COVID-19 and Social Distancing in the Absence of Legal Enforcement: Survey Evidence from Japan

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28 May 2020

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Abstract

Do people keep social distance to mitigate the infection risk of COVID-19, even without aggressive policy interventions? The Japanese government did not restrict individuals' activities despite the early confirmation of infections, and as a result, economic damages were limited in the initial stage of infection spread. Exploiting these features, we examine the association between the subsequent increase in infections and voluntary social-distancing behavior. Using unique monthly panel survey data, we find that the increase in risk is associated with the likelihood of social-distancing behavior. However, those with lower educational attainment are less responsive, implying their higher exposure to infections. We provide evidence that this can be attributed to their underestimation of infection risk, while we cannot fully rule out the roles of income opportunity costs and poor information access. These results suggest the utility of interventions incorporating nudges to raise risk perception, as well as financial support for low-income households.

Keywords: COVID-19; pandemic; social distancing; risk perception; nudge

JEL Codes: I12; I14; I18;

Funding: This paper was supported by KAKENHI (20K01689), KAKENHI (18K01501), KAKENHI (17H02478), and the Group-Joint-Research Project Grant ("Social Sciences of Digitalization") of the Institute of Social Science, The University of Tokyo.

1. Introduction

The COVID-19 pandemic has caused immense human losses worldwide. To mitigate the infection spread, it is essential for individuals to maintain appropriate social or physical distance from one another (Fenichel, 2013; Fenichel et al., 2011; Ipsen, 1959).[1] However, it can be difficult to achieve sufficient levels of distancing through voluntary individual compliance alone, because of its economic costs and uncertainties about transmission risk.[2] Therefore, many governments have sought to enforce social distancing through various interventions, such as closing public transportation and workplaces, making viral or antibody tests available to anybody, and providing financial support (Hale et al. 2020). However, an obvious concern regarding aggressive regulations is their economic consequences (Acemoglu et al., 2020; Inoue and Todo, 2020; Lin and Meissner, 2020). In the United States, the unemployment rate has jumped from 4.4% in March 2020 to 14.7% in April. Therefore, some countries have begun to lift social distancing requirements to restart economic activities, generating a new argument about whether governments can cope with the next wave of infections without relying on costly regulations. However, to the best of our knowledge, the extent to which individuals maintain social distance in the absence of aggressive regulation remains largely unexplored.

This study bridges this knowledge gap by examining the case of Japan during

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[1] Social distancing or physical distancing is defined as the practice of keeping physical space between oneself and other people outside of the home. This includes staying at least six feet from other people, not gathering in groups, staying out of crowded places, and avoiding mass gatherings (Center for Disease Control and Prevention, 2020).

[2] Decision-making under uncertainty is subject to various cognitive biases (Kahneman and Tversky 1972). In particular, the normalcy bias causes people to underestimate the probability and severity of transmission risk.

the initial phase of the COVID-19 infection spread. The Japanese government was less interventionist than other countries, in that it did not restrict residents' activities or provide financial support. Reverse-transcription polymerase chain reaction (RT-PCR) tests were not made widely available. Rather, the government simply requested that citizens maintain social distance and stay home voluntarily. Exploiting these features, this study analyzes the extent to which social-distancing behavior—such as face-to-face conversation, use of public transportation, and dining outside—changed with the increase in infection risk between January and March 2020, before the government announced a state of emergency on April 7th. This study also uncovers obstacles to social-distancing behavior, such as income opportunity costs, poor access to information, and underestimation of transmission risk. Disentangling these obstacles allows us to discuss the interactive roles between individuals' responses and public policies. For example, if people do not modify their behavior due to the underestimation of infection risks, then interventions that elevate risk perceptions should mitigate the spread of COVID-19 effectively, without the need for more drastic restrictions on activities.

Using original survey data, we regress changes in social-distancing behavior on the monthly average of confirmed cases per day in each prefecture, the main unit of subnational government in Japan. We discuss potential threats to identification carefully, particularly reverse causality and sample selection. Considering the absence of a natural experimental condition, it is difficult to fully rule out these possibilities. However, we provide evidence that these biases are unlikely to be severe, and if anything should work against our central hypotheses.

We find that the increase in the number of confirmed cases significantly encourages respondents to take social-distancing behavior. However, the effect is smaller among socio-economically vulnerable individuals, particularly the less educated, implying that exposure to infections may not be equal across individuals. We also provide suggestive evidence that the heterogeneous impact is mainly attributable to differences in the perception of infection risk, although we cannot fully rule out the roles of income opportunity costs and poor information access. These results suggest the importance of interventions that incorporate nudges to heighten perceptions of risk, as well as financial support.

This study is most closely related to Barrios and Hochberg (2020), who examine the impact of obtaining information about infection spread on perceptions of risk and social-distancing behavior in the U.S. A key distinction between this study and theirs is that their work analyzes social distancing after the government started to restrict residents' activities in the U.S., while we study Japan before the government intervened. The findings of this study are also in line with those of Muto et al. (2020) and Machida et al. (2020) that examine social distancing in Japan, Kushner Gadarian et al. (2020) in the U.S., and Barari et al. (2020) in Italy. In particular, Muto et al. (2020) also find less behavioral change among those with lower socio-economic status, although they do not test the potential reasons for the heterogeneity.

This study is also related to the literature of health inequality. Existing studies demonstrate the association between socio-economic status and health status (Balia and Jones, 2008; Cutler et al., 2008; Doorslaer et al., 2004; Kawachi et al., 2010; Williams et al., 1997; Winkleby et al., 1992). Researchers consider this relationship to be mediated by differences in health behavior, access to health care, exposure to health risk, and stress (Adler and Newman, 2002; Kristenson et al., 2004; Maurer, 2009). Others argue that knowledge and perception of health risk play pivotal roles in predicting health behavior, such as smoking, substance abuse, purchase of health insurance, immunization, and disaster evacuation (Apostolidis et al., 2006; Lin and Sloan, 2015; Lundborg and Andersson, 2008; Riad et al., 2006; Schaller et al., 2019; Zhou-Richter et al., 2010). In line with these works, our data support the hypothesis that differences in the perception and knowledge of health risks across education levels cause the heterogeneity in health behavior.

The rest of this study is organized as follows: Section 2 summarizes the infection spread and government responses in Japan. Sections 3 and 4 describe the dataset and identification strategy, respectively. Section 5 presents the results. Section 6 disentangles the obstacles to social-distancing behavior, and finally Section 7 concludes.

2. Background

2.1. Infection Spread of COVID-19 in Japan (January to March 24th, 2020)

On December 31st in 2019, the WHO China Country Office was informed of cases of pneumonia of unknown causes in Wuhan City, China. Due to its geographical proximity to China and frequent bilateral travel for tourism and business, Japan was one of the earliest countries to confirm COVID-19 cases outside of China, following Thailand (WHO, 2020). According to the Ministry of Health, Labour, and Welfare (MHLW), the first case in Japan was confirmed on January 15th, 2020 in Kanagawa, a region in the suburb of Tokyo, and 15 more cases were reported by the end of January (Figure 1).[3] Most of these cases (13 out of 16) were attributed to visitors and returnees from China. The first report of human-to-human transmission, however, appeared in January 28th in

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[3] The information on the number of confirmed cases is available from the MHLW website (https://www.mhlw.go.jp/stf/houdou/index.html, accessed on May 6th, 2020).

Nara, a tourist site in western Japan.

[Figure 1]

In February, the virus gradually and silently spread in several rural prefectures in addition to large cities. By February 10th, 28 cases had been confirmed, of which 15 were Japanese residents.[4] Infection of medical workers began to appear in the second half of the month. Serious cluster cases were also found in late February, including the participants of a snow festival in Hokkaido, the northern-most prefecture of Japan. By the end of February, a total of 239 cases were reported, of which 69 were in Hokkaido. However, more than half of the 47 prefectures had not yet confirmed any cases, and even populated prefectures, such as Miyagi and Osaka, had found only a few cases (Figure 2).

