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

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Abstract

Do people avoid risky behavior to mitigate the infection risk of COVID-19, even without legal regulations? 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 risky behavior, such as face-to-face conversations and dining-out. Using unique monthly panel survey data, we find that the increase in confirmed cases is negatively associated with the likelihood of risky behavior. However, high school graduates are less responsive than university graduates. We provide evidence that this can be attributed to their lower perception of infection risk, while we cannot fully rule out the roles of income opportunity costs. These results suggest the benefits of interventions incorporating nudges to raise risk perception.

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

JEL Codes: I12; I14; I18;

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1. Introduction

The COVID-19 pandemic has caused immense human losses worldwide. To mitigate the infection spread, it is essential for individuals to avoid risky behavior and 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 attendant economic costs, free-riding behavior, and uncertainties about transmission risk. Therefore, many governments have sought to enforce social distancing through various interventions, such as closing public transportation and workplaces, making viral or antibody tests widely available, and providing financial support (Hale et al. 2020). Existing studies suggest that these regulations can be an effective tool to control the infection spread (Gatto et al., 2020; Jarvis et al., 2020).

However, an obvious concern regarding these legal interventions is their economic consequences (Acemoglu et al., 2020; Inoue and Todo, 2020). In the United States, the unemployment rate jumped from 4.4% in March 2020 to 14.7% in April. Mandatory social distancing also affects residents' mental and physical health negatively (Liu, et al., 2020; Pfefferbaum and North, 2020), and exacerbates anti-social behavior including violence and suicide (Dsouza et al., 2020; Mazza et al., 2020). As a result, some countries have lifted social distancing requirements to restart social and economic activities, even though the infection spread has not been brought under control. This policy change generates a new argument about how governments can cope with infections without relying on costly regulations, suggesting the importance of uncovering the obstacles to voluntary social-distancing behavior in the absence of legal regulations. However, to the best of our knowledge, this issue remains largely unexplored.

This study bridges this knowledge gap by examining the case of Japan during the initial phase of the COVID-19 infection spread, prior to the announcement of a state

[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).

of emergency on April 7th, 2020. 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 recommended that citizens avoid risky behavior and stay home voluntarily. Exploiting these features, this study analyzes the extent to which increases in infection risk are associated with the prevalence of risky behavior—such as face-to-face conversation and dining outside—between January and March 2020.

Crucially, this study also uncovers obstacles to voluntary compliance with risk-reducing measures, such as income opportunity costs, poor access to information, and low perceptions of transmission risks. 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 low perception of infection risks, then interventions that elevate risk perceptions should mitigate the spread of COVID-19 effectively, without the need for drastic legal restrictions.

Using original survey data, we regress changes in risky behavior on the monthly average of confirmed cases per day in each prefecture—the main unit of subnational government in Japan. Considering the absence of a natural experimental condition, it is difficult to fully rule out the possibilities of reverse causality and sample selection. 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 is associated with decreases in risky behavior. However, the association is weaker among high school graduates than university graduates, implying that exposure to infections may not be equal across individuals. We also provide suggestive evidence that the differences in the perception of infection risk is the most plausible reason for the heterogeneity. These results suggest the importance of interventions that incorporate nudges to heighten perceptions of risk.

This study is most closely related to Barrios and Hochberg (2020), Machida et al. (2020), and Muto et al. (2020). Using daily panel data at the region level in the U.S., Barrios and Hochberg (2020) find that relative to Republicans, Democrats are more concerned about the infection spread and economic damages and are more likely to avoid risky behavior, given the increase in the confirmed cases. A distinction between this study and theirs is that they do not examine the role of socio-economic status. Furthermore, Barrios and Hochberg (2020) analyze risky behavior in the U.S. after the government started to restrict residents' activities, 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), who conducted a survey in Japan as early as or even earlier than this study to examine individuals' risky behavior. Muto et al. (2020) find a negative correlation between socio-economic status and risky behavior in line with this study, but they do not test the potential reasons for the correlation. Machida et al. (2020) find insignificant association between socio-economic status and behavior. Another distinction is that these studies analyze cross-sectional datasets, while we employ monthly panel data. This enables us to examine individuals' behavioral changes in response to the infection spread more rigorously.

This study also contributes to the literature on the relationship between risk perception and health behavior. Prior studies have argued that perceptions of health risk play pivotal roles in predicting risky/protective behavior, such as smoking, the purchase of health insurance, and immunization (Brewer et al., 2007; Lin and Sloan, 2015; Schaller et al., 2019; Zhou-Richter et al., 2010). The same patterns have been confirmed for protective behavior from infectious diseases (Bennett et al., 2015; Gidengil et al., 2012; Lakdawalla et al., 2006). Since the health impact of these behaviors are scientifically confirmed and widely known, individuals' risk perception for these behaviors is determined by their knowledge of and trust in scientific research. Hence, not surprisingly, those with higher socio-economic status, particularly with higher educational attainment, are more likely to take protective behavior (Lowcock et al., 2012; Maurer, 2009). By contrast, scientific knowledge about COVID-19 was still scarce during the initial phase of the pandemic. Furthermore, unlike other infectious diseases such as SARS and H1N1, COVID-19 has distinctive features, including a high proportion of asymptomatic infections, limited capacities to conduct RT-PCR tests, and frequent mutations of the virus. These features could cause the perceived risk of COVID-19 to vary even among those with similar educational backgrounds. Therefore, it is informative to confirm that even under these conditions, those with higher educational attainment have both higher risk perceptions and are more likely to avoid risky 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 avoiding risky 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 A1). 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 Nara, a tourist site in western Japan.

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.[2] 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 1).

[Figure 1]

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

[2] 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.

