a value of $R_0 = 2.2$ for Covid-19 as per the mean estimates in Guan et al. (2020), this results in $\beta_0 = \frac{2.2}{7}$.

These parameters also fall within the range of values that have been used in various economic studies that incorporate some version of the SIR epidemiological model of the Covid-19 pandemic.

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Table 1: Calibration for Benchmark Model

Macroeconomic Parameters (Households)			
Discount Factor	$\beta = 0.9999$	Risk Aversion	$\sigma = 2$
Frisch Elasticity	$\frac{1}{\psi} = 0.8$	Remote Work Cost	$\kappa = 0.9$
Time Spent in Remote Work	23.7%	Disutility of Market Work (Type-1)	$\chi_1^M = 4.0786$
Disutility of Remote Work (Type-1)	$\chi_1^R = 7.0189$	Disutility of Market Work (Type-2)	$\chi_2^M = 1.2384$
Share of Type-2 Households	$\theta = 0.6144$		
Macroeconomic Parameters (Firms)			
Elasticity of Substitution	$\varepsilon^P = 11$	Slope of Phillips Curve	0.1
Price Adjustment Parameter	$\chi^P = 110$	Market Labour Income Share	$\alpha_M = 0.31$
Remote Labour Income Share	$\alpha_R = 0.33$	Technology Shock Persistence	$\rho = 0.95$
Technology Shock Std. Dev.	$\sigma_z = 0.007$		
Macroeconomic Parameters (Central Bank)			
Inflation Response	$\phi_\pi = 1.5$	Monetary Shock Persistence	$\iota = 0.65$
Monetary Shock Std. Dev.	$\sigma_{R^n} = 0.0028$		
Epidemic Parameters			
Basic Transmission Rate	$\beta_0 = \frac{2.2}{7}$	Basic Reproduction Rate	$R_0 = 2.2$
Exposed Transition Rate	$\lambda_E = \frac{1}{5.2}$	Infectious Transition Rate	$\lambda_I = \frac{1}{7}$
Case Mortality Rate	$\gamma = 0.02$		

2.3 Other Parameters

The remaining set of parameters $\left(\beta, \sigma, \psi, \varepsilon_P, \chi^P, \phi_\pi, \rho, \iota, \sigma_z, \sigma_{R^n}\right)$ are chosen to match standard values in the literature. The Taylor Rule parameter $\phi_\pi = 1.5$ is standard in the New Keynesian literature.

The time discount factor β is chosen to ensure an annualised return of 4.2%, and $\sigma = 2$ is a standard value for the risk aversion parameter. A Frisch Elasticity of 0.8 is used which yields $\psi = \frac{1}{0.8}$, this is well within the standard range of values for this parameter.

The elasticity of substitution between goods, $\varepsilon_P = 11$, is chosen to ensure a steady state mark-up of 10%. Solving the Rotemberg Phillips curve forward via iterative substitution gives the slope of the forward looking Philips Curve as $\frac{\varepsilon_p}{\chi^P}$. The value of χ^P is set so that the slope of the Phillips Curve is $\frac{\varepsilon_p}{\chi^P} = 0.1$.(Schorfheide, 2008; Kaplan et al., 2018) Given $\varepsilon_P = 11$ this then implies that $\chi_p = 110$.

The parameters governing the technology shock and the monetary policy shock are taken as standard values from the literature. In the simulations autocorrelation parameters $\rho = 0.95$ and $\iota = 0.65$ are used together with standard errors of $\sigma_z = 0.007$ and $\sigma_{R^n} = 0.0028$.

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2.4 Generating Epidemic Shocks

The simulation of the model requires one to generate the epidemic shocks Γ_t. Epidemic shocks are drawn in three broad steps,

1. Simulate the epidemic model assuming $\mathcal{X} = 1$, i.e. $\beta_t^- = \beta_0 \; \forall \; t$. Set T to be the twice as long as the duration of the modelled epidemic.

   Setting T to be twice the length of the epidemic ensures that the model is not always in an epidemic state and alternates randomly between periods of epidemic and periods without disease.

2. Generating random epidemics.

   (a) Generate an initial epidemic start date τ_1 by drawing a random number from a Uniform$(1, T)$ distribution

   (b) Sequentially draw $\tau_t = \tau_{t-1} + \epsilon_\tau$ where $\epsilon_\tau \sim U\,(1, 20)$.
   This step captures the fact that epidemics have a natural ordering in time. It ensures that time moves in the right direction, i.e. it rules out the possibility of jumping to a point to the left of the distribution as this not possible conditional on your starting point unless one epidemic has ended and another randomly begun.

   (c) If $\tau_t > T$ then redraw τ_t from a Uniform$(1, T)$ distribution

   (d) Repeat these steps until there is a τ_t for each simulation period

3. Generating the Epidemic Shock for simulation period t

   (a) Draw the values for $S\,(\tau_t)\,, E\,(\tau_t)\,, I\,(\tau_t)\,, R\,(\tau_t)\,, D\,(\tau_t)\,, N\,(\tau_t)$ and set these as the start of period t values for each epidemic state

   (b) Using the realised values for $\mathcal{X}_t$ from the period t simulation of the model, forecast the end of period values using the epidemic model

   (c) The end of period values are used to define an epidemic model consistent Γ_{t+1} using the relationship,

   $$\Gamma_{t+1} = 1 + \beta_0 \mathcal{X}_{t+1}^- \mathcal{S}_{t+1}^- \frac{\mathcal{I}_{t+1}^-}{\mathcal{N}_{t+1}^-} \tag{2.4}$$

   where start of period values for $t+1$ are equivalent to end of period values simulated

   (d) Repeat for each simulated time period

Recall that the belief is formed on information available at the beginning of the period so that Γ_t pre-determined in any given period, i.e. it is a state variable in period t. Since Γ_t is a state variable in period t economic decisions are constrained by it so one can simulate economic decisions based on this state and use this information to update the state in the subsequent

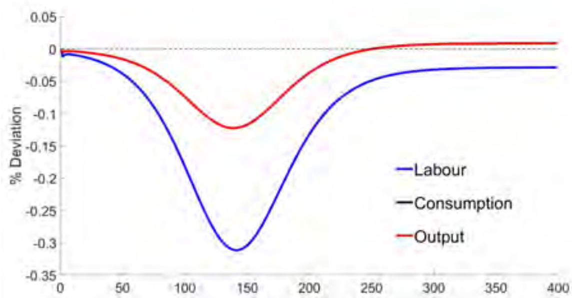

Figure 1: Aggregate Responses to Epidemic

period. The values that are drawn from the epidemic model at random constitute the epidemic shock since agents forecasts of the start of period values differ from what they observe. Agents then use the epidemic model to generate a consistent forecast of the end of period values in order to update the state variable for the subsequent period, i.e. Γ_{t+1}.

3 Epidemic Dynamics

Macroeconomic dynamics for in response to the epidemic are driven by the response of labour to the evolution of the epidemic. In order to study the dynamics I assume that initially 0.001% of the population are infected, this allows one to see the dynamics clearly. The dynamics of variables at the highest level of aggregation, i.e. a single aggregate series for labour, output and consumption, can be seen in Figure 1.

At the aggregate level it is seen that there is a gradual fall driven by the growing disutility from working in market labour as the epidemic spreads. As the epidemic eases, labour recovers as the fear of contracting the disease falls causing labour supply to increase. Aggregate labour never fully recovers to its pre-epidemic levels due to deaths, while the marginally higher level of output and consumption is the result of higher income as the marginal product of labour increases due to death.

The aggregate variables mask the underlying group level dynamics. Figure 2 highlights that dynamics of labour and consumption to the epidemic are very different when one considers the group level and labour type.[6] Figure 2a shows that it is Type-2 households, i.e. those that can only engage in market labour, that bear the brunt of the epidemic shock. The Type-2 households see their labour fall by about 4 times that of the Type-1 household, and a post-epidemic

[6]The disaggregated impulse responses have been corrected for the different population sizes as the epidemic progresses.

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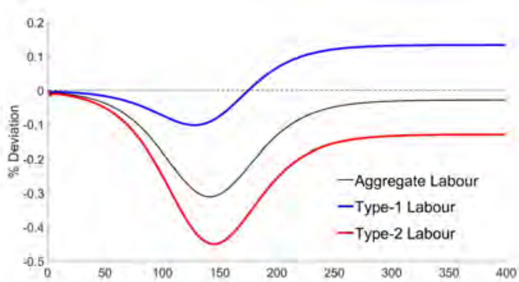
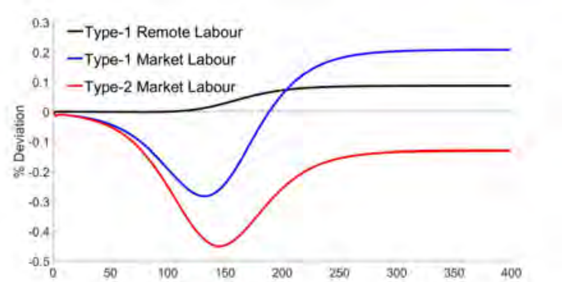
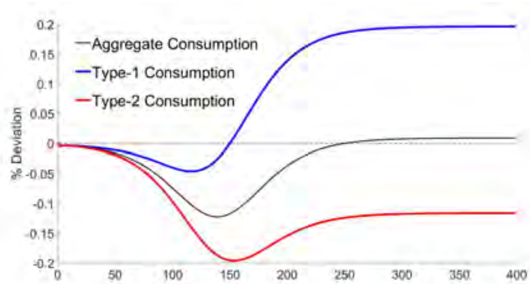


(a) Labour - Group Level



(b) Labour - Type and Group Level



(c) Consumption - Group Level

Figure 2: Group Level Responses to Epidemic

steady-state below the pre-epidemic steady state. Figure 2b shows that Type-1 households initially do not change their remote labour supply but only substitute away from market labour to remote labour to offset their increasing disutility of working in market labour as the epidemic evolves. Type-1 households, regardless of the wage rates, are also more wealthy post-epidemic than their Type-2 counterparts given that they supply more of both types of labour than their pre-epidemic steady states. As will be shown below this is driven by the higher death rates among the Type-2 agents. This leads to the observed consumption responses where it is again evident the Type-1 households are uniformly better off than their Type-2 counterparts. Thus a more unequal society materialises post-epidemic. So far it has been seen that the epidemic leads to worsening economic outcomes for the Type-2 household. But what about health outcomes? Figure 3 highlights that, when compared to a standard SEIR model of the epidemic, the dual feedback between economic activity and the epidemic leads to a significant 'flattening of the curve' and most importantly an overall reduction in deaths. The mechanism at work here comes from households responding to the epidemic and lowering supply of market labour as fear of contracting the disease increases. This lowers the aggregate time agents are exposed

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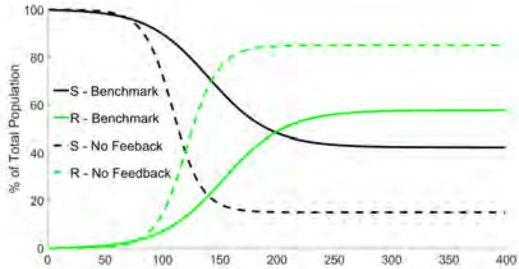
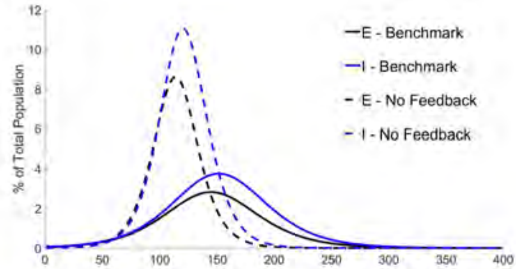
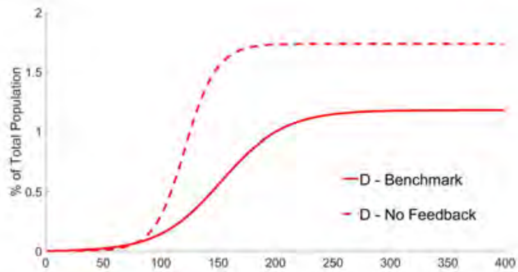


(a) Susceptible and Recovered



(b) Exposed and Infected



(c) Dead

Figure 3: Evolution of Epidemic for Total Population
Note: 'Benchmark' refers to the epidemiological model outlined in the model section. 'No Feedback' refers to an epidemiological model where $\mathcal{X}_t = 1; \forall\, t$.

to the disease in the early stages of the epidemic and works to slow its progress since a smaller proportion of the the population is ultimately exposed and infected with the disease. This lower level of exposed and infected populations drives the significantly lower number of deaths. While outside the scope of this paper, such a flattening effect places a lower burden on the health sector as not only are less people ultimately cared for, but it also evolves over a longer period of time placing less strain on capacity in the health sector. This shows that in the absence of any policy intervention the epidemic will be flatter than that predicted by the standard SEIR model with no feedback. This is does not mean that government intervention is not necessary to combat an epidemic like Covid-19, but rather that health systems are being put under extreme strain even in a world where the curve is much flatter than the pure epidemiological model predicts.

Turning to group level health outcomes from the epidemic, Figure 4 shows the group level evolution of the epidemic correcting for different group sizes. It is immediately apparent that

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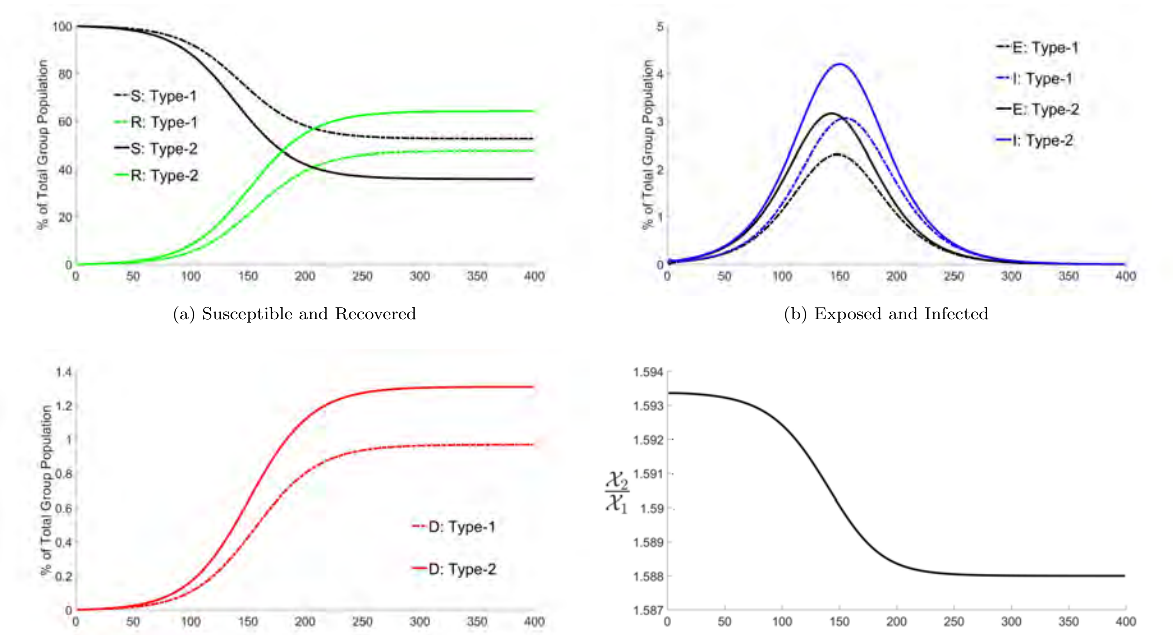

(a) Susceptible and Recovered

(b) Exposed and Infected

(c) Dead

(d) Exposure

Figure 4: Evolution of Epidemic at Group Level

there are significant differences in the impact of the epidemic on the two groups, were the impact symmetric then the figures in Figure 4 would have identical shape and location. Type-2 households have higher exposure, infection and deaths compared to Type-1 agents even when correcting for different population sizes. This is wholly due to Type-2 households having a greater exposure to the epidemic due to their inability to work from home. Figure 4d shows that not only do the Type-2 households have a higher exposure rate pre-epidemic but they continue to have a higher exposure during the epidemic and also post-epidemic despite a higher death rate. Hence the experience of the epidemic is worse for Type-2 households.

In order to get some sense of the quantitative implications impulse response analysis is conducted where a value of initial infections is chosen that leads to a $\sim 13.5\%$ fall in labour over 180 days. This value is chosen to mimic the sharp rise in the unemployment rate in the US since the Covid-19 pandemic and associated containment measures. Any quantitative calculations for the current Covid-19 pandemic must be treated very cautiously, the results presented below are no exception. The results of this quantitative calculation are presented in Table 2, and further

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Table 2: Quantitative Impact of Epidemic (180 Days From Initial Infection)

Output Loss	Total Death (% of Total Pop.)			Consumption Decline (%)		Labour Decline		
	Aggregate	Type-1	Type-2	Type-1	Type-2	Aggregate	Type-1	Type-2
5.473	0.350	0.102	0.248	2.723	7.351	13.499	5.296	18.674

highlight the different experience of the epidemic by the two types of household in the economy.

Inequality in consumption exists pre-epidemic with Type-2 households having lower consumption than Type-1 households in steady state. In the first 180 days of the pandemic there is clearly a large increase in inequality as Type-2 households see their consumption levels fall by more than double that of the Type-1 agents. So in the first 180 days of the epidemic the Type-2 households pay a higher cost in terms of loss in economic prosperity. To understand why this happens consider the Type-1 households. The opportunity to supply remote labour provides a buffer to the epidemic as they continue to earn the same or more from supplying market labour. Consequently the proportionate decline in their income is smaller than it is for Type-2 agents. Not only do Type-2 agents experience larger declines in their labour income as there is a fall in their only source of income, but given they begin relatively poorer than Type-1 agents this fall in income is proportionately larger as well.

Critically note that while Type-2 households constitute 61.44% of the population, they account for 71.21% of the total deaths 180 days after the start of the epidemic. So their loss in economic terms is compounded by a disproportionately higher death rate by the fact that they can only work in market labour. In the next section I consider how containment policies might change these values, and how these changes affect the observed group differences.

4 Containment Policies

The results presented so far are in stark contrast with the argument that an epidemic is a great leveller because disease does not discriminate between different people. While this may be true from a purely scientific point of view, it fails to take into account the fact that some groups are more at risk due to their economic circumstances and the opportunities available to them in the labour market. The results of this model highlight that epidemic shocks are unambiguously bad for Type-2 households - they have both worse economic and health outcomes.

In the wake of the Covid-19 pandemic many governments imposed stringent containment policies with the aim of reducing the spread of the disease. From an epidemiological perspective such containment measures are aimed at reducing the Basic Reproduction Rate, R_0. Containment policy is defined as any policy that seeks to reduce R_0 by imposing certain social restrictions

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in the interest of public health. Such policies include, but are not limited to, social distancing, curfews, quarantine, restriction of non-essential services, restriction on local travel, closure of borders (both domestic and international), wearing of face masks, compulsory sanitising of hands, etc., all of which were implemented to varying degrees in most countries.

Containment measures have the effect of reducing the amount of market labour available in the economy while it leaves amount of remote labour unaffected. Containment measures, $\mu_{t,j}$, are introduced into the model by modifying the budget constraint of the household and the production function of the firm to capture the exogenous reduction in market labour availability. The containment policy may be symmetric, ($\mu_{t,j} = \mu_t \; \forall \; j$) or non-symmetric ($\mu_{t,j}$ differs for each group). The modified budget constraints and production function are given by,

$$c_{t,j} + \frac{B_{t+1,j}}{R_t^n P_t} = (1-\mu_{t,j}) \frac{W_t^M}{P_t} n_{t,j}^M + \kappa \frac{W_t^R}{P_t} n_{t,j}^R + \frac{B_{t,j}}{P_t} + D_{t,j}$$

$$y_t = z_t \left[\left(1 - \sum_{j \in J} w_{t,j} \mu_{t,j} \right) n_t^M \right]^{\alpha_M} \left(n_t^R \right)^{\alpha_R}$$

The introduction of containment measures modifies the household equilibrium condition for market labour, (1.4), and the aggregate resources constraint, 1.28. Containment measures leave the equilibrium conditions of the firm unchanged as the production function is Cobb-Douglas.[7] The modified household condition for market labour and aggregate resources constraint are,

$$(1-\mu_{t,j}) \frac{W_t^M}{P_t} = \chi_j^M \Gamma_t \left(n_{t,j}^M \right)^{\psi} \tag{4.1}$$

$$y_t = c_t + (1-\kappa) \frac{W_t^R}{P_t} n_t^R + \mu_{t,1} (1-\theta_t) \frac{W_t^M}{P_t} n_{t,1}^M + \mu_{t,2} \theta_t \frac{W_t^M}{P_t} n_{t,2}^M \tag{4.2}$$

So containment measures reduce market labour and consumption in equilibrium via the introduction of a containment wedge. Eichenbaum et al. (2020) view containment measures as akin to a tax. Using this idea containment measures are introduced as a tax on market labour. This tax revenue is used to provide transfers to those agents prevented from participating in the labour market through welfare schemes outside of the model.