[Figure 2]

Infection spread accelerated in March. More populated prefectures started to find new cases regularly, and over 10 prefectures announced their first cases in the first week of March. While about 30 cases were found nationwide each day until the 9th, a big jump occurred on the 10th, when 70 cases were reported. Around the same time, fatalities from COVID-19 started being reported regularly.

2.2. Government Response and Economic Consequences

Despite the confirmation of infected citizens earlier than most countries, the national government's response was comparatively passive. It gradually tightened immigration controls to visitors from Hubei Province, China, and also asked Japanese residents in Wuhan to come back to Japan in the beginning of February. However, in stark contrast to

[4] Around the same time, passengers of the Diamond Princess, a cruise ship, tested positive, and the ship began to be quarantined from February 4th. Passengers and crew stayed on the ship for two weeks.

other countries which closed public transportation and workplaces, there was no legal regulation of residents' activities in Japan. In fact, as late as early April, the prime minister emphasized that there was no need to declare a state of emergency and only requested self-restraint (*Jishuku Yosei*) in hosting or attending large-scale public events.[5]

The one exception was on February 27th, when the national government requested the closures of all elementary, junior, and senior high schools until the beginning of the new academic year in April. However, the final decision was left to the governor of each prefecture, and some prefectures did not close their schools. No restrictions were placed on economic activities.

While the national government was cautious about declaring a state of emergency, several local governments took measures of their own. That said, these were also limited in the scope and time frame of regulated activities and, more importantly, lacked legal enforcement. On February 28th, the Governor of Hokkaido announced a state of emergency, although it lacked legal basis, and requested that residents avoid leaving their homes for three weeks.[6] The Governor of Osaka also asked for the refrainment of movement to and from Hyogo, the neighboring prefecture, between March 20th and 22nd.

The low number of RT-PCR tests in Japan is also striking when compared to South Korea, which made drive-thru tests available to anyone, including asymptomatic

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[5] The Constitution of Japan does not provide for a national state of emergency. As such, neither the national nor local governments has the formal authority to require business closures, shelter-in-place orders, or citywide lockdowns. However, amendments to the Infectious Diseases Control Law on March 13, 2020, newly allowed the Cabinet to declare a "soft" state of emergency, which delegates mores authority to prefectural governors to contain COVID-19. Even then, governors are restricted to urging (and if necessary shaming) businesses and citizens to follow its directives. The "state of emergency" referred to in this paper refers to this latter, softer variety.

[6] After this announcement, on March 13th, the National Diet (parliament) amended the law so that a state of emergency declaration could be issued.

people.[7] There were two paths for Japanese residents to be tested as of March 2020. First, those who had “close contact” with an infected person were requested to visit a designated medical facility.[8] Second, those who did not have close contact but suffered from severe symptoms could consult with their family doctor or local public health call center, who would then refer the patient to a designated facility, if considered necessary. Only those persons whom the facility suspected were infected could take a RT-PCR test, which was administered at public health centers or local public health institutions. Therefore, there was no way to detect asymptomatic infection except for those who had “close contact”. The accuracy of detecting infected people also depended on the screening ability of home doctors, call centers, and designated medical facilities.

Because of these passive policy interventions, economic conditions in Japan did not decline as much as in other countries during the first quarter of 2020. Although the number of bankruptcies increased from 651 cases in February to 740 in March, as shown in Figure A1, only 12 cases were related to COVID-19 (Tokyo Shoko Research, 2020). The unemployment rate was also stable between January and March, in contrast to other countries experiencing a rapid increase in infections, such as the U.S. and Ireland (Figure A2).

3. Data

This study employs two datasets. First, to approximate the risk of COVID-19 infection,

[7] According to an MHLW report on May 4, 2020, the low number of tests was due to the limited capacities of call centers, testing facilities, and medical facilities (https://www.mhlw.go.jp/content/10900000/000627553.pdf, accessed on May 10, 2020).

[8] A person is categorized to be in close contact with infected persons if he/she (i) touches an infected person directly without anti-infective measures, or (ii) meets an infected person at a distance of around 2 meters (6 feet) or less.

we construct prefecture-level monthly panel data on the average number of newly confirmed cases per day. We use this information as the main independent variable, because the number of newly confirmed cases is reported daily by the government and mass media, and thus is the most easily accessible information for people regarding the infection spread. While the ratio of positive-to-negative RT-PCR tests is one alternative measure of infection risk, we do not use it for this analysis, because that information was not widely disseminated and thus unlikely to affect behavioral patterns at that time.

Second, this study uses data from an original, nationwide online survey.[9] The first round of the survey was conducted between March 25th and 27th, 2020. Because working-age individuals account for a high proportion of confirmed cases, our survey targeted those in their 30s and 40s. The sample size is 2,798. The questionnaire is designed to elicit information about both behavior and preferences, such as the use of social media, political sentiment, health status, actions taken to protect oneself and others from COVID-19, perceptions about the severity of infection risk, and the assessment of the government's early responses to COVID-19. On April 27th to May 7th, we re-surveyed the same respondents to collect further information on their social and psychological traits, such as civic attitudes and social capital, although we use it only in Section 6. A total of 2,462 individuals participated in both surveys. Table A1 presents the summary statistics of prefecture and respondent characteristics. Online Appendix A1 discusses more details about the survey design, such as sampling methodology and

[9] A potential drawback to the use of online survey data is sample selection. However, we chose this approach because it was difficult to conduct a paper-and-pencil survey in a timely manner at that time. An alternative approach is to use publicly available data, such as the Google Trends interface and geolocation data from mobile phones (Barrios and Hochberg 2020). Although these may better capture behavioral changes, it is difficult to analyze the degree of and reasons for heterogeneity in behavior.

research ethics.

The first-round survey data contain three behavioral variables related to social distancing, our outcome of interest. The first is frequency of face-to-face conversations per day. The second is the number of days per week that respondents used public transportation for more than one hour, capturing the frequency of commuting. Third, we use the frequency per week of dining outside.[10] In this survey, retrospective information was collected, based on recall; the dataset contains the information on face-to-face conversations from December 2019 until March 2020, and on the other two variables from January to March 2020. From this retrospective information, a monthly pseudo-panel dataset was compiled. Figure 3 depicts the trend of these variables.

[Figure 3]

4. Identification Strategy

4.1. Estimation Model

This study estimates the following OLS model:

$$R_{ipt} = \alpha_0 + \alpha_1\, Inf_{pt} + \alpha_2\, Adj\_Inf_{pt} + \alpha_3\, Damage_{pt} + \delta_{ip} + T_t + \varepsilon_{ipt}, \qquad (1)$$

where, R_{ipt} denotes the binary indicators of social-distancing behavior of individual i in prefecture p in month t. For face-to-face conversations, R_{ipt} takes unity if the individual talks with five people or more per day, and zero otherwise (roughly around the median). For public transportation and dining outside, it takes unity if the individual undertakes these activities at least once a week. Inf_{pt} denotes the monthly average of newly confirmed cases per day in the prefecture in which the respondent resides. Adj_Inf_{pt} denotes the

[10] The transmission risk from these activities depends on various factors, such as the use of masks and physical distance from others, but we did not ask such detailed questions to mitigate the respondents' burdens and ensure a higher response rate.

summation of *Inf* over the adjacent prefectures, to account for high levels of cross-prefectural movement in urban areas in particular. $Damage_{pt}$ denotes proxies for the economic damages from the infection spread, such as the number of bankruptcies and the active job-openings-to-applicants ratio. Finally, δ_{ip} and T_t denote respondent and monthly fixed effects, respectively. The respondent fixed effects control for those characteristics invariant between January and March 2020, including socio-economic conditions at the prefecture and individual levels. Monthly fixed effects capture the impact of country-level shocks, such as news about the infection spread in other countries and restrictions on overseas travel.