Let us consider containment policy measures that reduce R_0 to 50% of its baseline value at full implementation. Full implementation of the policy occurs with a lag to more accurately mimic the actual behaviour of policy makers where decisions on lock-down policies take time

[7]This is a special case in for Cobb-Douglas production functions. If one considered more general CES production functions then the containment measures would affect the equilibrium conditions of the firm and introduce another wedge on the production side. The study of CES production functions is beyond the scope of the present paper and left for future work.

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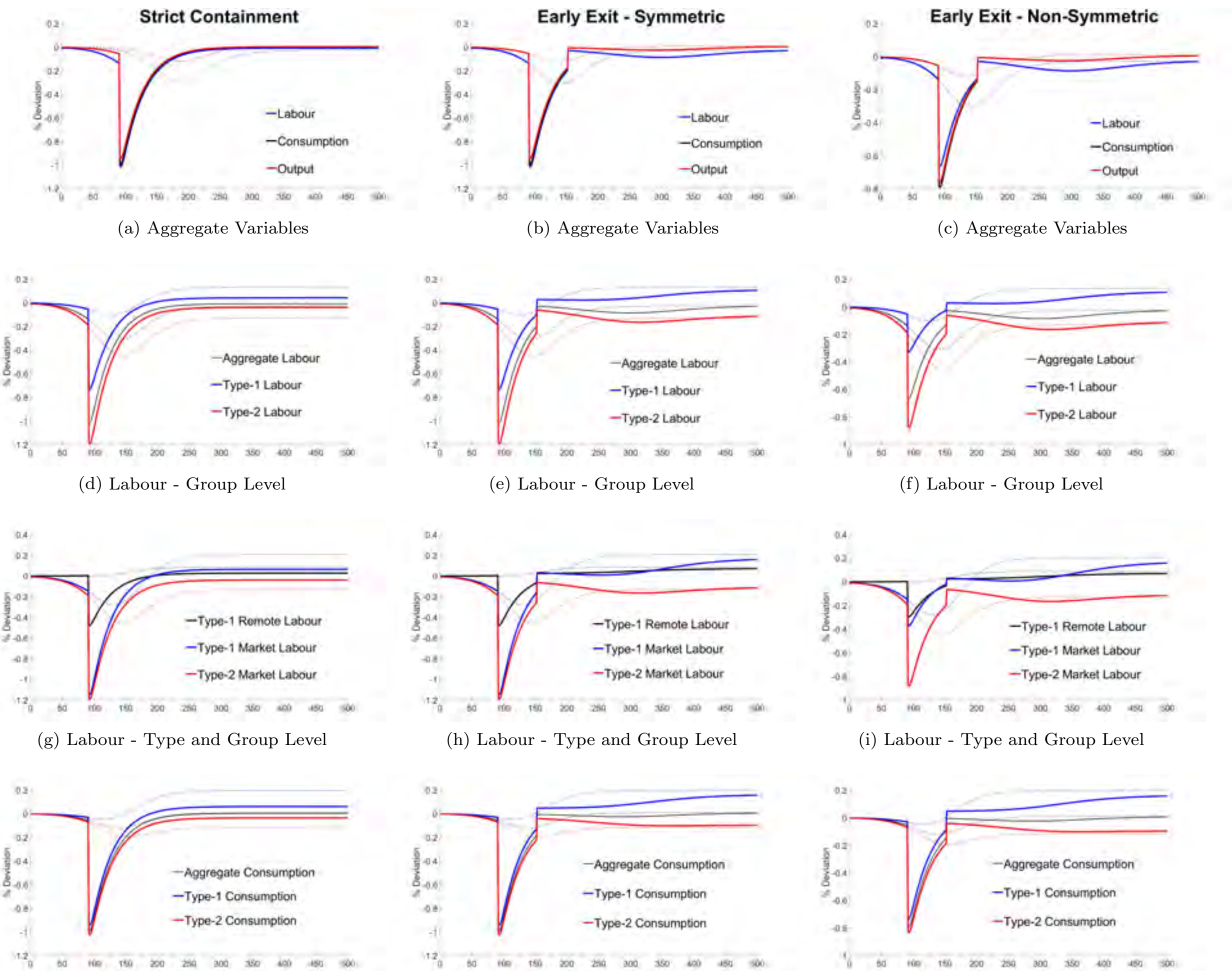
and lag the start of an epidemic. The following containment scenarios[8] are considered in this section:

1. Symmetric Strict Containment: Full implementation 90 days from start of epidemic and lasting for 1 year, $\mu_t = \frac{\mathcal{I}^-_{t,1}+\mathcal{I}^-_{t,2}}{\mathcal{N}^-_t}$
2. Symmetric Early Exit: Full implementation 90 days from start of epidemic and lasting for 60 days, $\mu_t = \frac{\mathcal{I}^-_{t,1}+\mathcal{I}^-_{t,2}}{\mathcal{N}^-_t}$
3. Non-Symmetric Early Exit: Full implementation 90 days from start of epidemic and lasting for 60 days, $\mu_{t,1} = \frac{\mathcal{I}^-_{t,1}}{\mathcal{N}^-_t}$, $\mu_{t,2} = \frac{\mathcal{I}^-_{t,2}}{\mathcal{N}^-_t}$

The containment policies considered differ in the sophistication of the information available to the government. Non-symmetric policy is more information intensive since it requires the policy maker to have information about agent types, while symmetric policy only requires information at the aggregate level. It is assumed that the government has access to perfect testing each period so that it implements policy by first removing all infected agents from the labour force, and then randomly removing other groups to meet the policy rate. Finally, the simulations assume that containment, under any scenario, will have long lasting behavioural impact leading to a reduction of R_0 to 90% of its baseline value once the containment policy ends. The Symmetric Early Exit containment scenario best mimics the types of policy that have been implemented by governments thus far in the Covid-19 pandemic.

The macroeconomic and epidemic responses to these lock-down policy scenarios are presented in Figure 5 and Figure 6. Containment policy changes the evolution of the epidemic by reducing the R_0 to 50% of its original value and restricting labour supply plays a significant role in allowing this to occur. These figures highlight a key temporal trade-off between macroeconomic variables and epidemic variables, i.e. large short-term macroeconomic losses in order to contain the spread of the epidemic. Considering the specific containment policies in this section, all of the containment responses in Figure 5 have large declines early but then intersect their respective benchmark curves before these have reached their minimum. So that after a period of large economic decline, macroeconomic variables perform better than if no containment policy were implemented. This occurs because the containment policy arrests the rise in Γ_t and moves it closer to unity much faster (see Figure 7) thereby reducing the disutility agents experience from working in market labour and hence increasing their supply of market labour. This macroeconomic loss is traded-off against the significant improvement in death rates as seen in Figure 6.

[8]Early Warning and Phased Early Exit scenarios. The Early Warning scenario was identical to Early Exit with added light containment implementation for 30 days before strict lock-down. The Phased Early Exit scenario was identical to Early Exit except it was followed by stepwise increase of 10% every 15 days until R_0 at 90% of baseline. Both of these additional scenarios led to results very similar to the Early Exit scenario and have been omitted for clarity.



(a) Aggregate Variables (b) Aggregate Variables (c) Aggregate Variables

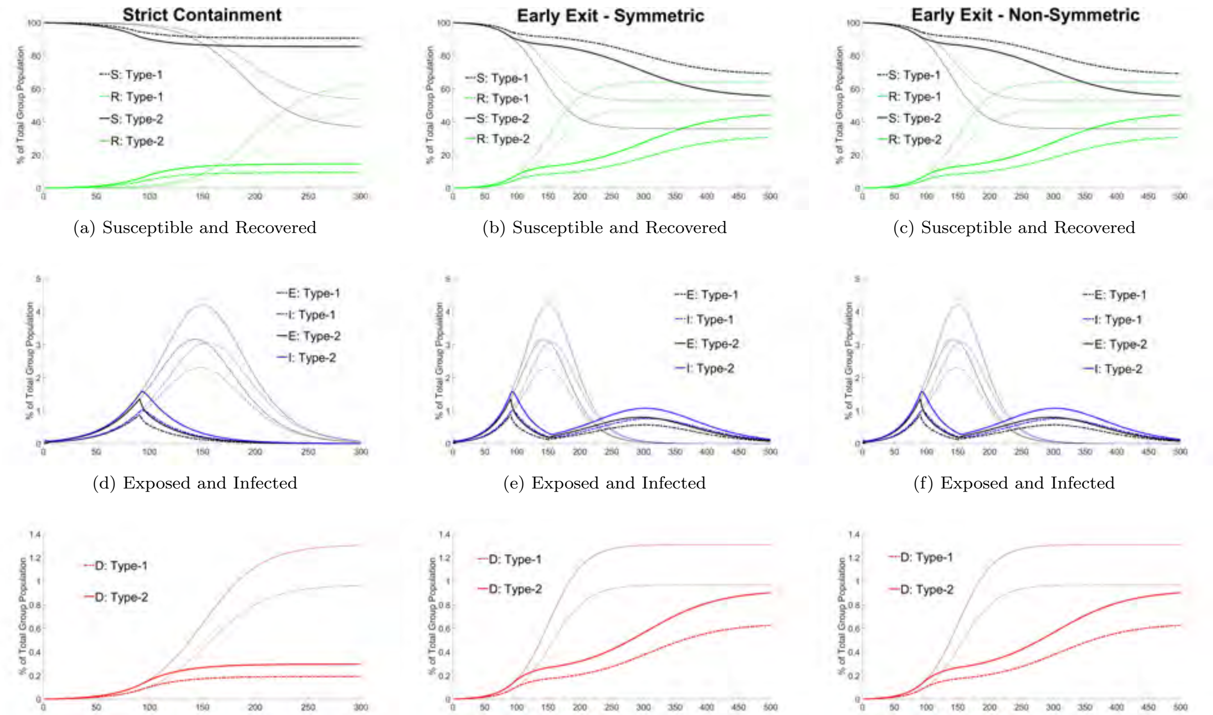
(d) Labour - Group Level (e) Labour - Group Level (f) Labour - Group Level

(g) Labour - Type and Group Level (h) Labour - Type and Group Level (i) Labour - Type and Group Level

(j) Consumption - Group Level (k) Consumption - Group Level (l) Consumption - Group Level

Figure 5: Macroeconomic Response to Lock-down Policy

Note: The responses to the 'Strict Lock-Down' and 'Early Exit' policies are provided by the thick coloured lines, while the dashed lines are reproductions of the 'Benchmark', i.e. no containment policy, case for ease of comparison.



(a) Susceptible and Recovered (b) Susceptible and Recovered (c) Susceptible and Recovered

(d) Exposed and Infected (e) Exposed and Infected (f) Exposed and Infected

(g) Dead (h) Dead (i) Dead

Figure 6: Epidemic Response to Lock-down Policy
Note: The responses to the 'Strict Lock-Down' and 'Early Exit' policies are provided by the thick coloured lines, while the dashed lines are reproductions of the 'Benchmark', i.e. no containment policy, case for ease of comparison.

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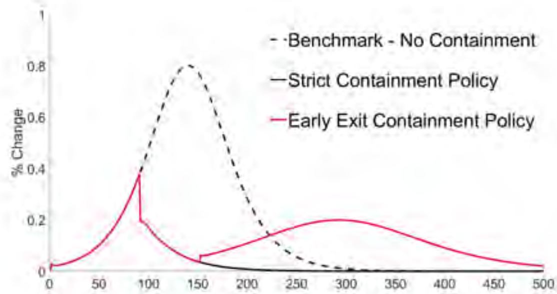

Figure 7: Containment Response of Γ_t

Strict Containment succeeds in eliminating the epidemic, but there is an endogenous second-wave of the epidemic in the Early Exit scenarios. This is an interesting response of the model is a consequence of the Early Exit policy not being long enough to remove all infected agents from the population. It does reduce the number sufficiently that the 'fear' of catching the disease falls, moving Γ_t closer to unity and increasing market labour supply. However, unlike Strict Containment, the presence of infected agents post containment means that as market labour increases the transmission of the disease increases as well. The second wave of the disease, while inevitable under Early Exit scenarios, is not as large as would have eventuated had no lock-down policy been implemented, and the economic impact is consequently smaller.

Turning to the quantitative impact - output decline, consumption decline at agent level and death rates 180 days from the start of the epidemic are computed; this compares all containment policies 30 days after the Early Exit scenario ends. The initial infection rate is once again set so that there is a $\sim 13.5\%$ fall in labour over the first 180 days of the epidemic in the Benchmark Case. The quantitative measures for each policy 180 days from the onset of the epidemic presented in Table 3.

The quantitative impact further highlights the trade-off that policy makers make between economic prosperity and saving lives in policy responses to an epidemic. One could adopt a laissez-faire policy that minimises the output loss from the epidemic, but this also results in an unacceptably high death rate and cases on the rise. The containment policies accept a lower level of output in order to significantly reduce the death rate. All of the containment scenarios studied reduce the aggregate death rate by around 85% of the benchmark value at a cost of increased output loss between $0.04 - 2.18\%$. While death rates do fall for both groups it must be stressed that Type-2 agents still have death rates double that of their Type-1 counterparts as they can

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Table 3: Quantitative Impact of Containment (180 Days From Initial Infection)

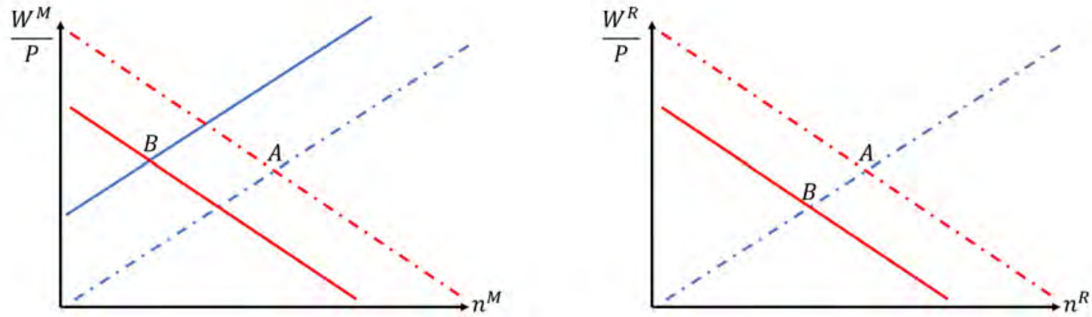
	Output Loss %	Total Death (% of Total Pop.)			Consumption Decline (% of Group Pop.)	
		Aggregate	Type-1	Type-2	Type-1	Type-2
Benchmark Model	5.473	0.350	0.102	0.248	2.723	7.351
Strict Containment	7.650	0.048	0.014	0.034	6.970	8.747
Early Exit: Symmetric	6.736	0.051	0.015	0.036	6.016	7.772
Early Exit: Non-Symmetric	5.514	0.051	0.015	0.037	4.582	6.495

only supply risky market labour.

The implementation of containment policies leads to more equal falls in consumption thereby minimising the increased inequality resulting from the epidemic. This is due to the fact that containment policies have demand side effect, as well as supply side effects in the labour market for both types of labour. The market labour supply curve shifts to the left for each agent type due to the tax, while the remote labour supply curve is unchanged. At the same time the demand for both types of labour shifts to the left in response to the restrictions placed on market labour. This is represented with simplified labour demand and labour supply curves in Figure: 8. The effect of the containment measures on market labour (see Fig: 8a) is a large reduction in market labour employed with a small, indeterminate[9] change in the wage paid to market labour. While for remote labour (see Fig: 8b) there is a decline in both wage and employment of remote workers. Thus containment measures reduce the remote labour buffer enjoyed by Type-1 agents consequently leading to larger declines in Type-1 consumption.

The Early Exit scenario with non-symmetric intervention significantly reduces the death rate while only reducing output by slightly more than the no policy benchmark. It outperforms the Early Exit scenario with symmetric intervention because it restricts less people from participating in the labour force. This is due to the fact that the two household types are differentially impacted by the epidemic due to the labour opportunities available to them. Remote labour opportunities mean that less Type-1 households get infected and so a symmetric policy restricts some Type-1 households who are not in the $\mathcal{I}$ group. Returning to Figure: 8, the improvement in consumption comes from the fact that non-symmetric taxes imply that the aggregate labour supply curve for market labour under non-symmetric policy will lay to the right of that under symmetric policy. This is entirely due to the additional Type-1 households not restricted under the non-symmetric policy. These additional Type-1 households push down the wage rate for both market and remote labour. Thereby further lowering the incomes of employed Type-2 agents which accounts for the marginal increase in inequality under the non-symmetric case. Thus if policy makers do not take into account the asymmetry in the experience of the epidemic at the group level there is ultimately a larger loss in output, however this must be balanced with the

[9]The sign of the change depends on the relative shifts of the labour supply and labour demand curves



(a) Market Labour

(b) Remote Labour

Figure 8: Stylised Labour Market Diagrams

Note: The dashed lines represent the labour demand and labour supply curves in the absence of containment measures. The solid lines represent the curves after containment measures are imposed.

consequences for economic inequality.

The implementation of non-symmetric policy is fraught with other issues key among them being timely availability of accurate of information at the group level and fairness considerations. Implementation of the non-symmetric policy requires access to accurate daily data of infections at the group level. This information ideal is clearly impractical and unlikely to materialise in the real world. The study of the containment policies taking into account of information availability and the presence of lags is an extension left for future work. Even if one had access to perfect data, issues surrounding about treating different groups differently would likely render non-symmetric policies difficult to implement on fairness grounds and would likely draw significant political backlash. The non-symmetric policy does not materially change the death rate from the symmetric case.

The Early Exit policies appear to tread the fine line between draconian measures that have a single minded focus on saving lives at the expense of liberty and maximising economic prosperity during the epidemic. Despite the inevitable second wave, such policies provides policy makers the breathing space needed to increase capacity in the health system, research the disease to improve care provided to those infected, search for a vaccine, etc. All of these efforts may allow policy makers to fundamentally alter the evolution of the epidemic post-containment. For example, research into improved care could reduce the time spent in the infectious state, or the development of a viable vaccine could remove whole swathes of the population from the susceptible group. The moral of the Early Exit story is that if policy makers aim to exit from their

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containment measures early they should use the time afforded to them to invest in programmes that will help to fundamentally alter the evolution of the epidemic post exit from containment.

5 Conclusion

The main conclusion of this paper is that entrenched differences between groups in the lead up to an epidemic can have a significant bearing on how individual groups experience the epidemic both in terms of health outcomes and economic prosperity. The main results of the paper show that such differences can be a powerful driving force behind post-epidemic inequality, while the study of containment scenarios highlight that government intervention can help to minimise any post-epidemic inequality.

This paper explores differences in the labour supply opportunities and highlights that entrenched differences along this dimension have a significant bearing on how an experiences the outbreak of an epidemic. Agents who cannot engage in remote labour and consequently only supply market labour end up experiencing higher death rates vis-*à*-vis the population as they must engage in labour that requires risky social contact. These agents also suffer larger declines in labour and consumption over the course of the epidemic. Post-epidemic, these agents are significantly worse off than their counterparts who have the opportunity to work from home and a more unequal society emerges.

This paper further highlights that simple containment policies, while leading to larger losses in economic prosperity, can significantly reduce death rates across the population and bring the death rates of the two groups closer together. However, even under containment policies the death rate of agents only supplying market labour is twice that of the other type of agent. Containment policies also reduce the inequality that emerges post-epidemic with falls in consumption more similar across agent types.

In future development of this work I plan to study how the differences in labour opportunities may interact with other entrenched differences in economic opportunity, e.g. the presence of hand-to-mouth agents who must work in the market to consume each period. I also plan to extend the model to allow for capital to play a role in reducing risky social contact in the labour market and hence study how allowing production to substitute away from labour to capital might affect the results studied. Finally, I plan to use the model to study how information constraints might play a role in slowing economic recovery while exacerbating the spread of the epidemic.

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CULTURE: A tool for mental health resilience in COVID-19 times

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What is the role of cultural goods and services during a universal pandemic crisis? This paper aims to demonstrate that culture is predominantly a public good for preserving mental health. We argue that the function of culture in human life has evolutionary roots in individual self-defence of mental health from uncertainty. The current paper uses primary data from a pilot survey conducted during the pandemic COVID-19 combined with Google trends data used to illustrate the effect of the pandemic on aggregate level. Our outcome variables are happiness during COVID-19 and propensity to help others in the periods before and after the start of the pandemic. The evidence from Probit and Heckman sample selection models suggests that people can obtain a mental-health shield for crisis periods through consumption of cultural goods and services in the past. Meanwhile, spontaneous cultural practices during times of uncertainty (such as singing with others) are associated with higher pro-social propensity to help other people. This shows that on micro-level culture is generally under-estimated in its potential role as a public good guaranteeing the psychological resilience in socio-economic shocks. On aggregate level, data about public spending on culture is associated with lower anxiety and less viral fear of death. Therefore, culture should be seriously explored as a tool for mental health prevention, which would be a primary justifications for much more extensive public spending on culture.

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Introduction

What is the role of culture in times of socio-economic shocks? Culture is usually defined as a mixed good which is partially a luxury good (necessary only once basic needs are satisfied), partially a public good (with beneficial impact to all and endowing us with useful cultural capital). The latter helps in social mobility and optimizes the utilization of our social networking and innate talents. In pandemic times, the cultural sector is generally left by policy makers to the mercy of serendipity. New Zealand seems to be seeing culture as a tool for recovery from the pandemic COVID-19. However, the cultural sector is traditionally perceived as a needy industry to be expensively maintained only by eventual self-selected generous benefactors. Which is this a justified attitude and are we not overlooking an essential role of culture as a public good with implications for mental health?

Concert halls, museums and even some of the Egyptian pyramids granted free online access for people during the pandemics. Meanwhile, funding for the cultural sector during the shock and in rebuilding the economy after the pandemic shock become clearly a secondary question on national and international policy-making level. A potential reason for this is the traditional attitude towards the cultural sector as a generally sluggish in economic growth sector. This is a condition termed the Baumol's disease (see Baumol and Bowen 1966; Cowen 1996; Baumol and Towse 1997; Heilbrun 2003; Last and Wetzel 2011) and due to it, culture has been always treated as a luxury in times of austerity and economic crisis, with libraries, theatres and other cultural venues being among the first to experience major cuts during austerity measures (Bramall 2012; Kloosterman 2014; Newsinger 2015; Bracci et al. 2015). The recent pandemic COVID-19 also saw the cultural sector left behind in most countries, except for the best surviving the pandemic Germany. The question that we raise here is whether evidence-based policy making is indeed in line with such a divesting from the cultural sector spending from the public budget. To do so we engage with the effect of the cultural spending on micro level, clearly outlining the potential effects this can have on aggregate level especially in the domain of general public's mental health.

Mental health is a spectrum of states but being in a balanced position mentally is an essential need for individuals and society. This paper argues that cultural goods, services and cultural participation are a tool for keeping the entire population in and around the golden mean of mental health.

The existing empirical evidence about the impact of culture on the economic system has demonstrated that it is scientifically unjustified to underestimate the significance of the cultural sector for the economy (Guiso, Sapienza and Zingales 2006; Benabou and Tirole 2011; Alesina and Giuliano 2015). There is a wealth of cultural economic evidence, both on micro-economic and macro-economic level, which clearly shows the important role of cultural participation of individuals and cultural endowment of places. On individual level, cultural capital endowment is responsible for the dynamics of socio-economic mobility of people and their success in transforming their abilities into skills and human capital (Bourdieu1986, 1973; Bourdieu, and Passeron 1979; Tubadji, Gheasi and Nijkamp 2014). On aggregate level, cultural endowment of cities has been demonstrated to make a major contribution both through living culture (concerts, festivals, exhibitions see Snowball 2007) and through the cultural heritage memory and tourism aspects (see McKercher, Ho and Du Cros 2005; Cerisola 2019). One of the leading streams in modern endogenous growth theory – the Creative Class concept of Richard Florida – has also highlighted the link between regional economic development and city smartness on the one hand, and the concentration of the cultural sector in a place on the other hand (Florida 2002, 2005). The latter indeed requires a filigree empirical work in order to disentangle the effect of the tolerant cultural milieu from the endogenous concentration of the Bohemian occupations in a place (Moeller

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and Tubadji 2009; Tubadji and Montalto 2020; Florida, Mellander and Stolarick 2017). Yet, one thing remains undeniable: the cultural sector has deep roots in the entire socio-economic process and neglecting its significance for the balanced and fair future economic development would be a harmful oversight.

The aim of the current paper is to study whether a particular major role of the cultural sector in the socio-economic development is not indeed overseen by policymakers – namely, the role of culture as a tool for the prevention of mental health crisis with national dimensions. We define here culture according to the Culture Based Development (CBD) paradigm, as a complex entity of living culture and cultural heritage, which both need to be considered with regard to public policy (Kagan 2014, Tubadji 2012, 2013; Tubadji and Montalto 2020). Looking at three different traditional measures of life-satisfaction and established approaches to quantifying happiness, the current study addresses the role of culture during the pandemic period on the utility function of individual consumers. As the respondents are random individuals, representing the general public, this pilot study can serve as an illustration of the role of the cultural sector in the lives of ordinary people. We distinguish between living culture and cultural heritage consumption during the pandemic COVID-19. We distinguish also between short term and long terms role of culture in the lines of arts for sustainability interventions versus regular cultural participation. Put differently, we study how mental health resilience of people is affected by cultural consumption during the pandemic period and by past-cultural consumption before the pandemic period. This allows us to identify whether culture is a tool for emergency intervention during crisis (subject to one-shot economic support) or a tool for continuous prevention measures (that merits a long-term continuous investment effort on public policy level). Finally, we distinguish between individual and community impact of the cultural consumption, by looking at the individual happiness on the one side, and at the shrinkage of social capital (measured as propensity to help a stranger) during the pandemic period and the moderating role that culture has for both outcomes (see Guiso, Sapienza and Zingales, 2008). We findings strong evidence for association between cultural consumption from pre-pandemic periods and a resilient mental health for individuals during the pandemic; also, during increased uncertainty, group cultural engagement is associated with a boost of the pro-social behaviour of people. In support of these micro findings, we also show that on aggregate level the mental health appears to be most resilient in places with increasing over time investments in the cultural sector.

The structure of this paper is as follows. Section 1 overviews the role of culture as an essential source of alleviation of the pains of uncertainty from evolutionary and behavioural economics point of view. Section 2 outlines the neuroscience motivation of considering culture as a tool for supporting psychological resilience and clarifies its links to economic resilience under shock conditions. Section 3 explains the CBD take on distinguishing the role of culture as a tool for emergency reaction and a tool for systematic prevention of mental health distress on national level. It outlines the regional and cultural economics implications of the micro-mechanism that is in place within the utility function of the general consumer, affecting happiness and mental health resilience. Section 4 offers empirical illustration the CBD approach for studying: (i) the cultural effect on mental health resilience (i.e. the effects from current and past consumption of culture on mental resilience in the moment of the COVID-19 pandemic) and (ii) the impact on the community spirit and social-capital levels in the behavioural propensities of people under the pandemic shock. Section 5 concludes and offers some fiscal policy insights with regard to culture from the point of view of the role of the cultural sector as a prevention tool for mental health resilience of the general public.

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1. Evolutionary View on Culture as Part of the Essentials

The evolutionary perspective on culture here refers to the way that we intuitively have used culture in the socio-economic life over the centuries. The theatre of the oppressed is a known tool used for mental health support (Boal 1974). Painting and music have been used as a tool for mental recovery of recidivists and criminals in prisons (Gussak, 2006; Johnson 2008). Painters are known to have been painting what they do not have in their lives; and even more broadly – neuroscience teaches us that music can improve the happiness of a healthy ordinary person within minutes (Koen 2008; De Botton and Armstrong 2013). Finally, music has been part of the lives of the first people, which obviously points towards the role of culture among the essentials rather than among the luxury goods (Huron 2001; Grewe et al. 2009; Wallin, Merker and Brown 2001; Bannan et al. 2012; Guiso, Sapienza and Zingales 2016). Meanwhile, over the centuries the access to culture might have become a luxury for some members of society. Yet, we interpret this as just another aspect of the experienced stark inequalities in redistribution over time. The lack of awareness among the general public and among policy makers about the inequality in cultural consumption only aggravates this type of inequality[1]. This is especially consequential in terms of the cultural capital endowment among the different socio-economic strata which leads to sticky cultural tastes and sluggish social mobility (Bourdieu 1986; Georg 2004; Bennett and Silva 2006; van Hek, M. and Kraaykamp 2013; Oakley and O'Brien 2015; Veal 2016; Gomes, Libero-Cano 2018; Katz-Gerro, Raz and Yaish 2009).

From a more global perspective, culture not only as art expression, but culture in its very essence of a set of affirmed beliefs and values, serves as a clear source of mental health tool for handling uncertainty (Delton et al. 2011). As well known from innovation and economic studies, and behavioural economics more generally, uncertainty is a major source of the biases in our behaviour (Kahneman and Tversky 1980). We are twice more strongly affected by the fear of loss than from the greed for gain. A general tendency to avoid uncertainty also explains why a potential surprise function exists in human behaviour which stops us from being sufficiently daring and innovative (Shackle 1949; Foldes 1958; Katzner 1986, 1989; Cantillo 2014; Derbyshire 2017.; Tubadji, Huggins and Nijkamp 2020). But the role of this uncertainty avoidance has mainly an evolutionary role, as it has helped us preserve ourselves in times of danger (Kahneman, Knetsch, and Thaler 1991; Akerlof and Shiller 2010). Having a certain set of heuristics, institutionalized up to the rank of social norms, beliefs and attitudes, is a survival strategy for securing mental health comfort zone of existence (Gudykunst 1995; Hirsh and Kang 2016). It is similar to the herd behaviour in other mammals, as we know from Hall (1966). Put differently, having culture makes us feel more certain what we have to do for our own good in an uncertain world. Moreover, evolutionary we have improved our smartness explicitly thanks to culture (Boyd and Richerson 2005; Richerson and Boyd 2008; Henrich 2017). The current study focuses on the understanding that having consistently accumulated this culture-related mental comfort feeling and smartness in one's psychological system is associated with important implications for our resistance to mental depletion and can improve our mental resilience under negative shock conditions.

[1] There is literature on inequality in cultural participation, but it is generally viewed as a niche boutique question of a luxury industry rather than a major type of inequality with significant socio-economic implications, as we argue here that cultural participation is, since it is an essential and not a luxury.

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2. Culture and Psychological Resilience under Economic Shocks

Psychological resilience is a concept very well known in psychological studies (Fletcher and Sarkar 2013). While behavioural economics has borrowed a lot from psychology, however, the notion of psychological resilience has not yet been sufficiently investigated in the contexts of economic thinking, while there are strong indications for its relevance (Graber, Pichon and Carabine 2015).

Firstly, on aggregate level we have already seen studies documenting the role of psychological types for local socio-economic development (Fritsch and Rusakova 2010; Obschonka et al. 2013; Stuetzer et al. 2014; Fritsch, Obschonka and Wyrwich 2019). Next, we have the topic of economic resilience emerging and gaining higher speed and deeper understanding in regional economics (Martin 2012; Reggiani 2012; Modica and Reggiani 2015; O'Kelly 2015; Martin and Gardiner 2019; Nijkamp 2007; Murray 2020). While mental health is known to be subject to depletion (Zyphur et al. 2007; Ainsworth et al. 2014; Banker et al. 2017), the question of psychological (mental health) depletion, its relation to economic impoverishment and negative shocks in the economy (Zahran et al. 2011) and the aftermaths of this mental resilience for economic resilience have not yet been explicitly addressed.

There are certain empirical economic studies that point towards the relevance of looking at a link between mental and economic resilience. It has been shown that under shock condition cultural hysteresis explains the different reaction of places to the same/similar economic shock (Tubadji et al. 2019; Tubadji, Nijkamp and Angelis 2016). It has also been debated whether the psychological types are constant over time or they are a subject of change (Obschonka et al. 2013; Stuetzer et al. 2014). Clearly, this links to the question of cultural persistence versus cultural change (Baddeley, Martin, and Tyler 1998; Guiso, Sapienza and Zingales 2016; Tubadji and Nijkamp 2020), which is also still an unresolved question, subject to undergoing debates in philosophy of language and narratives economics (Tubadji 2020; Tubadji Nijkamp and Pattitoni 2020, Sacco 2020). Tubadji, Boy and Webber (2020) show on aggregate level that country public policy affects general public mental health within the country itself and across its neighbouring countries too. The current study is however, the first of its kind to look explicitly at the micro-economic mechanism of culture as a source of mental resilience of the general public.

The role of culture as a source of stability and psychological comfort with socio-economic aftermaths is well-known from studies on social capital and organizational culture. Social capital helped the deprived regions of Italy find the means through cooperatives to pull themselves out of the economic deprivation (Helliwell and Putnam 1995; Siisiainen 2003). Organizational culture and management culture successful in risk management are essential for the productivity and creative flourishing of economic organizations (Denison and Spreitzer 1991; Hofstede 1998). Yet all these aggregate level economic studies only assume the existence of an individual mechanism linking psychological states and economic outcomes.

Secondly, on mirco-level, neuroscience self-management with the use of culture as a tool for maintaining personal balance and achieving further development is related to the study of cultural practices as a type of a meditation practice (Sudheesh and Joseph 2000; Koen 2008). Namely, playing violin and music per se are related to better neurological conditions (Zatorre 2005; Juslin 2009). Neurological conditions are associated with the general immune system of the person (Davydov et al. 2010; Pariante 2016), which might be strongly relevant in health emergencies and pandemics such as COVID-19. Therefore, we argue here further that cultural participation serves to increase in essence through mental health the

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overall immunity of the person. Put differently, cultural consumption serves for building the ability of the mental health of a person to be resilient under increased uncertainty.

The above argument is further supported by recent evidence from neuroscience which demonstrates that art practices serve as gymnastic of the brain – again using the example of the effect of playing a musical instrument – culture apparently increases brain plasticity (Johansson 2006). Culture builds neurological resilience against dementia (Cohen 2009). Dancing in cases of dementia (Palo-Bengtsson, Winblad and Ekman 1998) and generally music-engagement improved cognitive decline (Innes et al. 2016).

Yet, the question emerges – is then culture a question of a tool for boosting our mental health in times of stress and crisis, is it a personal hobby that can help us be healthier, like going to the gym? Or is culture an efficient tool to be provided by policy makers as prevention for mental health decline? In other words, is culture to be practiced as an opium dosing for alleviating the pain once stress has occurred (see IFACCA 2020), or is culture a prevention mechanism that has to be in place persistently and before the negative shock strikes the individual and the socio-economic system of people (see Holmes et al. 2020)? The answers to these questions will also clarify whether culture can be divested from as a luxury or is it an essential mechanism that has to be maintained under any budget constraints and fiscal polity cuts for the better good of all and maintained as a crucial security net for general public mental health prevention purposes.

3. A CBD Micro Model for Culture & Public Mental Health: Policy Relevance

Throsby (1999) has pointed to the cultural and economic valuation of assets, where the economic valuation accounts for the cost of the inputs, while the cultural valuation accounts for the perceived value added that the asset has to the socio-economic life of individuals and society. We argue here that culture has been significantly under-evaluated in public policy and investment considerations on policy level, due to being evaluated only in its direct economic value, associated with generating profit. Meanwhile, culture has an indirect value – which divides into two parts. The one is the indirect economic impact of culture on other processes such as innovation, entrepreneurship, social entrepreneurship and smartness of a city (Caragliu, Del Bo and Nijkamp 2011; Caragliu and Nijkamp 2011; Tubadji and Montalto 2020). The second indirect value of culture is a cultural valuation aspect, where the cultural milieu, the attitudes – these link to the social and economy impact that the mental health of people has on the development of places. Ponticelli and Voth (2020) offer a study on macro level in this direction – showing that fiscal policy cuts and not economic policy (such as increase of taxes) are the measures associated with social unrest. Put differently, it is not only the economic cost that matters for the feelings of the public, but also it is the cultural meaning of the policy measures – as to whether the public interest or the private interest is benefitted by these measures, that affects the psychological reaction of the people, the electoral vote and generally the behaviour of the masses in response to policy making. Fiscal policy is the pro-social policy-motivated spending and its cuts destabilize by creating feelings of left behind. The link between policy and the feelings of left behind has been demonstrated also in the context of Brexit (see for instance Rodríguez-Pose 2018). There are even rare studies documenting the existence of this mechanism on individual level (Lee, Morris and Kemeny 2018; Tubadji 2020). Tubadji, Colwell and Webber (2020) and Tubadji, Burger and Webber (2020) have looked at the link between cultural fiscal policy cuts, austerity and ultra-right voting. Tubadji, Boy and Webber (2020) demonstrate the role of public policy on mental health (in the UK, Sweden and Italy), and anxiety on aggregate level. All these studies demonstrate a link between fiscal policy for the arts, mental health on aggregate level and socio-economic aftermaths from overlooking this link. However, empirical analysis on micro level data linking cultural participation (the result of supportive cultural policy for the arts) and individual mental health, up to our knowledge has not been provided yet. The current study aims to provide the micro model and empirical evidence on that particular matter.

The CBD model, proposed in this study, has three main postulates. It starts with the CBD definition of cultural capital that distinguishes between living culture (current culture and art attitudes and assets) and cultural heritage (inherited attitudes and assets from the past) (Tubadji 2012; 2013). Our model builds on existing evidence that living culture and Bohemians are associated with creativity and mind plasticity, while cultural heritage is the more rigid component, linked to certainty-building feelings of identity, but associated with less creativity and less innovation (Tubadji and Montalto 2020). Based on this, CBD postulates that:

1) Living culture consumed through cultural participation is the source of mental health resilience
2) Cultural heritage is a source of stability of one's perception for identity, but needs to be in amounts lower than living culture in order to allow for brain plasticity[2].
3) Cognitive bias towards under-valuation of culture in its indirect cultural and economic value for society includes the oversight of culture as a tool for prevention of mental health disturbance during negative shocks to the economy.

The mechanism behind the above CBD postulates can be expressed as a micro-economic utility model that underlies the behaviour of agents in the socio-economic system:

$$U = f(C, Y, D)\,, \qquad (1)$$

where U is the utility of the consumer, which can be more generally defined as their life satisfaction and mental health condition (assuming that happier people are in a better state of satisfaction with life and in a better mental health); C is the cultural valuation of life vector, which stands for the need for culture, inspired by our love for certainty; this is strongly positively associated with cultural heritage and identity through the mechanism of love for homogeneity (as all mammals we feel more secure when surrounded with our own herd and its cultural symbols (Hall 1966); it is also related to living culture through the brain plasticity that cultural participation increases and generates potentials for resilience under stress conditions; Y is the economic valuation of life vector, which unites income of the person, occupation and/or their educational level; D is demographic characteristics such as gender, age, marital status, having children etc.).

In negative socio-economic shocks – such as the COVID-19 – we known that on aggregate level cultural hysteresis differs across places due to cultural identity. For example, in the economic crisis 2007, Greek youth became less entrepreneurially inclined, while German youth became more so (Tubadji et al. 2019). We argue here that across individuals from the same cultural background, the response to the shock also differs due to their differences in mental health resilience. It is known that such differences exist among entrepreneurs (Hopenhayn and Vereshchagina 2003; Ucbasaran, Westhead and Wright 2009). Yet, it is assumed this variation is exogenous. Our study argues that mental resilience is first

[2] This CBD postulate is very closely related and building on the work on cultural heritage and social change effects stemming from the important contributions by Chang (2014).

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varying across the entire population (not just entrepreneurs) and second, this variation is not exogenous. It is endogenous because the cultural participation is a tool through which the mental health resilience of the individuals can be and is intervened[3]. Therefore, our main expectation is that cultural participation affects the C component of model (1).

4. Happiness in COVID-Times: And Empirical Operationalization of the CBD Model

Data

The data used for the main part of this study is based on a pilot survey disseminated online in the beginning of the pandemic COVID-19 period, namely 23rd till 29th March 2020. The survey has five sections, requesting information on: (i) happiness and life satisfaction , (ii) exposure to art and cultural consumption (iii) exposure to human interaction (iv) social capital and altruism (v) experiment with impact of art on happiness in COVID-19 times. The questionnaire contains also questions about demographics on individual and household level.

Our main outcome variable of interest is happiness, in its short and long-term (life-satisfaction) dimensions. The former is measured through question about level of happiness on Likert scale from 1 to 10 about happiness feelings experienced on the day of responding to the survey. The long-term form of happiness is measured according to three alternative concepts of long-term happiness – i.e. the three key concepts for life-satisfaction, flow and meaning. These are based respectively on (Kahneman and Krueger 2006; Frey and Stutzer 2018; Weimann, Knabe and Schöb 2015). We have an additional special control variable that may affect the report on happiness in the moment of response (as noted relevant by Levinson 2013) – namely, a control for weather conditions.

Our culture related variables have three dimensions. First, we have information about the country of origin of the respondent (most responses coming from the UK, USA or Japan). As these are countries that experienced serious blow from the pandemic, we consider our data relevant for the intended pilot study. Second, we have data on cultural participation – both public and private versions of it. We have participation in 'publicly' provided free online access to cultural heritage (museum visits) and living culture experiences (concerts) (i.e. with no incurred economic cost and therefore supposedly the economic valuation does not differ and can be regarded as at a ceteris paribus condition). We have information on private experiences related to culture such as singing with others (as the behavioural pattern was from Wuhan communities (BBC 2020), throughout Italy (Kearney 2020) and also compassionate citizens from neighbouring countries (Xinhua 2020) singing to support each other's moral during the lockdown). Third, we have information about past cultural consumption behaviour related to frequency of visit to live cultural events[4]. This data helps us to distinguish between the effects of living culture and cultural heritage i.e. the different components of culture, as well as the temporal difference in culture as a tool for emergency alleviation or for long-term prevention of mental health crisis through breeding psychological resilience among the members of the society.

[3] In essence, this is the other side of the coin of the Marxist argument that culture can be used as a tool for power over the masses. However, we adopt a more behaviour economic and nudge-policy making implications perspective here.