4.2. Underlying Assumptions

4.2.1. No Reverse Causality

Our identification strategy relies on four assumptions. The first assumption is the absence of reverse causality. The residents' (lack of) social-distancing behavior may affect the level of confirmed cases in the prefecture. However, this should cause an upward bias between risky behavior and COVID-19 infection counts. Hence, as long as we find a negative association between risky behavior and confirmed cases, it should not affect the interpretation of results.

Furthermore, this issue is unlikely to be severe, because many whose infections were confirmed in March were likely to have been infected in the beginning of the month or even earlier. Symptoms generally develop 2 to 14 days following exposure to the virus (Center for Disease Control and Prevention, 2020). In addition, the Japanese government recommended home rest for a few days after becoming symptomatic to see whether the symptoms became serious. Only then were patients recommended to visit their home doctor or consult a call center to be assessed whether they should go to a designated medical facility, as mentioned in Section 2. Therefore, there is often a significant time lag between exposure to the virus and confirmation of the diagnosis.

It should be noted that the Japanese government has identified that at least 70% of newly confirmed cases between March 1st and 24th were transmitted by those who were previously confirmed.[11] Therefore, the increase in the confirmed cases in this period was mainly determined by the behavioral patterns of previously confirmed people (only 0.0002% of national population).[12] The social-distancing behavior of most respondents should have played a limited role in the increases in confirmed cases.

4.2.2. Parallel Trend Assumption

The second is the parallel trend assumption, which may be subject to the following two issues. First, the number of confirmed cases may grow faster in urban prefectures, which have greater testing capacity and population density, and these characteristics may be correlated with changes in social-distancing behavior. However, in the time period under observation, we would expect less social distancing in urban areas, causing an upward bias (less social distancing where there are more infections) that runs counter to our hypothesis (more social distancing where there are more infection). The frequencies of conversing with colleagues, commuting, and dining out are expected to increase in March, particularly in large cities, because March is the final month of the fiscal year and work

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[11] The Japanese government identifies the channel of transmission based on interviews with confirmed patients. The data on confirmed cases by transmission channels are available from https://datastudio.google.com/reporting/c4e0fe88-f72e-464e-a3b8-5e4e591c238d/page/ultJB?s=oA3tV-uQzaE (accessed on May 8, 2020).
[12] As of the end of February 2020, only 206 cases were confirmed, compared to the national population of 126 million.

hours generally increase. The Statistics Bureau of Japan (2020) finds that in 2018 and 2019, the revenues of restaurant business increased in March.

Furthermore, as mentioned in Section 4.2.1, the infection spread in March was mainly attributed to the unwitting behavior of infected persons before their diagnosis was confirmed, such as the frequency of going to bars before becoming symptomatic. Therefore, the socio-economic environment of the prefecture should have played a limited role in the increase in confirmed cases in March, if at all.

The second potential violation of the parallel trend assumption is that, if the timing of infection spread is controllable or predictable, people can prepare for it beforehand. Therefore, they may alter their behavior even in the pre-spread period. However, this is also unlikely because it is difficult to predict the timing that infections spread accurately. More importantly, these possibilities also attenuate the estimated effect of infection risk, i.e. the results would be biased against finding statistically significant results. Therefore, it should not affect the interpretation of results qualitatively, as long as we find a significantly negative effect.

To examine the validity of the parallel trend assumption, we conduct a falsification test by regressing R_{ipt} (social distancing behavior) between December and February on the individual fixed effects, monthly fixed effects, and interaction terms between monthly fixed effects and the number of confirmed cases in March. Table A2 shows that the coefficients of interaction terms are statistically jointly insignificant and small in magnitude for all the columns.

One may also be concerned about the ceiling effect. If the level of R_{ipt} in February is already low (i.e. high level of social distancing) in prefectures that subsequently had few confirmed cases in March, then R_{ipt} in March may be less likely to decrease even further than in prefectures with more cases, regardless of the severity of infection spread. We test this possibility by regressing the level of R_{ipt} in February on the number of confirmed cases in March. The coefficients are -0.003 (p-value=0.440) for face-to-face conversations, 0.060 (p-value=0.000) for the use of public transportation, and 0.009 (p-value=0.314) for dining out. Hence, the data show that the ceiling effect is negligible for the frequencies of face-to-face conversation and dining outside.

4.2.3. Limited Impact of Economic Damage and Government Intervention

The third underlying assumption for this model is that the increase in the number of confirmed cases affects individual behavior only through the increase in infection risk, but not through associated economic damages or government interventions. This assumption is likely to hold: as mentioned in Section 2, economic indicators, such as the unemployment rate and number of bankruptcies, were still stable during the survey period. Furthermore, using the prefecture-level monthly panel data, we find that the number of confirmed cases is not associated with bankruptcy cases or the active job-openings-to-applicants ratio (Table A3). Finally, our econometric specification controls for these economic conditions.

Regarding government interventions, after the prime minister recommended that local governors close schools in March, respondents with a schooling-age child may have had to stay home to take care of their children. To rule out this impact, we re-estimate the model after excluding respondents with a schooling-age child. In addition, we also drop the sample from Hokkaido prefecture, which unilaterally closed schools and encouraged residents to shelter in place, in order to eliminate the effects of imposing a state of emergency.[13]

4.2.4. Limited Spillover Effect

The fourth potential threat to our identification strategy is the spillover effect from other prefectures. A spike in COVID-19 cases in one prefecture may elevate perceived risks among residents of neighboring prefectures, motivating them to maintain social distance. This is particularly plausible for those who commute to adjacent prefectures for work. To address this potential issue, we control for the number of confirmed cases in the adjacent prefectures, Adj_Inf_{pt}, in the model.

5. Results

5.1. Benchmark Results

Table 1 presents the OLS results of Equation (1). It shows that the increase in confirmed cases is significantly associated with social-distancing behavior. As prefecture-level COVID-19 cases increase, people reduce face-to-face conversations, the usage of public transportation, and dining out. Furthermore, compared to the naïve models (Columns (1), (5), and (9)), the association becomes substantively larger after controlling for economic conditions (Columns (2), (6), and (10)). The results are also robust to the additional control for confirmed cases in adjacent prefectures (Columns (3), (7), and (11)) and the exclusion of respondents with a schooling-age child (Columns (4), (8), and (12)). Columns (4) and (8) show that a one standard deviation increase in COVID-19 cases (S.D.=1.9) is associated with a decrease in the likelihood of talking with more than five

[13] We do not exclude the sample of Osaka because the request to refrain from cross-prefecture movement was only in place for three days.

people per day and using public transportation by 1.5 and 1.3 percentage points, respectively. Column (12) demonstrates an insignificant coefficient, but the point estimate is still stable. Hence, changes in economic conditions or government interventions cannot explain the significantly negative coefficients of confirmed cases.

With regard to other coefficients, it is suggestive that the increase in confirmed cases in adjacent prefectures has a negative effect on commuting behavior. This is presumably driven by respondents who commute across prefectural borders. The coefficients of the job-opening-to-applicants ratio are negative. Although this is purely speculative, this result may be because a higher ratio enables individuals to select a job with better working conditions.