[4] We have also a survey question about past cultural heritage related consumption but there was too little variation in the responses to use the variable in our analysis.

We have also a second outcome variable of interest which stands for the happiness (or readiness and propensity) of the people to help other people. We have data on propensity to help a stranger in the past and during the pandemic period. This allows us to measure the change in social capital propensity due to the loss of certainty under the COVID-19 pandemic shock.

A bunch of socio-demographic characteristics such as age, gender, level of education, marital status, number of people in household, number of children in household, are available as control variables. All variables used in the analysis of this study are presented with definitions and descriptive statistics in Appendix 1. The full questionnaire is available as Appendix 2.

Finally, we have aggregate data from Google trends regarding searches in Google about the validated in positive psychology word 'anxiety', which stands for the mental health state of the searching individual, as well as the self-explained word 'death'. We use these linguistic signifiers of meaning and mental health on aggregate level and link them to indicators of socio-economic development (in this case public spending on cultural services). This is known as the linguistic narrative economics of meaning CBD approach (see Tubadji 2020; Tubadji, Pattitoni and Nijkamp 2020 for more details on this approach). It has been applied on aggregate level to study mental health and public policy during the pandemic periods across countries (Tubadji, Boy and Webber 2020). Here, it is used only as a validation and generalizability check for our results. We compare through this method the anxiety levels experienced in Germany, a country which both traditionally and now during the COVID-19 increasingly supports its art sector, as opposed to the rest EU countries, which gradually support the cultural sector less and less. While our inference relies on associations and should be subject to further analysis, it clearly illustrates which countries experienced higher anxiety during the same pandemic shock.

Method

There are three main sub-types of cultural impacts that need to be tested according to the above stated CBD postulates. These three impacts relate to the effect of the cultural consumption (living culture and cultural heritage) on happiness in COVID-19 times, the difference between past and present consumption of culture on happiness in COVID-19 times, the difference between public offer consumption and private engagement in culture as a hobby and the effect of culture on happiness in pandemic times. Additionally, we would like to test the relationship between the impact of cultural consumption and the pro-social capital propensity of the individual during the pandemic period. These expected relationships can be stated as four main testable hypotheses as follows:

H01: Present cultural consumption impacts individual happiness during COVID-19 times.

H02: Past cultural consumption impacts individual happiness during COVID-19 times.

H03: Present cultural consumption impacts individual propensity to social capital during COVID-19 times.

H04: Past cultural consumption impacts individual propensity to social capital during COVID-19 times.

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Each of these hypotheses can be tested through alternative operationalization of culture as follows. To distinguishing public and private aspects of the experienced cultural participation and consumption, the public one will be operationalized through art event visits (in pre-pandemic time) or online art consumption during pandemic times. The private aspect will be operationalized through personal engagement in art hobbies before or during the pandemics as well as singing with others. These variables can be used separately as determinants for the outcome of interest and shall be ultimately horse-raced against each other in one multiple regression. The most parsimonious latter specification will be reported in the results section.

In a first step, for testing hypotheses H01 and H02, we estimate a multiple regression using OLS with robust standard errors. This means that we operationalize model (1) in the following manner:

$$Happiness\_COVID19 = a + \beta_1 C1 + \beta_2 C2 + \beta_3 C3 + \beta_4 Y + \beta_5 X + e_1 \qquad (2)$$

where self-reported happiness during COVID-19 times is U, the component C is quantified in a filigree manner to reflect: C1 - the different types of cultural impact that we are interested in, (namely the type of event watched online – related to concert (living culture) or museum (cultural heritage); C2 - the past engagement in cultural activity based on public offer such as concert, theatre, etc.; C3 - singing alone activity during COVID-19 times which does not depend on any economic or public provision other than the cultural valuation of the cultural experience by the individual); Y is alternatively quantified either with self-reported income or with degree of education, as these might be strongly correlated. X is a vector of our control variables includeing demographics such as age, gender, marital status, information on whether the individual has children, type of area one lives in (rural or urban).

Similarly, to test H03 and H04, we assume that propensity to social capital, altruism and reciprocity can be regarded as utility, or happiness to help a stranger during COVID-19 times. This has been seriously analyzed in close relationship to resilience as well elsewhere (Trosper, 2009; Zahran et al. 2011). Therefore, we use again model (1), operationalized this time as follows:

$$Social\_Capital\_COVID19 = a + \beta_1 C1 + \beta_2 C2 + \beta_3 C3 + \beta_4 Y + \beta_5 X + e_2 \qquad (3)$$

where U is quantified here as a propensity to help a stranger during COVID-19 times, as well the eventual decrease or increase of this propensity in comparison to the individual's propensity to do so in the past. The explanatory variables are the same as in model (2).

We estimate model (2) using an OLS with country fixed effects to account for the cultural differences and state policy for handling the pandemics (which is studied elsewhere as an impact of interest with regard to mental health of the population (see Tubadji, Boy and Webber 2020)). To estimate model (3), we use an OLS when we employ the levels of the variable regarding social capital. When we estimate model (3) with dependent variable the decrease or increase of social capital in comparison to the 'pre-pandemic' social capital propensity of the individual, we use a Probit model as these are binary outcomes. In order to account for the cultural heterogeneity across space, we use country dummies to account for the fixed-effects in both OLS and Probit estimations, and across all our estimations discussed hereafter.

In a second step, we delve into the endogeneity of the cultural consumption. We explore the straight-forward relationship between potential pockets of endogeneity and life satisfaction in general. To do so, we consider pockets of endogeneity of consumption and life-satisfaction differences such as: income, education, type of place of living (urban vs rural). We also cross-check whether the consumption of culture in normal times acts as a source for people's preferences for art as a hobby. Further, we disentangle the relationship between expectations for the end of the pandemic and the cultural consumption prior to the pandemic, in order to establish whether mental resilience in its aspect of positive prospect to the future are statistically associated.. Pearson pairwise correlation coefficients are considered with regard to all these additional variables and past cultural consumption.

In a third step, we explore the heterogeneity of the happiness reported in COVID-19 times. We cross-check whether there is similar heterogeneity of the life satisfaction, when measured with our alternative three measure of happiness. In a presence of a heterogeneity a sample selection model requires to be applied.

In a fourth step, we explore the pre-selection into being happy during COVID-times based on the previous consumption of culture and the level of happiness during COVID-19 reported by the individual. To do so, we test model (2) and (3), by using a Heckman sample selection model. In its first equation, we model preselection, explaining above average happiness as a function of past consumption of culture. We obtain a correction term from this estimation and use it as an additional regressor in model (2) and model (3), respectively. The second equation of the Heckman selection model is the thus augmented with a correction term model (2) or model (3), depending if we want to test H01&H02 or H03&H04, as described above.

Finally, in a fifth step, in order to establish the link between the individual mechanism of culture as a tool for resilience and the aggregate effect of it for the entire population, we use some aggregate data for daily search of anxiety related terms in Google. We trace the development of the search word frequency time in several European countries and relate it to the public spending on culture in these countries during the non-pandemic period. A more extensive exploration of the effect of public policy on mental health on aggregate level is available in Tubadji, Boy and Webber (2020). Its exact relationship to public spending on culture is still a matter of further exploration. It will be demonstrated worth the effort of further exploration if the here investigated mechanism on individual level is found to be indeed present in reality.

Results

Culture and Happiness in COVID-19 Times

Table 1 below presents four specifications. Specification 1 represents estimation for happiness in COVID-19 times, Specification 2 explains level of social capital propensity in COVID-19 times, while Specification 3, and 4 explain respectively decrease and increase in the propensity to social capital in comparison to the pre-pandemic period. As the latter two specifications are estimated with Probit model, we present also marginal effects at means.

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As seen from Table 1, neither the economic-valuation-free art activities at home, nor the economically free online living culture or cultural heritage is associated with the happiness of the individual in the pandemic period. However, the pre-pandemic consumption seems to exhibit a very strong positive association with the mental resilience of the person under shock conditions. When we look at the propensity to social capital, there is no effect on the levels in Specification 2, because the pandemic increased the pro-social propensity of some people and decreased it with others. This differs across countries and across individuals[5]. When we look at the increase in pro-social propensity, we see that the spontaneous cultural expression of singing with others during the pandemics has a positive association with the pro-social behaviour of the individual and relates to less often loss of pro-social propensity. This is a clear sign that engaging in a cultural practice during the negative shock is associated positively with the social capital propensity during the pandemics. Meanwhile, women seem to be associated with higher loss of pro-social propensity due to the increased uncertainty during the pandemic. As further statistical check demonstrated (results available upon request from the author), this is however due to women having a higher propensity pre-pandemic and therefore the corresponding loss due to the shock is higher for women during the pandemic.

In short, the cultural consumption pre-pandemic seems to increase the individual resilience, while the cultural practice during the pandemics affects (more precisely, increases and even prevents loss of) the pro-social behaviour during the pandemic. The strongest predictor of mental health resilience seems to be the consumption of culture before the pandemic period with a coefficient of impact on happiness amounting to 20%. It seems therefore that we cannot reject our H01 and H03, while the other two hypotheses do not find support in our findings. Meanwhile however, it seems that both past and present cultural consumption have their associations with different aspects of the mental health reaction of the individual during pandemic period. This pointing that culture could be both a tool for: (i) prevention for individual mental health and (ii) resilience of social capital.

[5] We estimated a Probit also for no change of the propensity to help. We found that no change is negatively associated with online museum during the pandemic, which we interpret as the power of culture to induce change in pro-social behaviour.

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Table 1: Happiness and Social Capital during COVID-19

method	OLS						Probit											
dep.var.	*happy_during_COVID-19*			*help_others_during_COVID-19*			*increase_help*						*decrease_help*					
	coef.	t-value		coef.	t-value		coef.	z-value		dy/dx	z-value		coef.	z-value		dy/dx	z-value	
art_activity_covid	0.316	0.87		0.618	1.08		0.171	0.52		0.030	0.52		0.020	0.08		0.008	0.08	
online_concert	0.133	0.30		-0.294	-0.40		0.307	0.75		0.054	0.72		-0.111	-0.32		-0.044	-0.32	
online_museum	-0.076	-0.14		-0.833	-0.93		0.744	1.59		0.130	1.63		0.277	0.73		0.110	0.73	
old	0.447	0.71		1.055	0.89		-0.113	-0.22		-0.020	-0.22		-0.046	-0.10		-0.018	-0.10	
female	-0.173	-0.45		-0.222	-0.41		-0.027	-0.08		-0.005	-0.08		0.592	2.39	*	0.235	2.39	*
city	-0.006	-0.01		-0.874	-1.24		0.690	1.59		0.121	1.63		0.291	0.98		0.115	0.98	
high_edu	0.685	1.14		0.671	0.81		0.325	0.81		0.057	0.81		0.114	0.29		0.045	0.29	
married	0.395	0.67		-0.500	-0.55		-0.105	-0.23		-0.018	-0.23		-0.165	-0.43		-0.065	-0.43	
children	0.213	0.35		0.018	0.02		-1.180	-1.99	*	-0.206	-1.83		0.362	0.75		0.144	0.75	
sing_with_others	0.475	1.25		0.472	0.87		0.726	2.25	*	0.127	2.08	*	-0.741	-2.73	**	-0.294	-2.73	**
sunny	0.030	0.07		1.059	1.65		-0.681	-2.03	*	-0.119	-1.84		-0.102	-0.37		-0.041	-0.37	
insured	-0.238	-0.46		-0.888	-1.16		-0.465	-1.40		-0.081	-1.37		0.197	0.64		0.078	0.64	
cultural_consumption_pre-pandemic	0.203	2.94	***	0.108	0.96		0.073	1.30		0.013	1.31		-0.059	-1.18		-0.024	-1.18	
USA	-0.217	-0.34		-1.097	-1.06		-1.056	-2.22	*	-0.185	-2.26	*	0.307	0.77		0.122	0.77	
UK	0.770	0.79		-0.535	-0.43		0.468	0.76		0.082	0.74		0.122	0.22		0.048	0.22	
Japan	1.335	2.10	*	-0.687	-0.55		-0.327	-0.63		-0.057	-0.63		-0.258	-0.53		-0.102	-0.53	
Sweden	1.520	2.01	*	-2.005	-1.27		-0.330	-0.42		-0.058	-0.42		-0.037	-0.06		-0.014	-0.06	
Spain	0.311	0.27		0.582	0.44		-0.292	-0.35		-0.051	-0.35		-0.512	-0.72		-0.203	-0.72	
Italy	0.621	0.73		-0.545	-0.34		0.071	0.09		0.012	0.09		-0.172	-0.22		-0.068	-0.22	
Albania	0.397	0.37		2.508	1.30		0.148	0.18		0.026	0.18		-0.957	-1.20		-0.380	-1.20	
Canada	-0.853	-0.97		-2.431	-1.57		*omitted for collinearity*			*omitted for collinearity*			-0.139	-0.20		-0.055	-0.20	
China	1.523	2.06	*	-1.204	-0.97		*omitted for collinearity*			*omitted for collinearity*			*omitted for collinearity*			*omitted for collinearity*		
Germany	0.574	0.65		1.974	1.72		2.695	3.23	***	0.471	2.71	**	*omitted for collinearity*			*omitted for collinearity*		
_cons	4.544	5.54	***	5.664	4.16	***	-1.107	-1.71					-0.464	-0.89				
N	154			154			145						146					
R-squared	0.27			0.20														
Pseudo R-squared							0.30						0.12					

Notes: The table presents OLS estimations with robust standard errors and country of origin fixed effects.

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Endogenous Sources of Past Cultural Consumption

In order to explore the complex interaction of culture with other factors among the explanatory variables in our models (1), (2) and (3), we engage in simple regressions and pairwise correlation explorations of the cultural consumption in pre-pandemic period and respectively, income, education, life satisfaction (in all the three aspects that we have discussed above), preference for art as a hobby and expectations for the end of the pandemics as yet another aspect of mental health resilience. Tables 2 a, b & c below present the results of these further explorations.

Table 2a presents the correlation coefficients. We see that past cultural consumption has a somewhat positive correlation with the hobbies of the person but with no other potential source of economic or demographic endogeneity such as income or gender. Yet, it has a clear highest correlation with the expectation for the length of the lock down period. This means that cultural consumption from pre-pandemic period can be expected to be a strong explanatory factor for the response of the individuals to the shock of the pandemic in terms of happiness and expectations for the future.

Table 2b presents the relationship of the demographic and behavioural characteristics from model (2) as explanatory factors for the general long-term happiness of the individual. The intention here is to crosscheck whether the factors used for explaining happiness in the period of the pandemic are not associated with the general state of happiness of the individual, rather than being predictive for the state during pandemics. The reasons why the cultural consumption during pandemics is excluded from these regressions is the logical causal direction. As the consumption during pandemic is a behaviour that follows temporally the general state of happiness of the people it cannot explain it. We find that cultural consumption from the pre-pandemic period is clearly associated with long-term individual happiness.

Table 2c shows that there is almost no other variable that significantly correlates with the past consumption of culture except the happiness of the individual and the present expectations for the end of the pandemic crisis. This is a strong indication for the exogeneity of the cultural consumption from past period, especially with regard to economic influences. Therefore, culture seems to have acted as a plausible tool for mental health prevention in the group under investigation. Also, we see that the more culture was consumed in the past, the shorter the expected lockdown period is. This result highlights the previously commented high correlation in Table 2a between cultural consumption and expectations. It suggests that an important association exists between the past cultural consumption and the expectations and mental resilience of an individual under shock conditions. This justifies looking separately at those people who had a higher cultural consumption and those who had a lower one in the pre-pandemic period as two potentially different groups.

Table 2a: Endogenous Sources of Happiness during COVID-19 - correlations

	cultural_ consumption_ pre-pandemic	expect	income	high_edu	female	city	hobby_art
cultural_ consumption_pre-pandemic	1						
expect	-0.16	1					
income	0.04	0.06	1				
high_edu	0.05	-0.07	0.32	1			
female	-0.03	-0.04	-0.20	-0.18	1		
city	-0.01	-0.11	0.13	0.04	-0.07	1	
hobby_art	0.15	0.02	-0.11	-0.11	0.01	-0.09	1

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Table 2b&c: Endogenous Sources of Happiness during COVID-19 – regression estimates

dep. var.	*satisfied_with_life*		*smile_often*		*emition_in_work*	
	coef.	t-valeu	coef.	t-valeu	coef.	t-valeu
old	-0.050	-0.11	0.268	0.49	0.393	0.93
female	0.234	0.75	0.227	0.65	0.025	0.07
city	0.053	0.15	0.086	0.22	0.088	0.19
high_edu	0.222	0.59	-0.229	-0.47	0.366	0.67
married	0.923	1.92	0.425	0.80	0.272	0.65
children	0.587	0.89	0.206	0.28	0.575	1.26
sing_with_others	0.357	1.28	0.295	0.77	0.620	1.89
sunny	-0.050	-0.16	0.095	0.25	-0.386	-0.99
insured	-0.042	-0.09	0.104	0.22	-0.301	-0.67
cultural_consumption_pre-pandemic	0.199	3.24 ***	0.219	3.27 ***	0.205	2.97 **
USA	-0.622	-1.25	0.406	0.72	0.175	0.34
UK	-0.021	-0.03	0.820	1.24	0.696	0.95
Japan	0.551	0.93	0.512	0.77	1.064	1.70
Sweden	-0.073	-0.09	1.823	2.35 **	0.671	0.58
Spain	0.176	0.22	0.133	0.11	1.413	2.11 *
Italy	0.163	0.23	-0.330	-0.34	1.691	2.09 *
Albania	0.452	0.72	0.205	0.21	1.492	1.77
Canada	-1.724	-2.49 **	-0.301	-0.24	-0.274	-0.27
China	1.029	1.82	1.448	1.77	0.970	1.03
Germany	-0.122	-0.21	-0.038	-0.06	-0.026	-0.04
_cons	6.086	7.58 ***	5.298	6.22 ***	5.098	6.54 ***
N		154		154		154
R-squared		0.29		0.14		0.25

dep. var.	*expect_lockdown_long*		*cultural_consumption_pre-pandemic*											
	coef.	t-value	coef.	t-value	coef.	t-value	coef.	t-value	coef.	t-value	coef.	t-value	coef.	t-value
cultural_consumption_pre-pandemic	-0.570	-2.33 **												
income			0.044	0.62									0.043	0.57
high_edu					0.288	0.59							0.302	0.59
female							-0.149	-0.40					-0.076	-0.20
city									-0.038	-0.09			-0.006	-0.01
hobby_art											0.685	1.84 *	0.731	1.95 *
_cons	9.712	7.33	2.808	6.64	3.008	14.48	3.137	11.39	3.088	8.39	2.672	9.81	2.394	4.00
N		154		154		154		154		154		154		154
R-squared		0.027		0.002		0.002		0.001		0.000		0.021		0.027

Notes: The table presents OLS estimations with robust standard errors and country of origin fixed effects

Heterogeneity of Happiness in COVID-19 Times

Using histograms to explore the density of the statistical behaviour of our happiness and life satisfaction data allows us to delve deeper into the process under analysis. Namely, Figure 1 below shows the density of the life satisfaction (quantified through our three different measures) and the happiness and propensity to help others in COVID-19 times.

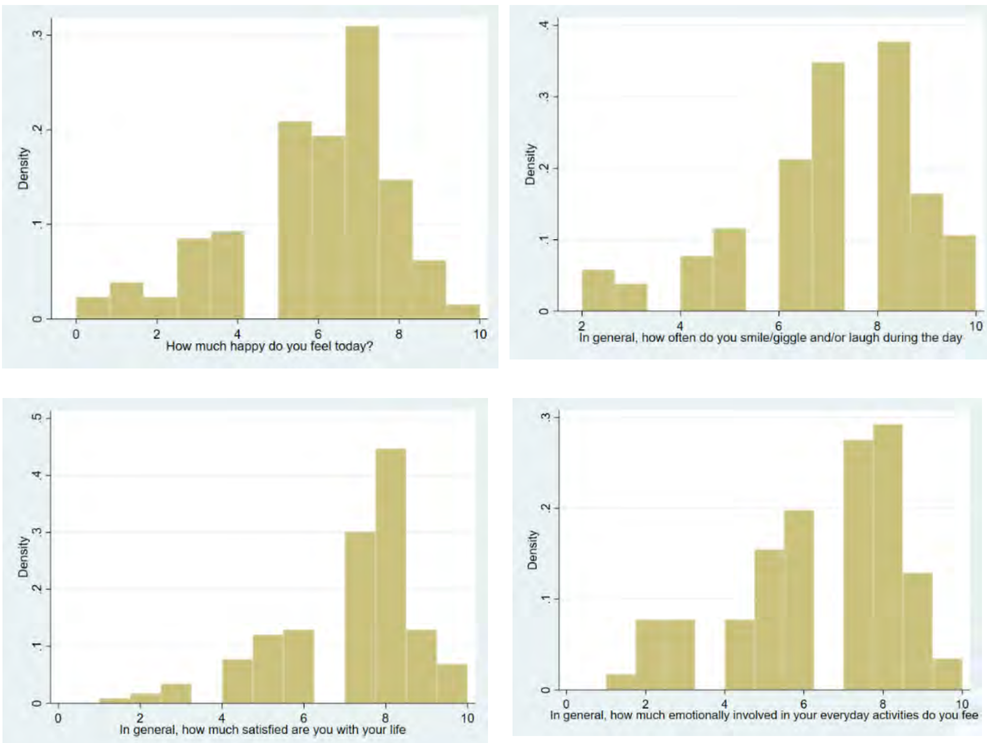

Figure 1: Distribution of Daily Happiness during COVID-19

Notes: The histogram presents the density of the response to 4 alternative happiness-related questions, measured on a Likert scale from 1 to 10. Namely, these questions are clockwise from top left: 1) 'How much happy do you feel today?', 2) 'In general, how often do you smile?', 3) 'In general, how much satisfied are you with your life?' and 4) 'In general, how much emotionally involved in your everyday activities do you feel?'.

As seen from Figure 1, there is a clear presence of heterogeneity in our outcome variables of interest, namely a group of low and a group of high happiness. This pattern seems to be related with long terms life satisfaction in a similar manner, although the division is most clear for the happiness during the pandemic period. Finally, we have learned from the above preceding results section that past consumption of culture is strongly related to the happiness levels. Moreover, it is associate with preferences for cultural consumption but not with any other potential factor for cultural consumption such as income or education etc. previously discussed. Therefore, we have statistical justification for exploring a sample selection bias in the happiness in COVID-19 times as potentially driven by the past consumption of culture.

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Cultural Preselection for Happiness in COVID-19 Times

We estimate three specifications of model (1) through the use of a Heckman sample selection model. All specifications model the sample selection based on the past consumption of culture. However, Specification 1 has as a dependent variable the level of happiness during COVID-19 period, Specification 2 & 3 have as a dependent variable the propensity to help a stranger (i.e. a proxy for social capital) as a dependent variable. The pre-selection is respectively done in Specification 1 vis a vis being above average of the mean of happiness during COVID-19 period; in Specification 2 the preselection regards having your propensity to help others decreasing and in Specification 3 having your propensity to help others during COVID-19 increasing in comparison to the usual such propensity in pre-pandemic times. The results are presented in Table 3 below.

Table 3 shows that indeed the individual happiness during pandemic times and the pro-social happiness to help others (propensity towards pro-social behaviour) is always strongly associated with a pre-selection based on the pre-pandemic consumption of publicly provided cultural goods and services. That does not apply for the decrease of social capital which is not associated in a statistically significant manner with the cultural consumption from the past. Yet, the sign of impact of past cultural consumption on the decrease of social capital seems to be indicating negative preselection for decrease of social capital. This is consistent with the fact that we find positive preselection effect from the cultural consumption for happiness and increase of social capital.

In terms of the corrected for pre-selection regressions, we see that our model explains best the increase of pro-social behaviour during the pandemic. The increase seems positively associated with singing with others during the lockdown and the decrease is clearly negatively (though not significantly) associated with this variable. Meanwhile, our results for gender from the Probit model are confirmed here. Women are found less likely to venture into pro-social risky behaviour during the pandemic. Interestingly, insurance becomes important positive predictor for helping others during the pandemic period. Even more importantly, while we saw that singing with others increased the change towards pro-social behaviour and decreased the likelihood to decrease pro-social behaviour, when we take the pre-selection by past cultural consumption into account, it seems that the people who sang with others were less likely to help others per se during the pandemic period. This clearly indicates that cultural consumption in the past is associated with a boost of the pro-social behaviour of those less likely to help others during uncertainty.

These results suggest that past consumption of culture can act as a shield for the individual mental health (expressed in higher levels of happiness for those having been on a higher cultural consumption level before the pandemic burst out). Moreover, cultural consumption seems not only associated with preservation, but also with a significant enhancement of the mental resilience and propensity to help others, i.e. culture seems able to act as a potential tool for boosting of social capital during times of negative external shocks such as the COVID-19 pandemics.

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Table 3: Cultural Pre-Selection for Happiness during COVID-19

dep.var.	*happy_during_COVID-19*					*help_others_during_COVID-19*				*help_others_during_COVID-19*					
	coef.	z-value		dy/dx	z-value	coef.	z-value	dy/dx	z-value	coef.	z-value		dy/dx	z-value	
art_activity_covid	0.324	1.20		0.324	1.20	0.212	0.18	0.061	0.18	1.445	0.96		1.429	0.96	
online_concert	0.073	0.22		0.073	0.22	-0.100	-0.06	-0.029	-0.06	3.655	1.78		3.615	1.74	
online_museum	0.054	0.13		0.054	0.13	-1.427	-0.81	-0.413	-0.74	-2.304	-1.49		-2.279	-1.48	
old	0.340	0.70		0.340	0.70	0.866	0.29	0.251	0.28	-6.967	-1.64		-6.890	-1.62	
female	-0.223	-0.77		-0.223	-0.77	-0.671	-0.55	-0.194	-0.52	-3.385	-2.08	*	-3.347	-2.04	*
city	0.207	0.64		0.207	0.64	-1.307	-0.97	-0.378	-0.83	-3.598	-1.43		-3.558	-1.41	
high_edu	0.508	1.43		0.508	1.43	2.049	0.99	0.593	0.87	-0.857	-0.52		-0.847	-0.52	
married	0.029	0.07		0.029	0.07	-1.748	-0.87	-0.506	-0.78	1.975	0.88		1.954	0.88	
children	0.036	0.06		0.036	0.06	0.785	0.27	0.227	0.27	2.591	0.97		2.563	0.95	
sing_with_others	0.308	1.20		0.308	1.20	-0.180	-0.12	-0.052	-0.12	-3.056	-2.00	*	-3.023	-1.99	*
sunny	-0.118	-0.40		-0.118	-0.40	1.276	0.91	0.369	0.80	0.874	0.47		0.864	0.47	
insured	0.141	0.40		0.141	0.40	0.012	0.01	0.004	0.01	7.911	2.27	*	7.825	2.24	*
USA	-0.070	-0.16		-0.070	-0.16	2.041	0.93	0.591	0.83	-4.884	-2.45		-4.830	-2.41	*
UK	0.755	1.42		0.755	1.42	2.280	0.77	0.660	0.73	3.342	1.44		3.305	1.44	
Japan	0.232	0.50		0.232	0.50	0.487	0.19	0.141	0.19	-5.523	-2.58	**	-5.462	-2.51	**
Sweden	0.397	0.68		0.397	0.68	0.700	0.22	0.203	0.22	5.403	1.58		5.343	1.56	
Spain	0.334	0.52		0.334	0.52	2.112	0.59	0.612	0.56	5.633	1.33		5.571	1.32	
Italy	-0.441	-0.56		-0.441	-0.56	2.452	0.60	0.710	0.57	10.199	1.47		10.087	1.47	
Albania	0.369	0.44		0.369	0.44	1.694	0.32	0.491	0.31	1.317	0.44		1.303	0.44	
Canada	*omitted for collinearity*			*omitted for collinearity*		2.422	0.66	0.701	0.64	*omitted for collinearity*			*omitted for collinearity*		
China	0.257	0.35		0.257	0.35	2.554	0.85	0.740	0.78	*omitted for collinearity*			*omitted for collinearity*		
Germany	-0.218	-0.28		-0.218	-0.28	0.000		0.000		-2.753	-1.05		-2.723	-1.04	
_cons	7.427	7.22	***			-3.587	-0.52			12.552	2.04	*	0.000		
sample selection for:	***really_happy***					***decrease_help***				***increase_help***					
cultural_consumption_pre-pandemic	0.099	2.17	*			-0.070	-1.55			0.102	2.09	*			
_cons	-0.031	-0.18				0.129	0.76			-1.298	-6.25	***			
/mills															
lambda	-1.576	-1.28				6.854	0.95			-4.171	-1.26				
rho	-1					1				-1					
sigma	1.576					6.854				4.171					
N	154					154				154					

Notes: The table presents a Heckman selection model, where respondents to the survey are self-selected into higher happiness during COVID-19 times according to their preference to consume culture more often during non-pandemic times.

National Cultural Policy and Happiness in COVID-19 Times

In a final step, to help generalize more safely the findings from the above explored CBD micro-economic mechanism, we aim at illustrating here the aggregate relationship between the cultural spending done over the period 2001-2018 and the mental health resilience of the countries on aggregate level. We do this by looking at respectively the governmental expenditure on cultural service for the period 2001-2018 (in Euros and in % of total national GDP) and compare this with the intensity of using the search word death during the COVID-19 period in terms of mental health distortion through increased anxiety[6].

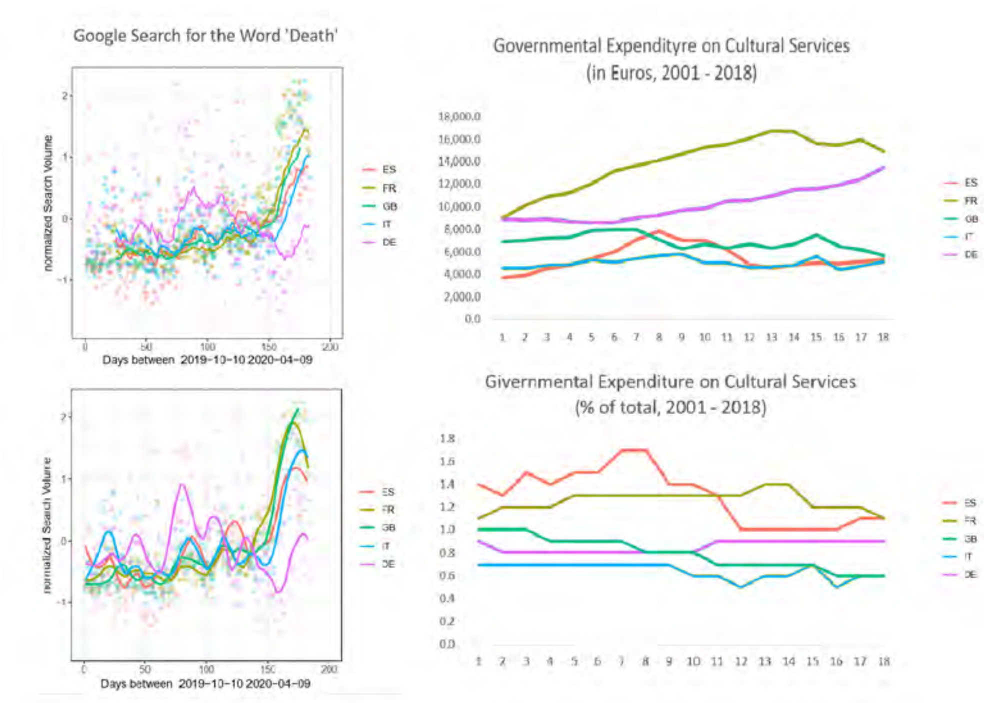

Figure 2: Anxiety from Fear of Death & Country Cultural Policy

Notes: The figure uses Google trends data about search for the word 'death' during the COVID-19 pandemic period 01/01/2020 – 09/04/2020. Data on cultural policy spending is obtained from Eurostat.

As seen from Figure 2, for the six countries Italy, Germany, Spain, France and the UK (the countries with some of the biggest cultural sectors in the EU), Germany is the only country that increased its governmental spending both in terms of percentage and in terms of actual amount in Euros during the period 2001-2018. All other countries either decreased the spending or are at a lower level than Germany in real numbers spent on the cultural sector.

[6] The author thanks Frederic Boy, Swansea University, for providing the linguistic mental health data on aggregate level.

Again, as visible from Figure 2, Germany seems to be the country with the highest mental health resilience in response to the pandemic. During the period 1st January to 9th April 2020, this is the country where the increased search for the word DEATH is the lowest.

Clearly, this is only descriptive aggregate level illustration of the tendencies. Yet, there is evidence on the effect of public policy per se on mental health during the pandemics, which takes into consideration the number of deaths and other COVID-19 related state measures following the methodology of Tubadji, Boy and Webber (2020) and related studies such as Armbruster and Klotzbücher (2020). Meanwhile, the above figures demonstrate that there really exists some at least anecdotal for the moment evidence in the data that the here explored micro-mechanism (of impact of culture on mental health of an individual during the pandemic period) seems to have a potentially serious impact on aggregate level of public mental health as well. Thus, New Zealand might as well be a pioneer in public policy in pandemics also with regard to how it handles the cultural sector.

5. Conclusion

The current study looks at the role of pre-pandemic and during pandemic consumption of culture and examines its impact on both individual mental health and resilience of pro-social propensity as fundamental for maintaining a healthy social climate. The study explores the micro-mechanisms of cultural impact of both organized and individual art engagement, as well as the role of living culture and cultural heritage. In a final step, the paper cross-checks the generalizability of the findings regarding the relationship between cultural services provision and the mental resilience of the general public during the pandemic on aggregate level.

The findings reveal that the hypothesis that past cultural consumption affects pandemic-period happiness levels and that during pandemics art engagement enhances pro-social behaviour cannot be easily rejected. The study delves in the direct associations behind these hypothesis as well as in detailed exploration of pairwise relationships that clarify the concerns about endogeneity versus exogeneity of the cultural consumption. Next, the outcome variable happiness is itself examined for heterogeneity, which seems to be strongly associated with individual cultural consumption before the pandemic period. Thus, using a Heckman sample selection model, we find a sample selection bias, where people are preselected to more happiness during the pandemics based on higher consumption of culture pre-COVID-19 period. The preselection based on culture cannot be rejected. It also seems to hold true in the cases of increase of the propensity towards pro-social behaviour.

The economic meaning of the results from this study points that consumption of culture in ordinary periods can serve for creating a mental health immune system, which ensures higher levels of mental health and happiness during negative external shocks such as the pandemic COVID-19. Cultural engagement seems also a potential a way to foster the mental health of people during crisis periods and to enhance the pro-social behaviour during such challenging times.

Our findings demonstrate that culture is associated both with the individual and the community-related mental health in micro-economic behaviour. As we know from the Agent Based modelling of Schelling (1969, 1978), the small change in the micro-behaviour can account for major change of the development of the entire socio-economic system. Thus, identifying clearly association between culture and the small changes in individual mental health and the state of mind towards the community on micro level, we provide a clear illustration for the potential high significance of this sector on macro level for the aggregate cultural milieu (i.e. for general public's mental health). On aggregate level, culture is of course well known to be a major factor for the socio-economic development of a place (as well known from Heilbrun 1992; Guiso, Sapienza and Zingales 2006, Tabellini 2010, Ottaviano and Peri 2006, Alesina, Tubadji and Nijkamp 2015; Tubadji, Nijkamp and Angelis 2016; Giuliano and Nunn 2013; Alesina and Giuliano 2015;, Sacco et al. 2013; Sacco 2020; Tubadji 2012, 2013, 2020; Shiller 2017, 2019). Yet, to cross-check the validity of the effect on aggregate level for mental health in specific, we show the difference in mental health anxiety experienced in different countries, having different cultural policy approaches. This anecdotal evidence on aggregate level is consistent with the findings based on our examined micro economic model.

The broader policy implications of the results from the current paper suggest that policy makers could use the nudging techniques already used in policy making for supporting and promoting health prevention practices by nudging people to consume more culture and to engage with cultural hobbies. There was such a cultural policy precedent in the past in the form of the Banner of Peace Initiative, organized and lead by Ludmila Zhivkova, Minister of Culture in Bulgaria, with the support of UNESCO, which was dedicated to nudging children around the world to engage with art for promotion for international peace. The current study suggest that this might as well have been a good practice, given the findings about pro-social behaviour and culture. Clearly, the more prone to cooperation and social capital in shock periods people are, the more prone to maintaining peace they will be. This is potentially a further long-term implication and extension of the current study.

Intended next waves of survey following the methodology of our pilot survey will take place close to the end of the lockdown period, after the removal of the lockdown, as well as six months after the end of the lock down period. Better statistical power and causal analysis will be potentially possible based on these further data collection efforts.

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Appendix 1: Descriptive Statistics of Main Variables

Model Component	Variable	Motivation	Obs	Mean	Std. Dev.	Min	Max
Happiness	*happy_during_COVID-19*	how much happy the respondent feels on the today of survey	154	5.8	2.3	0	10
	satisfied_with_life	life satisfaction (how much satisfied are you with your life)	154	7.0	1.8	1	10
	smile_often	savouring life attitude of happiness (how often smiling)	154	6.9	1.9	2	10
	emition_in_work	flow as a measure of happiness (emotion in daily activity)	154	6.3	2.1	1	10
	really_happy	dummy equal to above mean of happiness on day of survey	154	0.6	0.5	0	1
Social capital	*help_relative*	propensity to help a relative during COVID-19	154	7.2	3.1	0	10
	help_friend	propensity to help a friend during COVID-20	154	7.2	2.9	0	10
	help_remote_aquiaintance	propensity to help a remote acquaintance during COVID-21	154	5.7	3.1	0	10
	help_stranger	propensity to help a stranger during COVID-22	154	4.9	3.1	0	10
	help_others_pre-pandemic	propensity to help others measured on a Likert scale 0-10	154	6.2	3.0	0	10
	help_others_during_COVID-19	past propensity to help others measured on a Likert scale 0-10	154	4.9	3.1	0	10
	change_help_others	difference between the past and current propensity to help	154	-1.4	3.5	-10	10
	decrease_help	dummy variable equal to 1 if propensity to help decreased	154	0.5	0.5	0	1
	increase_help	dummy variable equal to 1 if propensity to help increased	154	0.2	0.4	0	1
Expectations	*expect*	expected length of lockdown in number of weeks	154	8.0	8.2	0	72
	toilet_paper	numbe of toilet paper rolls needed	149	3.4	4.5	0	48
Culture	*cultural_consumption_pre-pandemic (living culture)*	frequency of visit to living culture event before the pandemic	154	3.1	2.3	1	10
	cultural_consumption_pre-pandemic (heritage)	frequency of visit to cultural heritage before the pandemic	154	2.3	1.9	1	10
	online_concert	viewing online concert during COVID-19	154	0.2	0.4	0	1
	online_museum	viewing online museum during COVID-19	154	0.1	0.3	0	1
	art_activity_during_COVID19	engaging with art activity at home during lockdown	154	0.5	0.5	0	1
	sing	singing during pandemics period (alone) (dummy variable)	154	0.5	0.5	0	1
	sing_with_others	singing during pandemics period (with others) (dummy variable)	154	0.3	0.4	0	1
Demographics	*income*	income on a Likerts 0-10 scale, if average is 4	154	5.7	2.1	1	10
	high_edu	dummy variable equal to 1 for having a PhD	154	0.2	0.4	0	1
	married	dummy variable equal to 1 if married	154	0.2	0.4	0	1
	children	dummy variable equal to 1 if having children	154	0.2	0.4	0	1
	age	actual age reported by respondent	154	28.8	8.9	18	55
	old	dummy = 1 if above 45 years of age	154	0.2	0.4	0	1
	female	gender dummy	154	0.5	0.5	0	1
	female_art	interaction between gender female and hobby in the arts	154	1.6	2.2	0	10
Other controls	*city*	living in a metropolitan area	154	0.8	0.4	0	1
	hobby_art	having a hobby related to the arts and culture	154	0.6	0.5	0	1
	insured	having a health insurance	154	0.8	0.4	0	1
	sunny	responding to questionnaire on a sunny day	154	0.5	0.5	0	1
Geography	*Albania*	country dumy to serve as fixed effect	154	0.0	0.2	0	1
	Canada	country dumy to serve as fixed effect	154	0.0	0.2	0	1
	China	country dumy to serve as fixed effect	154	0.0	0.2	0	1
	Germany	country dumy to serve as fixed effect	154	0.0	0.2	0	1
	Italy	country dumy to serve as fixed effect	154	0.0	0.2	0	1
	Japan	country dumy to serve as fixed effect	154	0.1	0.3	0	1
	Spain	country dumy to serve as fixed effect	154	0.0	0.2	0	1
	Sweden	country dumy to serve as fixed effect	154	0.0	0.2	0	1
	UK	country dumy to serve as fixed effect	154	0.1	0.3	0	1
	USA	country dumy to serve as fixed effect	154	0.4	0.5	0	1

Notes: The table presents the main descriptive statistics for the variables form the WVS used on individual level in this study.

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Online consumption during the COVID-19 crisis: Evidence from Japan

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The spread of novel coronavirus (COVID-19) infections has led to substantial changes in consumption patterns. While demand for services that involve face-to-face contact has decreased sharply, online consumption of goods and services, such as through e-commerce, is increasing. The aim of this study is to investigate whether online consumption will continue to increase even after COVID-19 subsides, using credit card transaction data. Online consumption requires upfront costs, which have been regarded as one of the factors inhibiting the diffusion of online consumption. However, if many consumers made such upfront investments due to the coronavirus pandemic, they would have no reason to return to offline consumption after the pandemic has ended, and high levels of online consumption should continue Our main findings are as follows. First, the main group responsible for the increase in online consumption are consumers who were already familiar with online consumption before the pandemic and purchased goods and service both online and offline. These consumers increased the share of online spending in their spending overall and/or stopped offline consumption completely and switched to online consumption only. Second, some consumers that had never used the internet for purchases before started to use the internet for their consumption activities due to COVID-19. However, the share of consumers making this switch was not very different from the trend before the crisis. Third, by age group, the switch to online consumption was more pronounced among youngsters than seniors. These findings suggest that it is not the case that during the pandemic a large number of consumers made the upfront investment necessary to switch to online consumption, so a certain portion of the increase in online consumption is likely to fall away again as COVID-19 subsides.