We conduct the following robustness checks. First, people may react to the accumulated number of confirmed cases over multiple months, rather than the number of newly confirmed cases in the most recent month. Hence, as an alternative measure of infection risk, we re-estimate the model using the accumulated number of confirmed cases (Table A4). Second, behavioral patterns may differ between employed and unemployed persons, because of differences in the need to use public transportation and have face-to-face conversation. They may also differ in terms of budget constraint for dining outside. To control for these heterogeneities, we re-estimate our models after excluding respondents who do not work (Table A5). Third, our survey originally elicited information on social-distancing behavior as an ordinal variable (Figure 3), but we converted these into binary indicators for the panel data analysis. In Table A6, we use the original categorical values as the dependent variable and re-estimate the models using interval regressions and ordered probit models. The results are robust to all of these alternative specifications.

[Table 1]

5.2. Heterogeneous Effect

Does the impact of infection risk vary across individuals? In Table 2, we address this question by adding interaction terms between confirmed cases and respondent characteristics. We also control for month-prefecture fixed effects rather than the monthly fixed effects. These models demonstrate significant differences by education level. Columns (1), (3), and (5) suggest that the impact of a one standard deviation increase in confirmed cases is larger for university graduates by 1.7, 2.9, and 2.1 percentage points, respectively, than for high school graduates.

Regarding other characteristics, first, we find a difference in the frequency of dining outside by gender. Second, the coefficient of interaction with respondents' age is statistically insignificant for most columns and small in magnitude, presumably because our sample consists only of those in their 30s and 40s. Finally, those with a schooling-age child are less likely to eat out, given the increase in infection risk.

[Table 2]

6. Suggestive Evidence on the Mechanisms of Heterogeneous Impact

Why are less educated people less sensitive to the risks of COVID-19 infection? We test eight potential mechanisms. First, they may engage in a job that is not suitable for teleworking, such as in retail or the restaurant business. Second, their economic status may be lower, and so they may suffer from credit constraints. Therefore, the disutility from the income loss caused by staying home is larger than for the wealthy. The third potential mechanism is that they may not watch television news or read newspapers, and therefore have poorer knowledge of COVID-19. Fourth, even if they have knowledge, they may still underestimate the infection risk. Because the actual number of infected individuals is unobservable, people infer the infection risk from the information available, but news related to COVID-19 frequently includes professional, foreign language terms (e.g. RT-PCR tests). Fifth, they may be less risk averse. Sixth, they may possess less social capital than university graduates, and so may care less about their reputation or disapproval from neighbors. Seventh, they may take alternative actions to protect themselves, such as wearing masks and washing hands with disinfectants. Finally, they may recognize that the number of confirmed cases underestimates the actual infection risk, and therefore, they may react to other types of information, such as the ratio of positive RT-PCR tests. Among these, the first to fourth channels suggest that the less educated do not maintain social distance due to some constraints, whereas the fifth and sixth mechanisms imply that they do not keep social distance by intention. These six mechanisms suggest that the less educated are exposed to higher infection risks, and thus could be unwitting but significant vectors of COVID-19.

To test the relevance of the first channel—the unsuitability of certain jobs for teleworking—we construct an industry-level proxy using the survey results of Okubo and NIRA (2020). Based on an online survey in Japan, this study shows the proportion of respondents working at home by industry as of March 2020. We combine these proportions and our respondents' occupation to approximate the suitability of their jobs for teleworking.[14] Then, we regress it on the respondent characteristics to examine whether less educated respondents actually engage in a job unsuitable for telework. Column (1) of Table 3, however, shows that the coefficient for university graduate is

[14] The summary statistics of variables used for this section are presented in Table A1.

negative, counter to the hypothesis.[15]

Second, to examine the channel through income opportunity costs, we conduct a principal component analysis to construct a composite index of economic status from two variables: annual income, and a binary indicator that takes unity for self-employment, executive, or regular employment. We examine the correlation between this index and education level in Column (2) of Table 3. It confirms that the economic status of university graduates is significantly higher than that for high school graduates, in line with our hypothesis.

To test the third channel through information access, we construct a composite index from three variables: the frequencies of reading paper newspapers, reading newspaper websites, and watching television news. Then, we estimate the association between education level and the index in Column (3). The results are consistent with the hypothesis: educated respondents follow the mass media more frequently.

The fourth channel is underestimation of infection risk. We construct a composite index of risk perception using the following three questions: how many infected people they think there actually are in Japan; the extent to which COVID-19 will cause serious problems for themselves; whether the COVID-19 situation will be even worse after six months. The regression result in Column (4) shows that educated people are more likely to take the infection risk more seriously, supporting our hypothesis.

Fifth, given the difficulty in conducting an economic experiment to elicit the risk preference of respondents in our online survey, we test this channel through two proxy variables. First, we asked the following question: *which of the following two sayings*

[15] Okubo and NIRA (2020) also report the proportion of teleworking at the pre-spread period (January 2020). Changing the time period for telework suitability does not affect our results.

characterizes you better, "nothing ventured, nothing gained" or "a wise man never courts danger"? The answer options are in Likert-scale. Second, we also asked the following question: *at which precipitation probability do you go out with an umbrella*? A lower score to these answers indicates greater risk aversion. These questions are frequently used in the literature (Ikeda et al. 2016 p142; Iida 2016) and draws from earlier work in the United States. In Column (5), we estimate the relationship between the composite index of these variables and respondent characteristics, showing that education level is uncorrelated with risk preference.

Sixth, the second wave of our survey asks about respondents' social capital through six questions on general trust, pure altruism, and social norms. More detail about each question is reported in Table A1. We use these answers to construct a composite index. Column (6) demonstrates that social capital is lower for less educated respondents, supporting the hypothesis.

Seventh, although our survey does not include items on the use of facemasks or disinfectant soap, it does ask respondents whether they wished to buy them more than usual. We regress the composite index of these variables in Column (7). The result shows that highly educated individuals are more likely to answer affirmatively, counter to the hypothesis.

The eighth hypothesis pertains to respondents having less confidence of the confirmed number of infections cases as a proxy for infection risk. This hypothesis assumes that those with lower education have more knowledge about COVID-19 than educated respondents. This assumption, however, contradicts our findings that less educated respondents spend less time collecting information on COVID-19 (Table 3, Column (3)).

These results so far show that respondents' education levels are associated with economic status, information access, risk perception, and social capital. The observed patterns are robust to the full sample estimation (Table A7). These characteristics could be potential drivers of the heterogeneous effect of COVID-19 cases. To further test whether they are also associated with their social-distancing behavior, we additionally control for the interaction terms between these seven indices and the number of confirmed cases, based on the specifications in Table 2.

Table 4 presents the results. We find that in prefectures with many confirmed cases, those with high risk perception reduce the frequency of face-to-face conversations and dining out. Economic status and information access are also correlated with the frequency of commuting, but the results are not robust to the change in the sample. The interaction term for social capital has negative coefficients for most columns, but they are statistically insignificant. Intriguingly, the suitability of their jobs for teleworking is negatively associated with the frequency of commuting, as expected, but it is uncorrelated with the education level (Table 3). Overall, the results from Tables 3 and 4 support the hypothesis that differences in risk perception are the most likely driver of heterogeneity across education levels, whereas we cannot fully rule out the roles of income opportunity costs and information access.

Finally, if the heterogeneous effect across education levels is mediated by these differences in behavior and perception, the coefficient for university graduates should become smaller after controlling for them. However, we cannot directly compare the coefficient with that of Table 2, because some observations are dropped due to missing values in Table 4. Therefore, in Table A8 we re-estimate the model of Table 2 using the sample of Table 4. It shows that in the full sample model (odd-numbered columns), the coefficient of Table 4 is smaller by 25%, 17%, and 80%, respectively.