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1 Introduction

People's consumption patterns have changed substantially as a result of the spread of the novel coronavirus (COVID-19). One such change is a reduction of the consumption of services that involve face-to-face (F2F) contact. For instance, "JCB Consumption NOW" data, credit card transaction data provided jointly by JCB Co., Ltd. and Nowcast Inc., show that, since February this year, spending on eating out, entertainment, travel, and lodging have shown substantial decreases. Even in the case of goods consumption, there has been a tendency to avoid face-to-face contact such as at convenience stores and supermarkets. For example, with regard to supermarket shopping, the amount of spending per consumer has increased, but the number of shoppers has decreased. Another important change is the increase in the consumption of services and goods that do not involve face-to-face contact. The credit card transaction data indicate that with regard to service consumption, spending on movies and theaters has decreased substantially, while spending on content delivery has increased. As for the consumption of goods, so-called e-commerce, i.e., purchases via the internet, has shown substantial increases.

It is not surprising that consumers concerned about their health shifted their demand from F2F to non-F2F consumption activities amid the coronavirus pandemic. This trend was also spurred by requests for self-restraint from the national and local governments. The question is what will happen after COVID-19 subsides. Will demand shift back?

There are many who think that the world after the pandemic will be different from before. With regard to personal consumption, too, it has been argued that once demand patterns have shifted, they will not change back.[1] For example, the number of cinemas and theaters has been declining since before the pandemic, reflecting a shift toward the consumption of online content. The pandemic has simply accelerated this development, and it is possible that the pandemic may serve as the death knell for such services, making the demand shift irreversible.

[1]See, for example, the following articles:
`https://www.bloombergquint.com/business/outbreak-pushes-japan-s-shoppers-to-finally-buy-things-online`
`https://www.japantimes.co.jp/news/2020/05/09/business/economy-business/retail-reinvention-coronavirus/#.Xsc38mj7R1w`
WTO (2020) notes that the SARS epidemic in China in 2002-03 spurred the growth of firms such as Taobao, a Chinese online shopping website, and points out that COVID-19 may also bring about a sustained expansion in online consumption. See Clark (2018) for an interesting account of the take off of Taobao in the wake of SARS.

In this study, among these shifts in demand associated with the pandemic, we focus on online consumption and consider whether the demand shifts are irreversible. In order to examine whether or not the shifts are irreversible, it is not enough to look at whether a demand shift took place and, if it did, at its magnitude; it is also necessary to understand the mechanism that has caused the demand shift. In the following, we will investigate, how demand has shifted across different age groups and regions using the credit card transaction data, and based on this, consider whether the causes of the demand shift are irreversible or not.

Online consumption is more convenient than over-the-counter purchases in a number of respects.[2] The first is a reduction in transportation costs in the sense that one does not have to physically go to the store. Transportation cost savings also include cost savings in the sense that one does not have to carry what one bought. The second is the reduction in search costs. The internet is full of different products and services, and the variety of products and services offered is more diverse than that offered at physical stores. There is also a large variety of prices. The internet makes it easy to compare the quality and prices of products one wants to buy. While for the period before the coronavirus pandemic, studies by Dolfen et al. (2019) and Jo et al. (2019) examining the increase in consumer utility (consumer surplus) through the advantages of online consumption such as the reduction in transportation costs and the increase in product variety find that the gain in consumer surplus is equivalent to 1% of personal consumption.[3]

However, if online consumption is so attractive, all consumers should have switched to online consumption regardless of the pandemic; yet, this is not the case. In addition, the degree of adoption of online consumption varies widely across countries and regions and is relatively low in Japan compared to the United States, Europe, China, and South Korea.

Factors that inhibit the spread of online consumption are, firstly, the fixed costs involved in switching to online consumption.[4] Online shopping, needless to say, requires a smartphone or PC as well as internet access. Costs are not limited to these physical upfront investments. It is necessary to learn how to operate, e.g., a smartphone and how to browse websites

[2]For more details on this point, see, for example, Goldfarb and Tucker (2019a, b).

[3]Using data for Japan, Jo et al. (2019) examine the increase in the consumer surplus resulting from e-commerce. Meanwhile, using Visa card data from the United States, Dolfen et al. (2019) measure travel cost savings and the gains from product variety.

[4]For details, see, for example, Cai and Cude (2016).

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and make purchases. Given the need for hard upfront investment as well as soft investment in the form of learning, consumers decide whether to move to online consumption based on a comparison of those upfront investment costs and the benefits of online consumption. The second reason potentially inhibiting the switch to online consumption is concern about handing over information on purchases to stores and firms. For sellers, online purchases by consumers have the advantage that they significantly reduce the cost of tracking buyers. Moreover, they provide sellers with effective means for advertising and price discrimination. Buyers, on the other hand, may be concerned that online purchases may result in the leak of personal information. Consumers with these concerns are strongly reluctant to make online purchases. Third, online consumption gives rise to information asymmetry, where buyers cannot directly check the quality of goods and services. This problem is particularly serious when the quality of products such as fresh food varies widely, or when there is no relationship of trust between the buyer and the seller, and inhibits the adoption of online consumption.

The spread of coronavirus infections drastically increased the attractiveness of online consumption by allowing consumers to avoid face-to-face contact when making purchases and led many consumers to go online. However, once the coronavirus pandemic subsides, this attraction will fade. Will consumers then go back to offline shopping? There are two possible reasons why they might not return, that is, why the shift to online shopping could be irreversible. The first is the upfront costs of moving online. If consumers that had never shopped online have paid the upfront costs and started shopping online, there is no reason for them to go back to offline shopping. Since they paid the upfront costs, they will probably continue to shop online to recoup these costs. The second reason is that the concerns that consumers may have had about online shopping such as the leakage of personal information and information asymmetry likely will have been dispelled during the actual experience of online shopping. If this experience changes the perceptions of online shopping that consumers had before the pandemic, they will continue to shop online after the virus subsides.

What should be highlighted is that both of the above two reasons apply only to consumers that did not use the internet for online purchases before the pandemic and only started doing so during the pandemic. In contrast, consumers that were already used to making online purchases before the pandemic did not need to make any upfront investment or adjust their perceptions, so that even if they increased their online consumption during the pandemic,

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their online consumption will likely return to the level before the pandemic once the risk of infection subsides.

Thus, in order to discover whether the increase in online consumption demand due to the pandemic is irreversible, it is necessary to decompose the increase in online consumption into (1) the contribution due to the entry of new consumers that had never used the internet for purchases before, and (2) the contribution due to the increase in the share of online purchases of those that already shopped online before , and to examine whether the former, which is the extensive margin, dominates the latter, which is the intensive margin.

The remainder of the study is organized as follows. Section 2 introduces the data used in this paper and then explains the empirical methodology. The analysis in this study will focus on 1 million consumers, which are a sample of the "JCB Consumption NOW" data. To start with, using data for before the outbreak of the pandemic (January 2020), we classify consumers into whether they made online purchases. Then, using data for April 2020, we examine whether, during the pandemic, (1) consumers that had never made online purchases started to do so, and (2) whether consumers that were already making online purchases before increased the share of their purchases they did online. Section 3 then presents the estimation results, while Section 4 uses the estimation results to forecast how online consumption will change in the future. Section 5 concludes.

2 Empirical Methodology

2.1 Data

The "JCB Consumption NOW" data are collected from 1 million active JCB members that are randomly sampled from the entire card members.[5] The data have been processed according to the procedure adopted by JCB Co., Ltd. to make it impossible to identify individuals. The data used in this paper consist of individual transaction records for these 1 million consumers in January 2020, April 2020, and the corresponding two months a year earlier. For the analysis, we classify individual transactions of a consumer in a particular month into online purchases and offline purchases. By doing this for the month before the outbreak of the pandemic, we can define for each consumer whether or not they were already making purchases online. Similarly, by doing this for the month following the outbreak of the pan-

[5] See https://www.jcbconsumptionnow.com/en for more details on "JCB Consumption Now."

demic, we can see if consumers that had not made purchases online before started to do so during the pandemic. Moreover, for consumers that made online purchases in a particular month, we calculate the share of online purchases in their total spending in that month.

Specifically, in the analysis below, we use two types of information for each consumer in each month: whether the consumer made online purchases in that month or not (i.e., the extensive margin), and, if the consumer did so, the share of online purchases the consumer made as the percentage of that consumer's total spending (i.e., the intensive margin).

2.2 Consumers' switch between online and offline shopping

For a particular month, consumers can be categorized into three types: (1) those who make offline purchases only (labelled "Offline only"), (2) those who make both online and offline purchases (labelled "Both"), and (3) those who make online purchases only (labelled "Online only"). Taking April 2019 and April 2020 as an example, let us consider a person who fell into the "Offline only" category in April 2019 and switched to "Both" in April 2020. In other words, this consumer shopped offline only in April 2019 (before the pandemic) but started making online purchases due to the pandemic.[6] There are 9 possible transition patterns from April 2019 to April 2020.

Offline only → Offline only
Offline only→ Both
Offline only→ Online only
Both → Offline only
Both → Both
Both → Online only
Online only → Offline only
Online only → Both
Online only → Online only

[6]However, it should be noted that even if a person is classified as "Offline only" in April 2019, we cannot say for certain that the person never made any online purchases before. It could be that the consumer happened to not make any online purchases in April 2019 despite having done so before. Being able to go back in time and look at this consumer's transaction history would provide us with a more accurate picture of the person's online purchasing behavior. However, "JCB Consumption NOW" does not allow tracing the consumption of a particular individual back in time in order to protect personal information by making it impossible to identify individuals.

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2.3 Transition probabilities

In order to examine the transition from April 2019 to April 2020, we define the following conditional probability:

$$\Pr(\text{“Both” in April 2020} \,|\, \text{“Offline only” in April 2019}) \tag{1}$$

This probability indicates how many of the consumers classified as “Offline only” in April 2019 transitioned to “Both” in April 2020. Generalizing this, the probabilities of the nine different transition patterns described above are defined as follows:

$$a_{ij} \equiv \Pr(\text{Status}\, i \,\text{in April 2020} \,|\text{Status}\, j \,\text{in April 2019}) \tag{2}$$

where status i and j represent the three types of consumers, i.e., “Offline only,” “Both,” and “Online only.”

We denote the transition probability matrix consisting of elements a_{ij} defined in equation (2) by A. A is the transition probability matrix comparing April of this year with April of the previous year. Similarly, we define B as the transition probability matrix comparing January of this year with January of the previous year. Part (a) of Table 1 presents the transition probabilities from January 2019 to January 2020, i.e., matrix B calculated using actual data. The results for A, the transition probabilities from April 2019 to April 2020 are shown in part (c) of the table.

Matrix B in the table indicates that while the share of the consumers who fell into the “Offline only” category in January 2019 and transitioned to “Both” in January 2020 was 14.6% (0.1458), the transition probability from “Both” to “Offline only” was 4.0%, which shows that there was a trend toward online consumption before the pandemic. Similarly, the transition probability from “Offline only” to “Online only” was 3.9%, while the transition probability in the opposite direction was 1.4%. On the other hand, looking at the transition from “Both” to “Online only” shows that the probability was 14.4%, while the transition probability in the opposite direction was 17.4%, suggesting that here the trend toward online consumption was receding relative to a year earlier.

Next, looking at matrix A, the transition probability from “Offline only” to “Both” was 18.0%, suggesting that the trend to online consumption has increased since January 2020. Similarly, the transition probabilities from “Offline only” to “Online only” and from “Both”

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Table 1 Transition probabilities for online consumption

(a) Transition from Jan 2019 to Jan 2020

		Jan 2019		
		Offline only	Both	Online only
	Offline only	0.8154	0.0395	0.0139
Jan 2020	Both	0.1458	0.8164	0.1744
	Online only	0.0388	0.1441	0.8117

(b) Transition from Jan 2019 to Jan 2020: Quarterly basis

		Jan 2019		
		Offline only	Both	Online only
	Offline only	0.9494	0.0113	0.0031
Jan 2020	Both	0.0419	0.9463	0.0511
	Online only	0.0085	0.0422	0.9457

(c) Transition from Apr 2019 to Apr 2020

		Apr 2019		
		Offline only	Both	Online only
	Offline only	0.7425	0.0495	0.0174
Apr 2020	Both	0.1800	0.7331	0.1477
	Online only	0.0775	0.2174	0.8349

(d) Transition from Jan 2020 to Apr 2020: Based on Assumption A

		Jan 2020		
		Offline only	Both	Online only
	Offline only	0.9076	0.0162	0.0023
Apr 2020	Both	0.0608	0.8971	-0.0118
	Online only	0.0315	0.0866	1.0094

(e) Transition from Jan 2020 to Apr 2020: Based on Assumption B

		Jan 2020		
		Offline only	Both	Online only
	Offline only	0.8624	0.0258	0.0059
Apr 2020	Both	0.0953	0.8492	0.0348
	Online only	0.0422	0.1249	0.9591

Notes: "Online only" refers to those who make online purchases only, "Both" to those who make both online and offline purchases, and "Offline only" to those who make offline purchases only. Panel (b) shows the results in panel (a) converted to a quarterly basis by raising them to the power of 1/4.

to "Online only" are higher than before the outbreak of the pandemic (i.e., in January 2020). This suggests that many of those that used to shop offline only started to shop online due to the pandemic and many of those that used to shop both online and offline switched to online shopping only due to the pandemic.

2.4 Transition probabilities from January 2020 to April 2020

Both A and B provide comparisons with the same month of the previous year, so that seasonal factors are eliminated. Moreover, the effect of the pandemic on online consumption can be indirectly observed by comparing A with B. In addition, because the impact of the point reward system introduced by the government in October 2019 is included in both A and B,[7] comparing A and B is also convenient in that it makes it possible to exclude the impact of the point reward system.

By comparing April 2020 in the midst of the pandemic with January 2020, the month immediately preceding the pandemic, it is possible to extract the impact of the pandemic only. Unfortunately, the transition probability matrix between January 2020 and April 2020 is not available in the data due to data restrictions.[8] However, it can be estimated from A and B as shown below.

Denoting the transition probability matrix from January 2020 to April 2020 by X, the following relationship holds:

$$XB = AY \tag{3}$$

where Y is a matrix that represents the transition probabilities from January 2019 to April 2019. B on the left-hand side of equation (3) is the matrix presenting to which of the three

[7]The point reward system was introduced in October 2019 as part of the Ministry of Economy, Trade and Industry's Point Reward Project, which provides subsidies for small and medium-sized enterprises and micro enterprises that wish to issue point rewards for consumers using cashless payment. The aim of the project was to prevent a drop in consumption after the consumption tax hike in April 2019, to improve the productivity of eligible businesses, and to increase convenience for consumers through the further dissemination of cashless payments. For example, consumers making a purchase using a cashless payment method such as a credit cards will receive 2% or 5% of the purchase price back in points or cash. See `https://www.meti.go.jp/english/press/2019/0312_001.html` for more details on this program.

[8]In our dataset, transaction records for January 2020 and a year earlier, January 2019, are available for a random sample of card members taken in January 2020. Similarly, transaction records for April 2020 and a year earlier, April 2019, are available for a different random sample of card members taken in April 2020. To protect personal information, the data provided by JCB Co. Ltd. makes it impossible to identify individuals, so that we cannot link the January and April samples to examine how individual consumers changed their purchasing behavior.

statuses a consumer that in January 2020 was "Offline only" transitioned to. X is a matrix that links the status in January 2020 and the status in April 2020. Therefore, XB links the status in January 2019 with the status in April 2020. Similarly, Y on the right-hand side connects the status in January 2019 with the status in April 2019, while A connects the status in April 2019 with the status in April 2020. Therefore, AY links the status in January 2019 with the status in April 2020. Equation (3) yields

$$X = AYB^{-1} \tag{4}$$

Since A and B can be calculated from the "JCB Consumption Now" data, X can be estimated if Y is known.

For Y, we make the following two types of simplifying assumptions and then estimate X under each assumption. The first assumption is

$$Y = I \tag{5}$$

where I is a 3×3 identity matrix. Equation (5) assumes that between January 2019 and April 2020 there were no significant shocks that may have affected the trend toward online consumption and, moreover, that consumers' online consumption status (i.e., "Offline only," "Online only," and "Both") remained unchanged. In the following, equation (5) will be referred to as Assumption A.

However, it is likely that the trend toward online consumption has continued to advance steadily even without major shocks such as the introduction of the point reward system or the pandemic. Therefore, assuming that the underlying trend toward online consumption can be captured by the transitions from January 2019 to January 2020, and assuming that the transitions between January 2019 and April 2019 followed this trend, we have

$$Y = B^{3/12} \tag{6}$$

The reason for raising B to the power of $3/12$ is that we need to adjust for the difference in the length of the periods, i.e., 3 months (from January to April) and 12 months (from January to January of the following year). We refer to this as Assumption B.

Substituting (5) into (4) yields

$$X = AB^{-1} \tag{7}$$

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and (6) into (4) yields

$$X = AB^{-3/4}. \tag{8}$$

Panels (d) and (e) of Table 1 show the results of calculating the transition probabilities from January 2020 to April 2020 using equations (7) and (8). Comparing the two shows that the individual elements of the matrices do not exactly match, and for some matrix elements there are substantial differences. However, the relative sizes qualitatively are almost identical, suggesting that equations (7) and (8) provide reliable estimates of X. In what follows, to check the robustness of our results, we will use both of the two equations.

2.5 Online consumption shares

So far, we have explained how we examine the transitions between the three statuses of "Offline only," "Online only," and "Both." However, among those falling into the "Both" category, there will be some that make almost no offline purchases and are extremely close to falling into the "Online only" classification and, conversely, some that make hardly any online purchases and are close to falling into the "Offline only" category. The follows describes in more detail our approach for analyzing consumers in the "Both" category.

Taking April 2019 and April 2020 as an example, we start with extracting only consumers that made both online and offline purchases in both months. Next, for each consumer, we calculate the share of online consumption in April 2019 as the percentage of that consumer's total spending. We calculate the same share for online consumption in April 2020. We divide the interval from 0 to 1 into 10 bins and determine which bin a consumer belongs to in terms of the online consumption share. Then, we define the following conditional probability:

$$\begin{aligned}\hat{a}_{ij} \equiv \Pr(&\text{Online consumption share in April 2020 falls into the } i\text{th bin} \\ &\mid \text{Online consumption share in April 2019 falls into the } j\text{th bin})\end{aligned} \tag{9}$$

where $i, j = 1, 2, \ldots, 10$. We define matrix $\hat{A}$ with the (i, j) element representing the conditional probability $\hat{a}_{ij}$. $\hat{A}$ is similar to A in Section 2.4, but differs from it in that we now focus on the transition of those consumers belonging to the "Both" category in each month.

Similarly, the transition probability matrix $\hat{B}$ can be calculated using the data for January 2019 and January 2020. Finally, denoting the transition probability matrix from January 2020

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to April 2020 by $\hat{X}$, we obtain

$$\hat{X} = \hat{A}\hat{B}^{-1} \tag{10}$$

under Assumption A and

$$\hat{X} = \hat{A}\hat{B}^{-3/4} \tag{11}$$

under Assumption B.

3 Estimation results and implications

The increase in online consumption demand due to the coronavirus shock can be decomposed into (1) the contribution due to the entry of new consumers that had never used the internet for purchases before (i.e., the extensive margin), and (2) the contribution due to the increase in the share of online purchases of those that already made online purchases before (i.e., the intensive margin). Sections 3.1 and 3.2 present the results on the extensive margin and the intensive margin, respectively.

3.1 Extensive margin

Transition probabilities Panels (d) and (e) of Table 1 show the estimated transition probabilities from January 2020 to April 2020 using equations (7) or (8). The results based on Assumption A in panel (d) indicate that the transition probabilities from “Offline only” to “Both,” from “Both” to “Online only,” and from “Offline only” to “Online only” are all higher than those in the opposite direction, indicating that more people switched to online consumption during this period. The same pattern can be found in the results based on Assumption B.

The transition probabilities from January 2019 to January 2020 shown in panel (a) of Table 1 are the one-year transition probabilities that are unrelated to the pandemic and can be interpreted as representing the transition during a normal period. Let us compare this to the coronavirus period (January to April 2020). The coronavirus period consists of only 3 months, while the January 2019 to January 2020 consists of 12 months. To make them comparable, we convert the transition probabilities from January 2019 to January 2020 to a quarterly basis by raising them to the power of 1/4. The results are shown in panel (b) of Table 1, “Transition from January 2019 to January 2020: Quarterly basis.”

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Comparing panels (d) and (e) with (b) shows the following. First, the transition probability from "Both" to "Online only" is much larger in (d) and (e) than in (b). Specifically, the estimated value from January to April 2020 is 8.7% under Assumption A and 12.5% under Assumption B. On the other hand, the probability from January 2019 to January 2020 is only 4.2%. Second, the transition probability from "Offline only" to "Online only" is also larger in (d) and (e) than in (b). While the estimated values from January to April 2020 are 3.2% under Assumption A and 4.2% under Assumption B, the probability from January 2019 to January 2020 is only 0.9%.

These results suggest that many consumers that fell into the "Both" or "Offline only" categories before the pandemic switched to "Online only" to avoid the risk of getting infected with the coronavirus. On the other hand, while the transition probability from "Offline only" to "Both" for January 2020 to April 2020 is larger (6.1% under Assumption A and 9.5% under Assumption B) than the transition probability from January 2019 to January 2020 (4.2%), the difference is not that great. Taken together, these results suggest that what many consumers were aiming for amid the spread of COVID-19 was to completely stop shopping offline rather than only going halfway by doing some online shopping.

Results by gender Tables 2 and 3 show the same transition probabilities estimated by gender. Looking at the transitions from January 2020 to April 2020 shown in panels (d) and (e) of each table, it is clear that women were more likely than men to switch to online shopping due to the pandemic. Specifically, for each of the transitions from "Offline only" to "Both," "Both" to "Online only," and "Offline only" to "Online only," the transition probabilities for women exceed those for men.

Results for goods consumption and services consumption The increase in online consumption due to the pandemic may differ between the consumption of goods and of services. Tables 4 and 5 show the results of estimating the transition probabilities by dividing consumption into goods consumption and services consumption and distinguishing between "Offline only," "Both," and "Online only."

Starting with goods consumption, comparing the transition probabilities from January 2020 to April 2020 with those from January 2019 to January 2020 shows a high transition probability from "Both" to "Online only." Specifically, the estimates for January to April

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Table 2 Transition probabilities for online consumption: Men

(a) Transition from Jan 2019 to Jan 2020				
		Jan 2019		
		Offline only	Both	Online only
Jan 2020	Offline only	0.8285	0.0350	0.0120
	Both	0.1371	0.8333	0.1687
	Online only	0.0343	0.1317	0.8194
(b) Transition from Jan 2019 to Jan 2020: Quarterly basis				
		Jan 2019		
		Offline only	Both	Online only
Jan 2020	Offline only	0.9534	0.0099	0.0027
	Both	0.0389	0.9518	0.0488
	Online only	0.0076	0.0381	0.9484
(c) Transition from Apr 2019 to Apr 2020				
		Apr 2019		
		Offline only	Both	Online only
Apr 2020	Offline only	0.7645	0.0464	0.0163
	Both	0.1709	0.7598	0.1475
	Online only	0.0646	0.1938	0.8362
(d) Transition from Jan 2020 to Apr 2020: Based on Assumption A				
		Jan 2020		
		Offline only	Both	Online only
Apr 2020	Offline only	0.9198	0.0165	0.0030
	Both	0.0558	0.9108	-0.0082
	Online only	0.0242	0.0726	1.0051
(e) Transition from Jan 2020 to Apr 2020: Based on Assumption B				
		Jan 2020		
		Offline only	Both	Online only
Apr 2020	Offline only	0.8776	0.0250	0.0062
	Both	0.0887	0.8672	0.0367
	Online only	0.0336	0.1077	0.9569

Notes: "Online only" refers to those who make online purchases only, "Both" to those who make both online and offline purchases, and "Offline only" to those who make offline purchases only. Panel (b) shows the results in panel (a) converted to a quarterly basis by raising them to the power of 1/4.

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Table 3 Transition probabilities for online consumption: Women

(a) Transition from Jan 2019 to Jan 2020				
		Jan 2019		
		Offline only	Both	Online only
Jan 2020	Offline only	0.7954	0.0479	0.0168
	Both	0.1590	0.7853	0.1829
	Online only	0.0456	0.1669	0.8003
(b) Transition from Jan 2019 to Jan 2020: Quarterly basis				
		Jan 2019		
		Offline only	Both	Online only
Jan 2020	Offline only	0.9432	0.0140	0.0037
	Both	0.0468	0.9359	0.0547
	Online only	0.0098	0.0500	0.9414
(c) Transition from Apr 2019 to Apr 2020				
		Apr 2019		
		Offline only	Both	Online only
Apr 2020	Offline only	0.7093	0.0551	0.0191
	Both	0.1936	0.6846	0.1480
	Online only	0.0971	0.2603	0.8329
(d) Transition from Jan 2020 to Apr 2020: Based on Assumption A				
		Jan 2020		
		Offline only	Both	Online only
Apr 2020	Offline only	0.8886	0.0156	0.0015
	Both	0.0702	0.8708	-0.0155
	Online only	0.0411	0.1135	1.0139
(e) Transition from Jan 2020 to Apr 2020: Based on Assumption B				
		Jan 2020		
		Offline only	Both	Online only
Apr 2020	Offline only	0.8389	0.0272	0.0057
	Both	0.1068	0.8152	0.0333
	Online only	0.0541	0.1575	0.9609

Notes: "Online only" refers to those who make online purchases only, "Both" to those who make both online and offline purchases, and "Offline only" to those who make offline purchases only. Panel (b) shows the results in panel (a) converted to a quarterly basis by raising them to the power of 1/4.

2020 are 7.6% for Assumption A and 10.9% for Assumption B, while for January 2019 to January 2020 the value is 3.6%. Moreover, the transition probability from “Offline only” to “Online only” is also high. The estimates for January to April 2020 are 2.6% for Assumption A and 3.6% for Assumption B, while the value for January 2019 to January 2020 is 0.7%. On the other hand, although the transition probability from “Offline only” to “Both” for January to April 2020 is higher than that for January 2019 to January 2020, the difference is relatively small. These results are similar to those found in Table 1 for overall consumption.

Regarding services consumption, the transition probability from “Both” to “Online only” is very high. The estimates for January 2020 to April 2020 are 28.3% under Assumption A and 33.6% under Assumption B and thus more than three times as large as the probability for January 2019 to January 2020 (7.6%). On the other hand, the transition probabilities from “Offline only” to “Both” and from “Offline only” to “Online only” are not very different from the probability for January 2019 to January 2020. Whereas the consumption of services involving close proximity to others, such as cinemas, theaters, and eating out, decreased sharply with the spread of coronavirus infections, spending on online services continued to increase, and the results suggest that the dominant factor in this change was that consumers that used to make both online and offline purchases switched to making online purchases only.

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Table 4 Transition probabilities for online consumption: Goods consumption

(a) Transition from Jan 2019 to Jan 2020				
		Jan 2019		
		Offline only	Both	Online only
Jan 2020	Offline only	0.8011	0.1723	0.0716
	Both	0.1658	0.7156	0.2249
	Online only	0.0331	0.1121	0.7034
(b) Transition from Jan 2019 to Jan 2020: Quarterly basis				
		Jan 2019		
		Offline only	Both	Online only
Jan 2020	Offline only	0.9416	0.0529	0.0163
	Both	0.0510	0.9109	0.0725
	Online only	0.0074	0.0362	0.9112
(c) Transition from Apr 2019 to Apr 2020				
		Apr 2019		
		Offline only	Both	Online only
Apr 2020	Offline only	0.7216	0.1321	0.0470
	Both	0.2100	0.6890	0.1786
	Online only	0.0685	0.1790	0.7744
(d) Transition from Jan 2020 to Apr 2020: Based on Assumption A				
		Jan 2020		
		Offline only	Both	Online only
Apr 2020	Offline only	0.9079	-0.0315	-0.0155
	Both	0.0667	0.9559	-0.0586
	Online only	0.0255	0.0757	1.0741
(e) Transition from Jan 2020 to Apr 2020: Based on Assumption B				
		Jan 2020		
		Offline only	Both	Online only
Apr 2020	Offline only	0.8532	0.0187	-0.0017
	Both	0.1111	0.8722	0.0170
	Online only	0.0358	0.1091	0.9847

Notes: "Online only" refers to those who make online purchases only, "Both" to those who make both online and offline purchases, and "Offline only" to those who make offline purchases only. Panel (b) shows the results in panel (a) converted to a quarterly basis by raising them to the power of 1/4.

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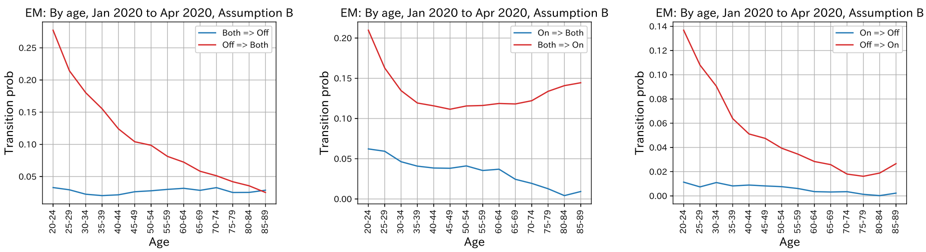
Table 5 Transition probabilities for online consumption: Services consumption

(a) Transition from Jan 2019 to Jan 2020				
		Jan 2019		
		Offline only	Both	Online only
Jan 2020	Offline only	0.7114	0.0317	0.0092
	Both	0.1816	0.7174	0.1319
	Online only	0.1071	0.2509	0.8589
(b) Transition from Jan 2019 to Jan 2020: Quarterly basis				
		Jan 2019		
		Offline only	Both	Online only
Jan 2020	Offline only	0.9173	0.0100	0.0022
	Both	0.0571	0.9143	0.0398
	Online only	0.0255	0.0757	0.9580
(c) Transition from Apr 2019 to Apr 2020				
		Apr 2019		
		Offline only	Both	Online only
Apr 2020	Offline only	0.6927	0.0540	0.0121
	Both	0.1353	0.4883	0.0803
	Online only	0.1719	0.4576	0.9075
(d) Transition from Jan 2020 to Apr 2020: Based on Assumption A				
		Jan 2020		
		Offline only	Both	Online only
Apr 2020	Offline only	0.9656	0.0330	-0.0013
	Both	0.0174	0.6841	-0.0117
	Online only	0.0171	0.2829	1.0130
(e) Transition from Jan 2020 to Apr 2020: Based on Assumption B				
		Jan 2020		
		Offline only	Both	Online only
Apr 2020	Offline only	0.8876	0.0398	0.0022
	Both	0.0547	0.6247	0.0160
	Online only	0.0577	0.3355	0.9818

Notes: "Online only" refers to those who make online purchases only, "Both" to those who make both online and offline purchases, and "Offline only" to those who make offline purchases only. Panel (b) shows the results in panel (a) converted to a quarterly basis by raising them to the power of 1/4.

Figure 1 Transition probabilities for online consumption by age: Jan 2020 to Apr 2020



Note: "On" refers to those who make online purchases only, "Off" to those who make offline purchases only, and "Both" to those who make both online and offline purchases.

Results by age Figure 1 shows the estimation results of the transition probabilities from January to April 2020 by age group. The top panel of the figure shows the transition from "Offline only" to "Both" and vice versa, the middle panel shows the transition from "Both" to "Online only" and vice versa, and the bottom panel shows the transition from "Offline only" to "Online only" and vice versa. Note that the results shown here are based on Assumption B, but almost the same results are obtained under Assumption A as well.

The three figures have in common that younger people under the age of 35 have a higher probability of turning to online consumption than other age groups. This tendency is particularly noticeable in the transition from "Offline only" to "Both." While most of the young likely were already used to making online purchases before the pandemic to some extent, the findings suggest that even more of them turned to online consumption to avoid getting infected with the coronavirus.

On the other hand, the transition probabilities for older people aged 65 and over are extremely low both for the transition from "Offline only" to "Both" shown in the upper panel and the transition from "Offline only" to "Online only" shown in the lower panel and in fact are not very different from the transition probabilities in the opposite direction represented by the blue line. The fact that the blue line has the same value for all age groups means that it can be regarded as representing the size of noise contained in the data. In that sense, if the impact of noise is excluded, the transition probabilities both from "Offline only" to "Both" and from "Offline only" to "Online only" for seniors can be regarded as being

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Figure 2 Transition probabilities for online consumption of goods by age: Jan 2020 to Apr 2020

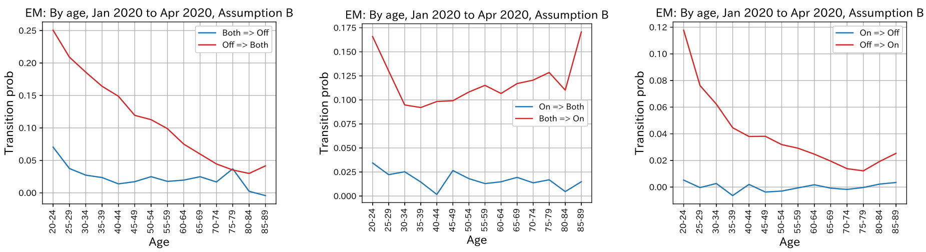
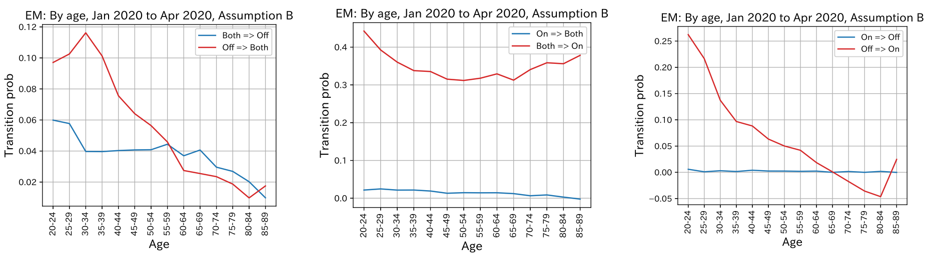


Figure 3 Transition probabilities for online consumption of services by age: Jan 2020 to Apr 2020



Note: "On" refers to those who make online purchases only, "Off" to those who make offline purchases only, and "Both" to those who make both online and offline purchases.

close to zero. These results suggest that seniors are more likely to be unfamiliar with making online purchases than the young and that the pandemic did not prompt such seniors to start making online purchases.

Where the transition probability for seniors over the age of 65 is high is in the transition from "Both" to "Online only" shown in the middle panel.[9] Interestingly, after age 70, the red line in the figure increases slightly with age. This can be regarded as indicating that some seniors were familiar with making online purchases before the pandemic and that among them those that were sensitive to the risk of corona infection completely stopped shopping offline to avoid that risk.[10]

[9]That said, the pattern that the probability rises with age is not found in the results based on Assumption *A*.

[10]Figures 2 and 3 show the results by age for goods consumption and services consumption separately. The

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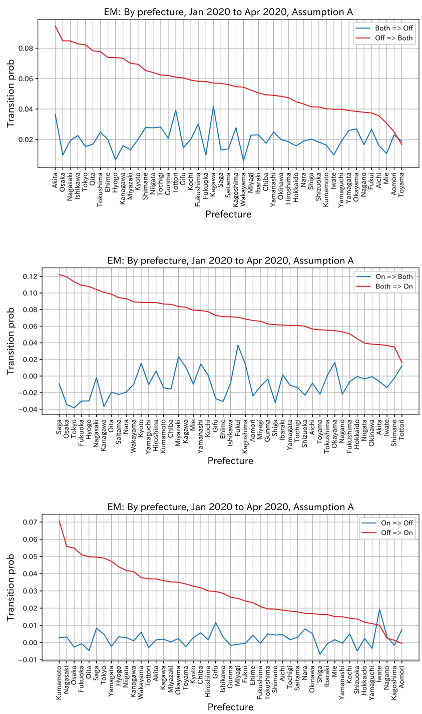
Figure 4 Transition probabilities for online consumption by prefecture: Jan 2020 to Apr 2020



Note: "On" refers to those who make online purchases only, "Off" to those who make offline purchases only, and "Both" to those who make both online and offline purchases.

Results by region Figure 4 shows the results of estimating the transition probabilities from January to April 2020 by prefecture. The upper panel of Figure 4 shows the transition

red lines in Figures 2 and 3 indicate that the transition probabilities for switching to online consumption are higher among the young for all transition types. A notable difference from Figure 1 is that the transition probability from "Both" to "Online only" for goods purchases (the red line in the middle panel of Figure 2) is lowest for the 30-34 age group and then rises with age. A similar pattern could be seen in Figure 1, but it is more pronounced in goods purchases. Regarding online purchases of goods, this indicates that middle-aged and senior consumers that used to shop online before the pandemic completely shifted to online shopping because of the fear of getting infected with the coronavirus.

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from “Offline only” to “Both” and vice versa, the middle panel shows the transition from “Both” to “Online only” and vice versa, and the lower panel shows that from “Offline only” to “Online only” and vice versa. The results shown here are based on Assumption A, but almost identical results are obtained under Assumption B.

The three panels suggest the following. First, comparing the scale on the vertical axis in Figure 4 with that of Figure 1 indicates that while the variation in transition probabilities across prefectures is not zero, it is smaller than the variation across generations.

Second, among the prefectures with the highest transition probabilities in the three panels are urban areas such as Tokyo, Osaka, Kanagawa, and Hyogo. On the other hand, Akita (a rural prefecture in the north of Honshu), for example, is at the top in the transition from “Offline only” to “Both” shown in the upper panel, but it is not among the top-ranked in the middle and lower panels. Based on these results, it cannot be said that consumers in Akita were more likely to turn to online shopping than those in other prefectures. Similarly, in the transition from “Both” to “Online only” shown in the middle panel, Saga (another non-urban prefecture, located in Kyushu) is at the top, but in the other panels it is not among the top prefectures. Moreover, Kumamoto (another non-urban prefecture in Kyushu) is at the top in the transition from “Offline only” to “Both” shown in the lower panel, but it is not among the top prefectures in the other panels.

One reasons why urban areas such as Tokyo are among the top prefectures likely is that younger generations make up a large population share. As seen in Figure 1, there is a close link between age and transition probabilities, and the results by prefecture may reflect this. Another reason is that the severity of the spread of coronavirus infections varies across prefectures. In urban areas such as Tokyo, the spread of infections was more serious, and consumers were more likely to avoid contact with others. Yet another factor leading consumers in urban areas to turn to online consumption likely is that the degree to which local governments requested people to exercise self-restraint and avoid physical stores was stronger in urban areas.

3.2 Intensive margin

Transition probabilities Figure 5 shows the estimation result of the transition probability matrices for the share of online consumption in consumers’ total spending. The top left matrix in Figure 5 shows the transition from January 2019 to January 2020 ($\hat{B}$), while the top right

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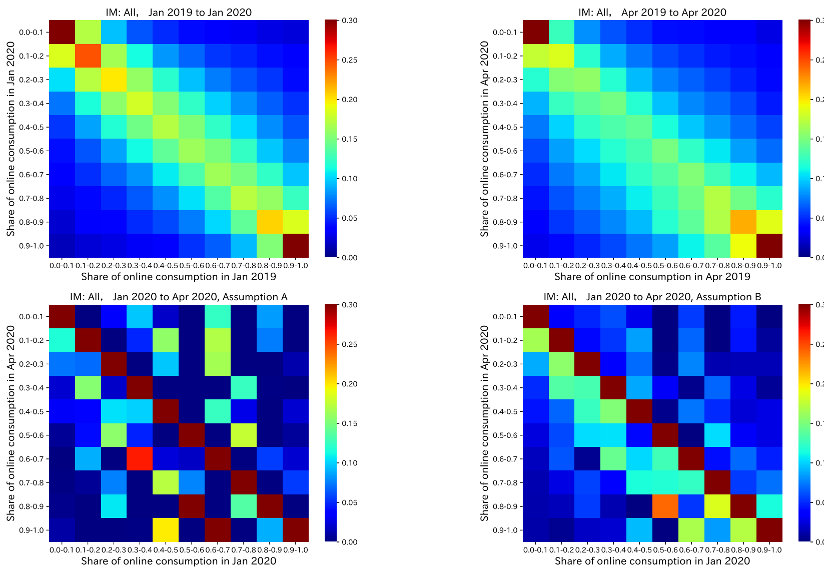
Figure 5 Transition probabilities for the share of online consumption



Note: Probabilities greater than 0.3 are represented by the same color as 0.3.

matrix shows the transition from April 2019 to April 2020 ($\hat{A}$). In both matrices the diagonal elements show high transition probabilities, indicating that for many consumers the share of online consumption has remained unchanged from a year earlier. Comparing $\hat{B}$ with $\hat{A}$ shows that whereas the probabilities of off-diagonal elements in $\hat{B}$ are symmetric about the diagonal, in $\hat{A}$ probabilities are higher below the diagonal. As of April, many consumers had increased their online consumption share compared to a year earlier, reflecting the impact of the pandemic.