[Table 3]

[Table 4]

7. Conclusion

Do people keep social distance to mitigate the infection risk of COVID-19, even in the absence of aggressive government intervention? Using unique survey data collected in Japan, we find that an increase in the number of confirmed cases is negatively associated with the frequency of face-to-face conversation, public transportation use, and dining out. However, less educated people do not respond as much as those with higher education. We provide suggestive evidence that this heterogeneity is driven primarily by the former's underestimation of infection risk, although we cannot fully rule out the roles of income opportunity costs and information access.

The following policy implication can be derived. Some countries have lifted aggressive regulations before eliminating new COVID-19 infections in order to restart economic activities, but concerns remain about how governments will cope with the next wave of infections (Acemoglu et al., 2020; Inoue and Todo, 2020; Lin and Meissner, 2020). Our findings suggest that when the government prioritizes economic activities, socio-economically vulnerable individuals are exposed to particularly higher risk, and they could also become the primary vectors of the virus. This is consistent with the argument of Ahmed et al. (2020). It is, therefore, incumbent upon the government to implement a targeted intervention for this subpopulation promptly.

One approach is for governments to provide financial compensation to those experiencing economic hardship. This could be effective if three obstacles are mutually related: low income causes poor information access, which in turn affects perceptions of infection risk. However, this may not be enough to stop the infection spread. It may also be important to provide information on the risks of infection transmission in an easily accessible and understandable manner. Another promising approach is interventions that incorporate nudges to elevate risk perceptions. Van Bavel et al. (2020) argue in favor of nudges in eradicating COVID-19. Whether these policies—providing more information or financial compensation—are complements or substitutes in encouraging social-distancing behavior depend on how risk perception and health knowledge are formed. Further studies are required to design the optimal combination of these policies.

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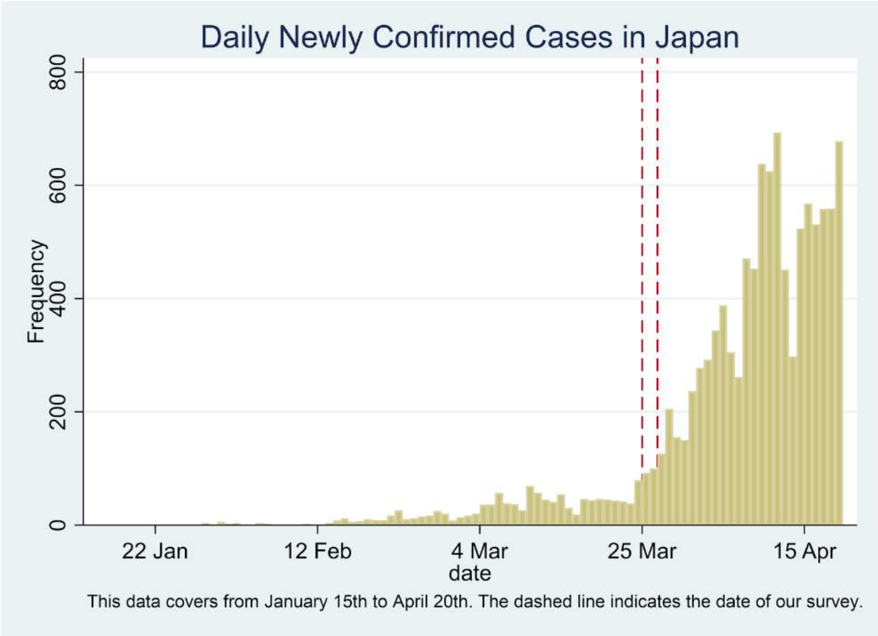
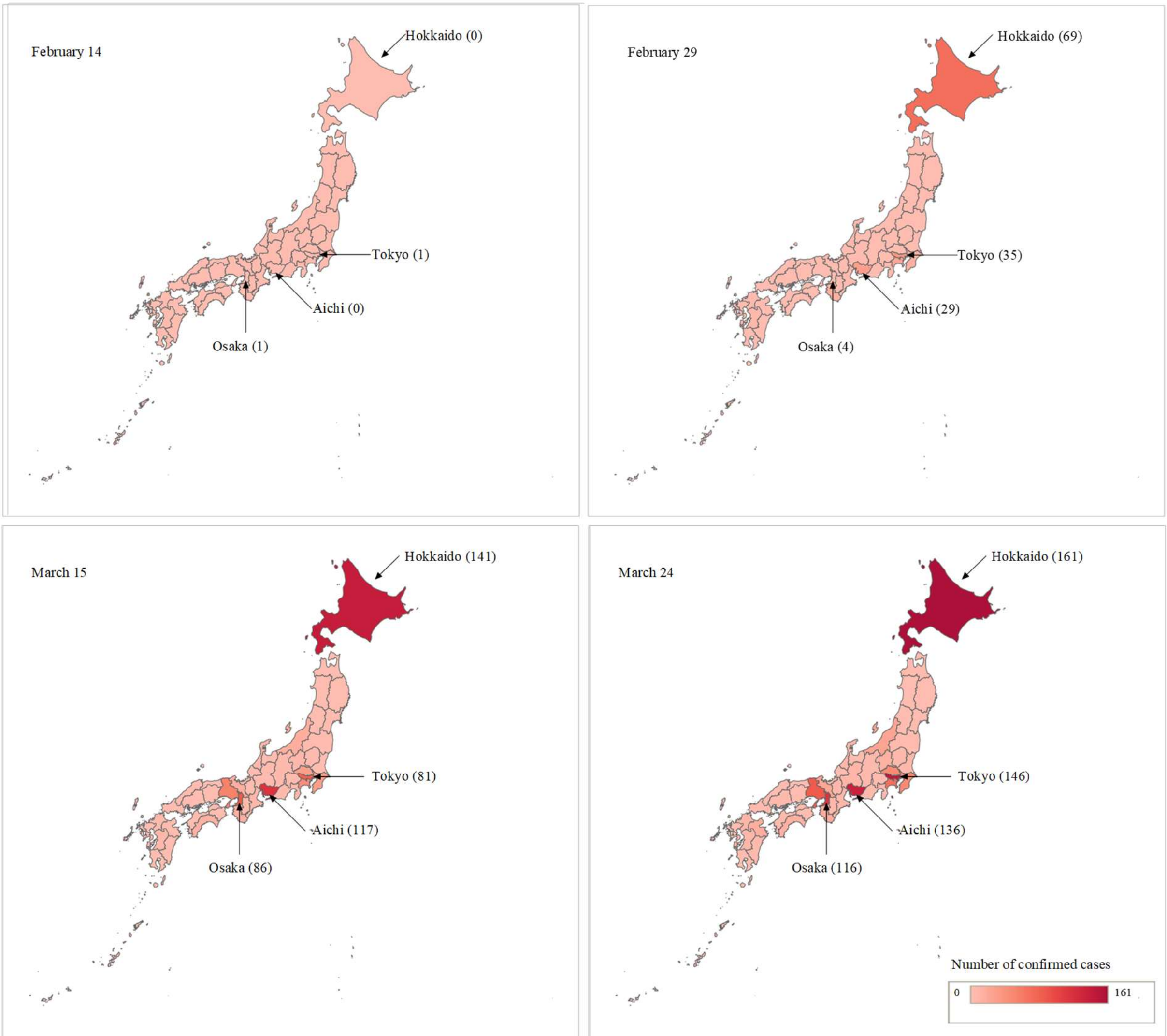


Note: The passengers and crew of the Diamond Princess are not included.
Source: MHLW (https://www.mhlw.go.jp/stf/houdou/index.html)

Figure 1: Infection Spread in Japan



Note: The passengers and crew of the Diamond Princess are not included.

Source: MHLW (https://www.mhlw.go.jp/stf/houdou/index.html)

Figure 2: Cumulative Number of Confirmed Cases

Figure 3: Trend of Social-Distancing Behavior

Table 1: The Impact of Infection Spread on Social-Distancing Behavior

	Conversation			
Sample:	All	All	All	No child
	(1)	(2)	(3)	(4)
Confirmed cases	-0.007**	-0.008***	-0.009***	-0.008**
	(0.003)	(0.003)	(0.003)	(0.004)
Confirmed cases			0.001	0.002
in adjacent prefectures			(0.002)	(0.003)
Bankruptcy cases		0.371	0.370	0.220
		(0.281)	(0.281)	(0.335)
Job-openings- to-applicants ratio		-0.164**	-0.173***	-0.123
		(0.066)	(0.066)	(0.080)
Monthly FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Mean Dep. Var.	0.518	0.518	0.518	0.486
Observations	10,439	10,439	10,439	7,299
Number of respondents	2,613	2,613	2,613	1,827
	Commute			
Sample:	All	All	All	No child
	(5)	(6)	(7)	(8)
Confirmed cases	-0.008***	-0.008***	-0.006**	-0.007**
	(0.002)	(0.002)	(0.002)	(0.003)
Confirmed cases			-0.005***	-0.005**
in adjacent prefectures			(0.002)	(0.002)
Bankruptcy cases		0.283	0.300	0.531
		(0.359)	(0.359)	(0.413)
Job-openings- to-applicants ratio		-0.172**	-0.137*	-0.191**
		(0.080)	(0.078)	(0.096)
Monthly FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Mean Dep. Var.	0.235	0.235	0.235	0.249
Observations	7,799	7,799	7,799	5,458
Number of respondents	2,619	2,619	2,619	1,832
	Dining			
Sample:	All	All	All	No child
	(9)	(10)	(11)	(12)
Confirmed cases	-0.006*	-0.007**	-0.005*	-0.005
	(0.003)	(0.003)	(0.003)	(0.004)
Confirmed cases			-0.002	-0.003
in adjacent prefectures			(0.002)	(0.003)
Bankruptcy cases		0.457	0.464	0.630
		(0.431)	(0.430)	(0.451)
Job-openings- to-applicants ratio		-0.009	0.006	-0.032
		(0.094)	(0.093)	(0.098)
Monthly FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Mean Dep. Var.	0.458	0.458	0.458	0.464

Observations	7,855	7,855	7,855	5,494
Number of respondents	2,624	2,624	2,624	1,835

The OLS coefficients are reported. Standard errors clustered at the respondent level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2: Heterogeneous Effect

	Conversation		Commute		Dining	
Sample:	All	No child	All	No child	All	No child
	(1)	(2)	(3)	(4)	(5)	(6)
Confirmed cases	-0.009*	-0.013**	-0.015***	-0.017***	-0.011**	-0.003
x University	(0.005)	(0.006)	(0.004)	(0.005)	(0.005)	(0.005)
Confirmed cases	-0.009	-0.015**	-0.008	-0.008	-0.007	0.001
x Vocational	(0.007)	(0.007)	(0.005)	(0.006)	(0.007)	(0.008)
Confirmed cases	-0.000	0.000	-0.000	-0.001	0.000	-0.000
x Age	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Confirmed cases	-0.007	-0.005	-0.005	-0.006	-0.017***	-0.011**
x Female	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)
Confirmed cases	-0.004		0.000		-0.015**	
x Live with schooling-age child	(0.005)		(0.005)		(0.006)	
Month-Prefecture Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var.	0.518	0.486	0.235	0.249	0.458	0.464
Observations	10,192	7,203	7,619	5,389	7,665	5,422
Number of respondents	2,551	1,803	2,556	1,807	2,559	1,810

The OLS coefficients are reported. Standard errors clustered at the respondent level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: The Relationship Between Education and Socio-Economic Indices (Samples with no schooling-age child)

	Suitability of job for teleworking (1)	Economic status (2)	Information access (3)	Risk perception (4)	Risk preference (5)	Social capital (6)	Alternative protective measures (7)
University	-0.101***	0.780***	0.231***	0.145**	0.040	0.607***	0.220***
	(0.024)	(0.064)	(0.077)	(0.062)	(0.045)	(0.084)	(0.062)
Vocational	-0.048	0.306***	0.189***	0.021	0.051	0.494***	0.278***
	(0.035)	(0.076)	(0.066)	(0.087)	(0.076)	(0.093)	(0.072)
Age	-0.001	-0.005*	0.028***	0.009**	-0.002	-0.001	-0.016***
	(0.002)	(0.003)	(0.005)	(0.004)	(0.004)	(0.008)	(0.004)
Female	0.157***	-0.534***	-0.157***	-0.073	-0.268***	0.339***	0.497***
	(0.021)	(0.059)	(0.056)	(0.046)	(0.044)	(0.071)	(0.059)
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,468	1,586	1,798	1,784	1,790	1,454	1,787

The OLS coefficients are reported. Standard errors clustered at the prefecture level are in parentheses. The sample sizes of Columns (1) and (6) are smaller than the others, because the data on respondents' occupation and social capital were collected in the second-wave survey. Column (2) also has a small sample size due to missing values in the annual income data. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: The Relationship Between Socio-Economic Indices and Social-Distancing Behavior

	Conversation		Commute		Dining	
Sample:	All	No child	All	No child	All	No child
	(1)	(2)	(3)	(4)	(5)	(6)
Confirmed cases	-0.009	-0.016	-0.024**	-0.025*	-0.009	-0.002
x Suitability of job for teleworking	(0.010)	(0.011)	(0.012)	(0.013)	(0.013)	(0.014)
Confirmed cases	-0.002	-0.004	-0.005*	-0.004	-0.004	-0.002
x Economic status	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Confirmed cases	0.000	-0.002	-0.003	-0.004*	-0.003	-0.004
x Information access	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Confirmed cases	-0.005**	-0.007**	-0.002	-0.003	-0.006**	-0.004*
x Risk perception	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Confirmed cases	-0.001	0.000	0.000	0.002	-0.005*	-0.004
x Risk preference	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Confirmed cases	-0.002	-0.002	-0.000	0.001	-0.001	-0.002
x Social capital	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Confirmed cases	-0.001	0.000	0.001	0.001	-0.001	-0.001
x Alternative protective measures	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Confirmed cases	-0.009	-0.012*	-0.010*	-0.015**	-0.001	0.006
x University	(0.007)	(0.007)	(0.006)	(0.007)	(0.008)	(0.007)
Confirmed cases	-0.015*	-0.020**	-0.010	-0.010	-0.002	0.006
x Vocational	(0.009)	(0.010)	(0.008)	(0.009)	(0.010)	(0.010)
Confirmed cases	-0.000	-0.000	-0.001	-0.001*	0.000	-0.000
x Age	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Confirmed cases	-0.007	-0.003	-0.003	-0.003	-0.024***	-0.014**
x Female	(0.006)	(0.007)	(0.005)	(0.006)	(0.007)	(0.007)
Confirmed cases	-0.013*		-0.001		-0.018**	
x Live with schooling-age child	(0.007)		(0.006)		(0.009)	
Month-Prefecture Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var.	0.530	0.495	0.244	0.260	0.465	0.471
Observations	6,912	4,897	5,175	3,670	5,196	3,684
Number of respondents	1,738	1,230	1,739	1,232	1,740	1,233