The lower part of Figure 5 shows the results for the transition probabilities from January 2020 to April 2020. The left matrix represents the results under Assumption A, while the right matrix shows those under Assumption B. Looking at the results under Assumption B, there is a clear tendency for the probabilities to be higher below the diagonal. This shows that many consumers reduced the share of online purchases due to the pandemic. Taking a closer look at the part below the diagonal shows that consumers with a high share of online

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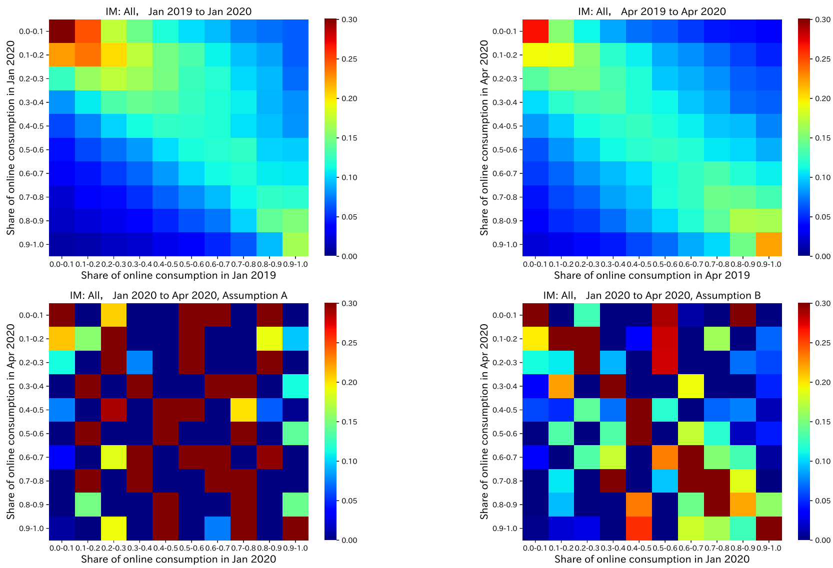
Figure 6 Transition probabilities for the share of online consumption: Goods consumption



Note: Probabilities greater than 0.3 are represented by the same color as 0.3.

purchases as of January 2020 tended to increase their share as of April 2020. In other words, consumers that were used to making online purchases before the pandemic increased their online consumption share even further. On the other hand, although a clear pattern cannot be visually discerned from the results under Assumption A, when looking at the actual numbers, a comparison of the figures above and below the diagonal shows that the probabilities below the diagonal are high er, indicating that it was consumers that already did make a large share of their purchases online to begin with that increased their share of online purchases.

Goods purchases and services purchases Figures 6 and 7 show the results of the transition of the online shares for goods purchases and services purchases, respectively. The matrices at the bottom of Figures 6 and 7 are the results for the transition probabilities from January 2020 to April 2020, with the matrices on the left showing the results under Assumption A and those on the right showing those under Assumption B. The estimation

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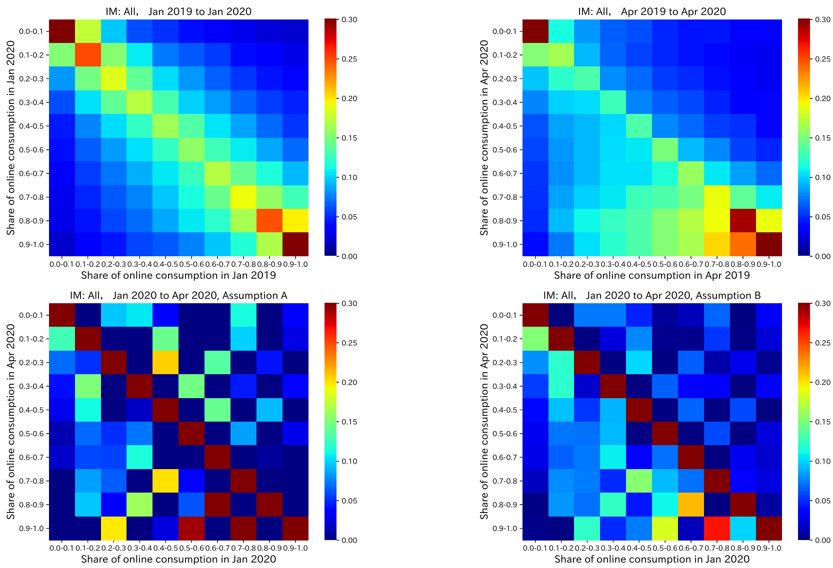
Figure 7 **Transition probabilities for the share of online consumption: Services consumption**



Note: Probabilities greater than 0.3 are represented by the same color as 0.3.

results for goods purchases under Assumption B indicate that probabilities tend to be higher below the diagonal. Taking a closer look, consumers who made a large share of their purchases online as of January 2020 tended to make an even larger share of their purchases online in April 2020. This pattern is identical to that found in Figure 5. Moreover, the pattern is even more pronounced in services spending. The bottom right matrix in Figure 7 shows that the probabilities below the diagonal are higher, that is, consumers that already spent a large share of their total service spending on online services in January 2020 had increased it even more by April.

Results by gender Figure 8 shows the results of the transition probability matrices for online consumption shares by gender. They show that while for both men and women the probabilities are highest in the diagonal elements, for men they are also high below the diagonal, indicating that many men increased their online consumption share due to the

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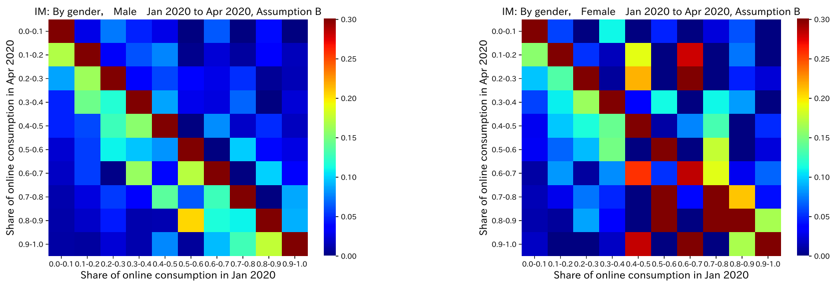
Figure 8 Transition probabilities for the share of online consumption by gender



Note: Probabilities greater than 0.3 are represented by the same color as 0.3.

pandemic. Moreover, this pattern is particularly strong for men that already made a large share of their purchases online before the pandemic. On the other hand, for women, the estimation results do not show any clear differences above and below the diagonal.

Results by age Figure 9 shows the results of estimating the transition probability matrices for online consumption shares by age group. The top row shows the results for the young (aged 20-39 years), the middle row shows those for the middle-aged (aged 40-59), and the bottom row is for seniors (60-89).

Starting with the middle-aged, we find that compared to the matrix for January 2019 to January 2020 (first matrix in the middle row), in the matrix for April 2019 to April 2020 (second matrix in the middle row) the transition probabilities decline in the diagonal and instead increase immediately below the diagonal. This shows that there were many consumers that increased their online consumption share due to the pandemic. In the matrix for January 2020 to April 2020 (third matrix in the middle row), too, the probabilities are higher below than above the diagonal. Taking a closer look at the part below the diagonal shows that consumers with a high share of online consumption as of January 2020 tended to have increased their share as of April 2020.

Next, looking at the results for seniors, the probabilities in the diagonal elements of the second matrix in the bottom row are lower than in the first matrix in the bottom row, and the probabilities below the diagonal have increased instead. Moreover, the third matrix shows

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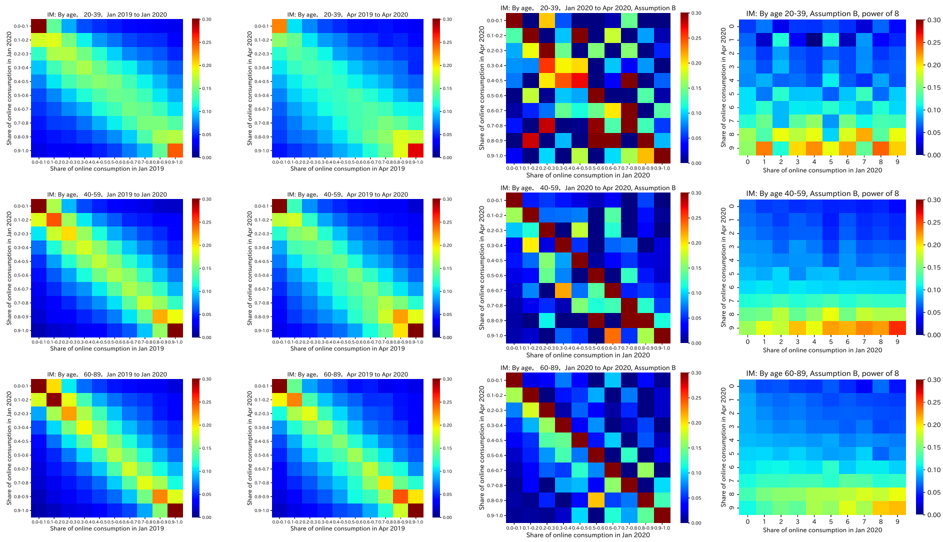
Figure 9 **Transition probabilities for the share of online consumption by age**



Note: Probabilities greater than 0.3 are represented by the same color as 0.3.

the same pattern as that for the middle-aged, although it is weaker than for the middle-aged.

Finally, looking at the young, the transition matrix for April 2019 to April 2020 in the second column in the top row shows that compared with the matrix for January 2019 to January 2020 the probabilities in the diagonal elements declined. This aspect is similar to the result for the middle-aged and seniors. However, for the off-diagonal elements, unlike for the middle-aged and seniors, it is not possible to visually ascertain that the probabilities below the diagonal are higher than those above the diagonal. Also, in the transition matrix for January 2020 to April 2020 in the third column, no clear correlation between the values for January 2020 and the values for April 2020 can be observed.[11]

To show how the results for the young differ from those for the other two age groups, the last column presents the matrices in the third column raised to the power of 8. In other words, it looks at what would happen if the three-month transition from January 2020 to April 2020

[11]While the estimation results presented here are based on Assumption B, the results under Assumption A also do not show a clear correlation.

lasted for 24 months. Cells with high probabilities are concentrated in the lower part of the matrix, meaning that the online consumption share for most consumers will approach 1 after 24 months. However, comparing the matrix for the young with those for the middle-aged and seniors shows that more middle-aged and senior consumers are near an online ratio of 1. This result indicates that the young are turning to online consumption at a slower pace.

4 Forecasts

In the previous section, we examined the transition matrix estimation results. In this section, we use the estimated transition probability matrices to forecast future online consumption. Specifically, we forecast how the prevalence of online consumption, that is, the shares of consumers falling into the "Offline only," "Both," and "Online only," will change in the future.

The premise of our forecast is the assumption that the risk of coronavirus infection disappears in July 2020, followed by a period of no risk of infection (that is, there is no second or third wave of infections). Concretely, for our forecast, we regard January 2020 (i.e., before the spread of the coronavirus) as the starting point ($t = 0$) and April 2020 ($t = 1$) as the period when there was a high risk of infection. Further, we assume that infections will subside by July ($t = 2$) and that from October 2020 ($t = 3$) there will be no new infections. Based on this setting, we then forecast the share of consumers falling into the "Offline only," "Both," and "Online only" categories for $t = 2$ and later.

The column vector s_t is used to represent the shares of consumers falling into the "Offline only," "Both," and "Online only" categories at time t. The vector s_1 consists of actual values and can be written as

$$\begin{aligned} s_1 &= X s_0 \\ &= \left(X - B^{1/4}\right) s_0 + B^{1/4} s_0 \end{aligned} \tag{12}$$

where X is the transition matrix from January to April 2020. Matrix B is the transition matrix from January 2019 to January 2020 and represents the transition during normal times. The first term on the right-hand side of equation (12) represents the shock associated with the coronavirus pandemic in the first period. The coronavirus shock can be further

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decomposed as follows:

$$\left(X - B^{1/4}\right) s_0 = \underbrace{\begin{pmatrix} x_{11} - b^q_{11} & 0 & 0 \\ x_{21} - b^q_{21} & 0 & 0 \\ x_{31} - b^q_{31} & 0 & 0 \end{pmatrix} s_0}_{\text{Persistent component of the coronavirus shock}} + \underbrace{\begin{pmatrix} 0 & x_{12} - b^q_{12} & x_{13} - b^q_{13} \\ 0 & x_{22} - b^q_{22} & x_{23} - b^q_{23} \\ 0 & x_{32} - b^q_{32} & x_{33} - b^q_{33} \end{pmatrix} s_0}_{\text{Transitory component of the coronavirus shock}} \tag{13}$$

where x_{ij} and b^q_{ij} are the (i, j) elements of X and $B^{1/4}$, respectively.

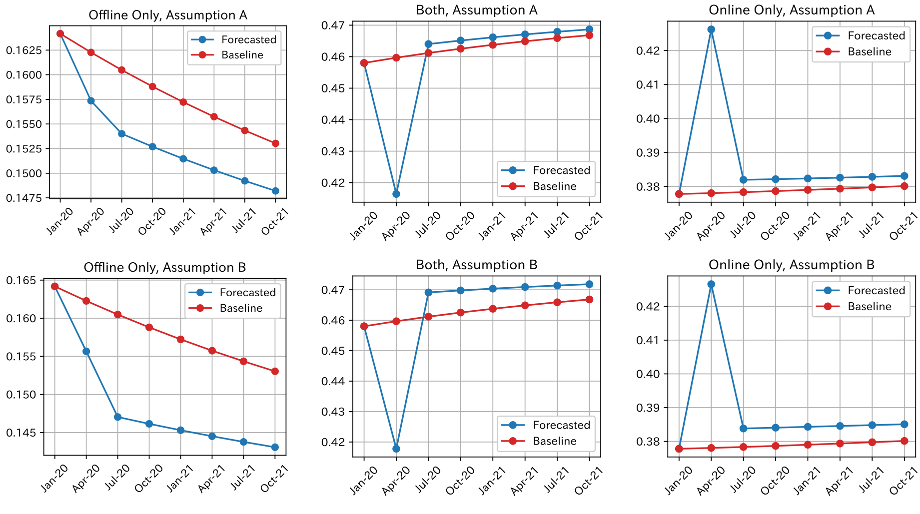
As mentioned in Section 1, reasons pointed out why consumers who have never used the internet to make purchases are hesitant to start doing so include the following: (1) the upfront costs of going online, (2) concern that their personal information might be leaked, and (3) information asymmetries on the quality of goods and services. However, consumers that started to use the internet for shopping and services during the coronavirus pandemic have already paid the upfront cost, and their concerns about the leakage of personal information and the quality of goods and services may have been dispelled by their actual experience of using the internet for purchases. If the pandemic has an irreversible effect on online consumption, it will be through this channel. In the following, to reflect this channel in the forecasts for online consumption, we make the following assumptions for the first and second terms on the right-hand side of (13).

To start with, looking at the first term on the right-hand side, this shows where consumers that fell into the "Offline only" category in period 0 transitioned due to the coronavirus shock and how much s_1 changed as a result. Since these consumers had not used the internet for purchases before the pandemic, where they transitioned to in the first period affects the results from the second period onward; in other words, we assume that the first term on the right-hand side of (13) is a persistent shock.

On the other hand, the second term on the right-hand side of (13) represents where consumers that fell into the "Both" or "Online only" categories in period 0 transitioned during the shock and hence how much s_1 changed as a result. Since these consumers had used the internet for purchases before the pandemic, we assume that where such consumers transition in period 1, and how s_1 changes as a result, does not affect s_t in period 2 and later. In this sense, the second term on the right-hand side of (13) is a transient shock.

Under the above assumptions, the second term on the right-hand side of equation (13)

Figure 10 Forecast of online purchasing behavior



Notes: The left column shows the share of consumers falling into the "Offline only" category, the middle column those falling into the "Both" category, and the right column those falling into the "Online only" category. The results in the upper row are based on Assumption A for X, while those in the lower row are based on Assumption B. The blue lines show the forecasts calculated using equations (14) and (15). The red lines are calculated using $s_t = \left(B^{1/4}\right)^t s_0$ and represent the baseline assuming that online consumption behavior had continued to follow the trends observed until January 2020.

does not affect s_2. Therefore, s_2 can be expressed as follows:

$$s_2 = B^{1/4}\left[\begin{pmatrix} x_{11}-b^q_{11} & 0 & 0 \\ x_{21}-b^q_{21} & 0 & 0 \\ x_{31}-b^q_{31} & 0 & 0 \end{pmatrix} s_0 + B^{1/4}s_0\right] = B^{1/4}\begin{pmatrix} x_{11} & b^q_{12} & b^q_{13} \\ x_{21} & b^q_{22} & b^q_{23} \\ x_{31} & b^q_{32} & b^q_{33} \end{pmatrix} s_0 \tag{14}$$

Finally, s_t $(t = 3, 4, \ldots)$ can be calculated using the following equation:

$$s_t = \left(B^{1/4}\right)^{t-2} s_2 \tag{15}$$

Figure 10 shows the forecast results using equations (14) and (15). The blue lines in the panels represent the forecast values, while the red lines show the counterfactual values; i.e., the values that would be obtained if the transition continued to follow the trend before the coronavirus shock ($s_t = \left(B^{1/4}\right)^t s_0$ for $t = 0, 1, 2, \ldots$).

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Starting with the results for April 2020 ($t = 1$), when the coronavirus shock occurred, we find that the share of consumers falling into the "Online only" category increased substantially. Looking at the estimation results for X under Assumption A (in the upper row of Figure 10), the share of "Online only" is 42.6%, and the deviation from the baseline shown by the red line is 4.8 percentage points (all figures below are from the results based on Assumption A). On the other hand, the share of consumers falling into the "Both" category decreased sharply, falling 4.3 percentage points below the baseline. This shows that due to the coronavirus shock, the share of consumers falling into the "Both" category declined and there was a corresponding increase in consumers falling into the "Online only" category. On the other hand, although the share of consumers falling into the "Offline only" category decreased, the size of the decrease relative to the baseline is only 0.5 percentage points. We can therefore say that not many consumers transitioned from "Offline only" to "Online only."

The fact that most of the increase in "Online only" consumers in April 2020 came from the transition of consumers in the "Both" category has important implications for the forecast for July 2020 ($t = 2$). As explained in equation (13), the transition from "Both" to "Online only" is a transient shock associated with the pandemic and does not affect the shares in July and later. On the other hand, although the transition from "Offline only" to "Online only" was a persistent shock, the share of consumers making this transition was very small, so that the shock is also very small. Reflecting these two results, the forecast for "Online only" in July 2020 falls back sharply. Although the "Online only" share for July 2020 continues to be higher than the baseline, the difference is negligible (0.3 percentage points).

The forecast results remain essentially unchanged when X is estimated based on Assumption B (see the lower row of Figure 10). They suggest (1) that the share of consumers that used the internet to purchase goods and services for the first time during the pandemic is limited, and that the increase in online consumption was largely due to those that were already used to purchasing goods and services online, and (2) that for this reason, once the pandemic subsides, it is highly likely that online consumption activity will return to the level before the pandemic.

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5 Conclusion

With the spread of novel coronavirus infections, people's consumption patterns have changed dramatically. While demand for services that involve face-to-face contact, such as eating out and entertainment, has decreased sharply, online consumption of goods and services such as e-commerce has increased, and some expect such patterns to continue once the pandemic subsides. In this study, using credit card transaction data, we examined whether the increase in online consumption will persist once the pandemic has subsided.

Online consumption requires upfront costs such as the purchase of devices, maintaining internet access, and acquiring know-how, and such costs are regarded as one of the factors impeding the spread of online consumption. In addition, there are strong concerns about the potential leakage of personal information and the inability to check the quality of products and services before buying them. These factors are also said to impede the spread of online consumption. However, if the coronavirus outbreak led many consumers to make these upfront investments, they would have no reason to return to offline consumption after the pandemic. In addition, it is possible that actually using the internet for purchases during the pandemic may have dispelled the various concerns. Given this, one would expect online consumption "novices" to continue to use the internet for purchases even when the risk of getting infected with the coronavirus has disappeared.

The main findings of this paper are as follows. First, the main group responsible for the increase in online consumption during the coronavirus period were consumers who were already familiar with online consumption before the pandemic and purchased goods and serviced both online and offline. The fact that these consumers stopped all their offline consumption and switched to online only consumption substantially contributed to the increase in online consumption. Second, there were some consumers that had never used the internet for purchases before and that started to do so during the pandemic, but the share of such consumers was limited. Third, by age group, the switch to online consumption was more pronounced among youngsters than seniors. The difference between the age groups in terms of switching to online consumption is not due to differences in digital literacy but likely reflects differences in attitudes with regard to the risk of infection.

Further, based on these findings, we attempted to forecast online consumption after the pandemic subsides. The increase in online consumption during the coronavirus period is due

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to the increase in online consumption among consumers that already were used to making purchases online and that were worried about the risk of infection. The level of online consumption of these consumers is likely to return to pre-pandemic levels as the risk of infection recedes. Thus, while it is widely argued that the changes in consumers' behavior due to the coronavirus shock are irreversible, the forecast results obtained in this study suggest that the increase in online consumption is not irreversible.

In this study, we focused on the switching costs from offline consumption to online consumption as the reason why the increase in online consumption might be irreversible and conducted our analysis based on the assumption that these costs are particularly high for consumers that have never been online. However, some argue that in the post-coronavirus era, social and economic customs will change substantially, and we recognize that this could clearly have an effect on online consumption. As data gradually become available in the future for the period in which the risk of infection is reduced, further investigation into whether the shift to online consumption is irreversible or not and the reasons will be necessary.

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