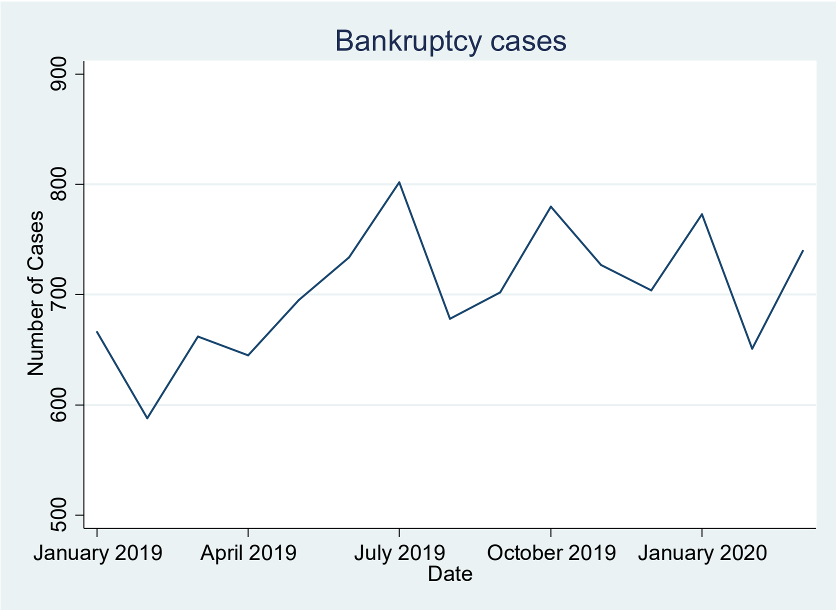
The OLS coefficients are reported. Standard errors clustered at the respondent level are in parentheses. The sample size is smaller than Table 2, because the data on respondents' occupation and social capital were collected in the second-wave survey. *** p<0.01, ** p<0.05, * p<0.1.

Online Appendices

Appendix 1: Further Discussion on the Survey Design

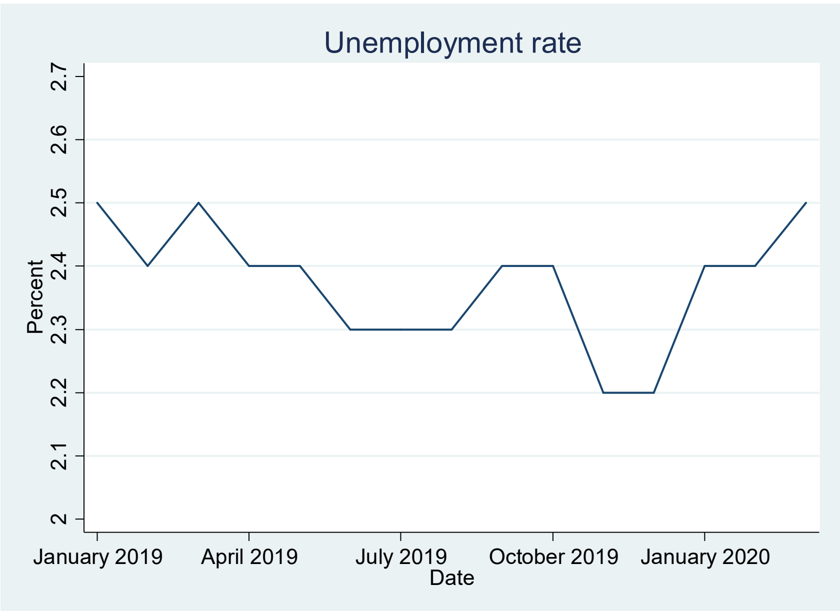
Our survey targeted those in their 30s and 40s because working-age individuals account for the high proportion among the confirmed cases. Respondents were recruited by Rakuten Insight, which has 2.2 million registrations. Among them, we conducted a quota sampling with regard to gender (two categories), age group (four 5-year categories), and location of residence (10 categories), so that the distribution of these characteristics becomes comparable to that of the Japanese population. The respondents received some token for shopping at Rakuten.com as financial incentive. After dropping the sample of Hokkaido prefecture, the sample size is 2,637 for the first round, of which 2,293 participated in both rounds. We obtained informed consent from the respondents. This survey was approved by Research Ethics Committee of the Institute of Social Science in the University of Tokyo.

Table A1 presents the summary statistics of respondent characteristics. Among employed workers, temporary employment accounts for 26.6%. According to the Labor Force Survey, a nationally representative survey conducted by Japanese government, the corresponding statistic is 28.7%, supporting the representativeness of our survey data. However, it should be noted that 51.8% of respondents are university graduates, while the School Basic Survey predicts 35.7% for these birth cohorts. This suggests that our dataset may oversample those with higher socio-economic status.



Source: https://www.tsr-net.co.jp/news/status/monthly/index.html

Figure A1: The Trend in Bankruptcy Cases: Jan 2019 – Mar 2020



Source: https://www.stat.go.jp/data/roudou/sokuhou/tsuki/index.html

Figure A2: The Trend in Unemployment Rate: Jan 2019 – Mar 2020

Table A1: Prefecture and Respondent Characteristics

	Obs.	Mean	S.D.
Prefecture Characteristics			
Confirmed cases in the prefecture (per day)			
January 2020	2,637	0.011	0.024
February 2020	2,637	0.306	0.441
March 2020	2,637	1.705	1.905
Bankruptcy cases (thousand cases)			
January 2020	2,637	0.039	0.039
February 2020	2,637	0.035	0.041
March 2020	2,637	0.040	0.045
Job-openings- to-applicants ratio			
January 2020	2,637	1.532	0.263
February 2020	2,637	1.496	0.269
March 2020	2,637	1.439	0.253
Respondent Characteristics			
Age	2,624	40.635	5.747
Female	2,634	0.498	
Live with schooling-age child	2,598	0.291	
Schooling	2,608		
High school or lower		0.223	
Vocational/ Jr college		0.259	
University or higher		0.518	
Socio-Economic Characteristics			
Suitability of job for teleworking	2,103	0.229	0.325
Occupation	2,616		
Executive / Self-employed		0.093	
Regular employment		0.539	
Temporary employment		0.195	
Homemaker		0.115	
No job		0.040	
Others		0.018	
Income	2,283	3.526	1.433
(1) Less than 2 million, (2) 2 - 4 million, (3) 4 - 6 million, (4) 6 - 8 million, (5) 8 - 10 million, (6) More than 10 million			
Read newspaper	2,613	1.866	1.242
(1) Rarely, (2) 1-3/week, (3) 4-6/week, (4) Daily			
Read web newspaper	2,616	2.077	1.297
(1) Rarely, (2) 1-3/week, (3) 4-6/week, (4) Daily			
Watch TV news	2,629	3.412	1.009
(1) Rarely, (2) 1-3/week, (3) 4-6/week, (4) Daily			
Estimate of the actual number of infected people in Japan (x 10^3)	2,588	3.910	2.135
(1) Less than 2,000, (2) 2,001-5,000, (3) 5,001-20,000, (4) More than 20,000			
COVID-19 causes serious problems for self	2,632	4.072	0.997
(1) No, (2) Weakly No, (3) Neutral, (4) Weakly Yes, (5) Yes			
The situation will be even worse after 6 months	2,624	1.842	1.166

(1) No, (2) Weakly No, (3) Neutral, (4) Weakly Yes, (5) Yes			
Precipitation probability above which you would carry an umbrella (%)	2,637	51.600	19.468
Which of these sayings characterizes you better?	2,600	2.495	1.293
(A) Nothing ventured, nothing gained (B) A wise man never courts danger			
(1) B, (2) Lean B, (3) Neutral, (4) Lean A, (5) A			
Generally speaking, would you say that most people can be trusted?	2,097	3.048	1.059
(1) No, (2) Weakly No, (3) Neutral, (4) Weakly Yes, (5) Yes			
It is important to do something for the good of society.	2,093	3.530	0.984
(1) No, (2) Weakly No, (3) Neutral, (4) Weakly Yes, (5) Yes			
It is important to help people nearby and care for their well-being	2,096	3.633	0.979
(1) No, (2) Weakly No, (3) Neutral, (4) Weakly Yes, (5) Yes			
It is important to always behave properly.	2,096	4.141	0.881
(1) No, (2) Weakly No, (3) Neutral, (4) Weakly Yes, (5) Yes			
It is important to avoid doing anything people would say is wrong.	2,097	3.063	1.001
(1) No, (2) Weakly No, (3) Neutral, (4) Weakly Yes, (5) Yes			
I often donate.	2,098	2.327	1.090
(1) No, (2) Weakly No, (3) Neutral, (4) Weakly Yes, (5) Yes			
Tried to buy masks more than usual? (1) Yes, (0) No	2,610	0.500	0.500
Tried to buy disinfectant soaps more than usual? (1) Yes, (0) No	2,604	0.321	0.467

Table A2: Falsification Test

	Conversation	Commute	Dining
	(1)	(2)	(3)
January	0.006		
	(0.007)		
February	-0.014	0.001	-0.036***
	(0.009)	(0.005)	(0.008)
January x	-0.001		
Confirmed cases in March	(0.002)		
February x	-0.002	-0.003	0.001
Confirmed cases in March	(0.003)	(0.002)	(0.003)
January x	-0.001		
Confirmed cases in adjacent prefectures in March	(0.002)		
February x	-0.001	-0.001	0.003
Confirmed cases in adjacent prefectures in March	(0.002)	(0.001)	(0.002)
Constant	0.535***	0.246***	0.484***
	(0.003)	(0.002)	(0.002)
Monthly FE	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Mean Dep. Var.	0.529	0.243	0.472
P-values of F-test for joint significance of interaction terms	0.904	0.173	0.152
Observations	7,827	5,203	5,236
Number of respondents	2,611	2,617	2,623

The OLS coefficients are reported. Standard errors clustered at the respondent level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: The Impact of Infection Spread on Economic Conditions

	Bankruptcies	Job-openings- to-applicants ratio
	(1)	(2)
Confirmed cases	0.696	0.00012
	(1.544)	(0.00423)
Monthly FE	Yes	Yes
Prefecture FE	Yes	Yes
Mean Dep. Var.	15.35	1.42
Observations	141	141
Number of prefectures	47	47

The OLS coefficients are reported. Standard errors clustered at the prefecture level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Using the Cumulative Number of Confirmed Cases

	Conversation		Commute		Dining	
Sample:	All	No child	All	No child	All	No child
	(1)	(2)	(3)	(4)	(5)	(6)
Cumulative number of confirmed cases	-0.423***	-0.441***	-0.249**	-0.307**	-0.225	-0.223
	(0.134)	(0.159)	(0.103)	(0.128)	(0.138)	(0.149)
Monthly FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Other prefecture characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var.	0.518	0.486	0.235	0.249	0.458	0.464
Observations	10,439	7,299	7,799	5,458	7,855	5,494
Number of respondents	2,613	1,827	2,619	1,832	2,624	1,835

The OLS coefficients are reported. Standard errors clustered at the respondent level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Exclusion of Unemployed Respondents

	Conversation		Commute		Dining	
Sample:	All	No child	All	No child	All	No child
	(1)	(2)	(3)	(4)	(5)	(6)
Confirmed cases	-0.008**	-0.008**	-0.006**	-0.007**	-0.004	-0.004
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)
Monthly FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Other prefecture characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var.	0.585	0.551	0.261	0.279	0.476	0.484
Observations	8,829	6,134	6,594	4,583	6,647	4,615
Number of respondents	2,209	1,535	2,215	1,538	2,220	1,541

The OLS coefficients are reported. Standard errors clustered at the respondent level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Categorical Dependent Variables

OLS	Conversation		Commute		Dining	
Sample:	All	No child	All	No child	All	No child
	(1)	(2)	(3)	(4)	(5)	(6)
Confirmed cases	-0.027***	-0.029***	-0.013***	-0.016***	-0.008*	-0.010**
	(0.007)	(0.008)	(0.004)	(0.005)	(0.004)	(0.005)
Monthly FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	No	Yes	No	Yes	No
Prefecture FE	No	Yes	No	Yes	No	Yes
Other prefecture characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,439	7,299	7,799	5,458	7,855	5,494
Number of respondents	2,613	1,827	2,619	1,832	2,624	1,835

Interval Regression	Conversation		Commute		Dining	
Sample:	All	No child	All	No child	All	No child
	(7)	(8)	(9)	(10)	(11)	(12)
Confirmed cases	-0.093***	-0.107***	-0.026***	-0.032***	-0.014*	-0.018**
	(0.028)	(0.031)	(0.008)	(0.010)	(0.008)	(0.009)
Monthly FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	No	Yes	No	Yes	No
Prefecture FE	No	Yes	No	Yes	No	Yes
Other prefecture characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,439	7,299	7,799	5,458	7,855	5,494

Standard errors clustered at the respondent level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A7: The Association Between Education and Socio-Economic Characteristics (Full Sample)

	Suitability of job for teleworking	Economic status	Information access	Risk perception	Risk preference	Social capital	Alternative protective measures
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
University	-0.084***	0.725***	0.261***	0.202***	-0.079*	0.503***	0.161***
	(0.020)	(0.049)	(0.057)	(0.053)	(0.040)	(0.068)	(0.051)
Vocational	-0.047*	0.235***	0.181***	0.078	-0.044	0.432***	0.201***
	(0.026)	(0.046)	(0.055)	(0.058)	(0.050)	(0.086)	(0.060)
Age	-0.001	-0.000	0.028***	0.007**	-0.005	0.005	-0.019***
	(0.001)	(0.002)	(0.004)	(0.003)	(0.004)	(0.007)	(0.004)
Female	0.170***	-0.720***	-0.174***	-0.105***	-0.269***	0.260***	0.469***
	(0.019)	(0.056)	(0.062)	(0.034)	(0.033)	(0.064)	(0.049)
Live with	-0.022	0.240***	0.220***	0.004	0.057	0.322***	0.217***
schooling-age child	(0.017)	(0.054)	(0.045)	(0.046)	(0.054)	(0.087)	(0.037)
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,054	2,256	2,543	2,524	2,536	2,038	2,534

The OLS coefficients are reported. Standard errors clustered at the prefecture level are in parentheses. The sample sizes of Columns (1) and (6) are smaller than the others, because the data on respondents' occupation and social capital were collected in the second-wave survey. Column (2) also has a small sample size due to missing values for annual income. *** p<0.01, ** p<0.05, * p<0.1.

Table A8: Heterogeneous Effect Model Using the Sample of Table 4

	Conversation		Commute		Dining	
Sample:	All	No child	All	No child	All	No child
	(1)	(2)	(3)	(4)	(5)	(6)
Confirmed cases	-0.012*	-0.015**	-0.012**	-0.016**	-0.005	0.002
x University	(0.007)	(0.007)	(0.006)	(0.007)	(0.008)	(0.008)
Confirmed cases	-0.017*	-0.022**	-0.011	-0.010	-0.003	0.005
x Vocational	(0.009)	(0.010)	(0.008)	(0.008)	(0.010)	(0.010)
Confirmed cases	-0.000	-0.000	-0.001	-0.001*	0.000	-0.000
x Age	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Confirmed cases	-0.007	-0.003	-0.002	-0.003	-0.021***	-0.012**
x Female	(0.006)	(0.007)	(0.005)	(0.006)	(0.006)	(0.006)
Confirmed cases	-0.013**		-0.002		-0.020**	
x Live with schooling-age child	(0.006)		(0.006)		(0.009)	
Month-Prefecture Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var.	0.530	0.495	0.244	0.260	0.465	0.471
Observations	6,912	4,897	5,175	3,670	5,196	3,684
Number of respondents	1,738	1,230	1,739	1,232	1,740	1,233

The OLS coefficients are reported. Standard errors clustered at the respondent level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.