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 in most countries, the Japanese government's response was comparatively passive. It gradually tightened immigration controls for visitors from Hubei Province, China, and also asked Japanese residents in Wuhan to return to Japan in the beginning of February. However, in stark contrast to other countries that 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.[3] 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 initiated 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

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[3] The Constitution of Japan does not provide for a national state of emergency. As such, neither the national nor local governments have 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 more 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.

of emergency, although it had no legal force, and requested that residents avoid leaving their homes for three weeks.[4] 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.[5] 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.[6] 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 A2, 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 A3).

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

[5] 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).

[6] 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.

3. Data

This study employs two datasets. First, to approximate the risk of COVID-19 infection, 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, it 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 at that time and thus was unlikely to affect behavioral patterns. We similarly do not use the number of COVID-19-related deaths, because only a few prefectures reported the death toll during our period of analysis.

Second, this study uses data from an original, nationwide online panel survey.[7] We discuss the survey design in detail in Online Appendix A1. Our survey targeted those in their 30s and 40s, given that working-age individuals account for a high proportion of confirmed cases compared to the elderly and teenagers.[8] While the behavior of the elderly, who are susceptible to COVID-19, is undeniably important, it is difficult to collect a representative sample of older generations due to disparities in internet access and low likelihood of owning smartphones (Ministry of Internal Affair and Communication, 2018 p156).

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[7] 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, due to the spread of COVID-19. 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; Gupta et al. 2000). Although these may better capture behavioral changes, it is difficult to analyze the reasons for heterogeneity in behavior.

[8] As of April 1st, those aged between 20 and 59 accounted for 62% of confirmed cases (https://www.mhlw.go.jp/content/10906000/000618475.pdf accessed on October 27, 2020).

The first round of the survey was conducted between March 25th and 27th, 2020. We conducted quota sampling with regard to gender (two categories), age group (four 5-year categories), and location of residence (10 categories) among those who registered with Rakuten Insight, a survey company in Japan, so that the distribution of these characteristics was comparable to that of the Japanese population. Table A1 presents the summary statistics of prefecture and respondent characteristics. The distribution of age, gender, and occupation is comparable with the population, supporting the national representativeness of our data. However, our dataset may oversample those with higher socio-economic status (Online Appendix A1).

The first-round survey data contain two behavioral variables related to risky behavior, our outcome of interest.[9] The first is the frequency of face-to-face conversations per day. The second is the frequency of dining outside per week.[10] In this survey, we elicited information on face-to-face conversations from December 2019 to March 2020, and on dining out from January to March 2020. To mitigate potential concerns about recall bias, we asked respondents to choose an answer from a list of frequency intervals which included the option, "do not want to answer."[11] After dropping the sample of Hokkaido prefecture, 2,624 respondents answered these questions. From this information, a monthly panel dataset was compiled.

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[9] This study also elicited information about both behavior and preferences, including the use of social media, political sentiment, health status, perceptions about the severity of infection risk, and the assessment of the government's early responses to COVID-19.

[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.

[11] For conversations, we asked the following question: "On a typical day, with how many people do you have face-to-face conversation in your daily life and job?" The answer options included: (1) Rarely, (2) 1 to 2, (3) 3 to 5, (4) 5 to 10, (5) 11 or more, (6) do not want to answer. For eating out, we asked: "On a typical week, how often do you dine out for dinner per week?" The answer options included: (1) Rarely, (2) 1 to 3, (3) 4 to 6, (4) everyday, (5) do not want to answer.

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 these only in Section 6. A total of 2,293 individuals participated in both surveys, but the sample size in Section 6 becomes even smaller because of missing values.

Figure 2 depicts the geographical variation in risky behavior across prefectures.[12] It shows reductions of risky behavior over time, but the changes are small, likely due to two reasons. First, there was no legal regulation of residents' activities in Japan. Therefore, many Japanese firms did not take actions to encourage social distancing among employees, such as remote work, at that time (Okubo and NIRA, 2020). Second, people were not yet aware of the severity of virus, given the scarcity of scientifically confirmed information.

[Figure 2]

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 risky 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 dining outside, it takes unity if the individual undertakes the activity 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 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

[12] Specifically, the figure depicts the mean distributions of the dependent variables (binary indicator of risky behavior). See Section 4.1 for their definition.

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. In this model, α_1 is the coefficient of interest.

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 respondents' risky behavior may affect the level of confirmed cases in the prefecture. However, this should cause an upward bias between the behavior and COVID-19 infection counts. Hence, as long as we find a negative coefficient for confirmed cases (Inf_{pt}), our results can be considered to be conservative estimates.

Furthermore, 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.[13] 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).[14] The risky behavior of most respondents should have played a negligible role in the actual increase in confirmed cases.

4.2.2. Parallel Trend Assumption

The second is the parallel trend assumption: if infections had not spread, the difference in risky behavior between prefectures with more and fewer confirmed cases would have been constant over time. This is also required for the number of confirmed cases in adjacent prefectures. This assumption may be subject to the following three issues. First,

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[13] 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).

[14] As of the end of February 2020, only 206 cases were confirmed, compared to the national population of 126 million.

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 risky behavior. However, in the time period under observation, this should produce more risky behavior where there are more infections, causing an upward bias that runs counter to our hypothesis (less risky behavior where there are more infection). The frequencies of conversing with colleagues 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 hours generally increase. The Statistics Bureau of Japan (2020) finds that in 2018 and 2019, the revenues of restaurant business increased in March.

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 due to difficulties in accurately predicting the timing that infections of this novel coronavirus will spread. 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, our results are considered to be conservative estimates.

Third, one may also be concerned about the ceiling effect. If the level of R_{ipt} is already low in prefectures that subsequently had few confirmed cases in the next month, then R_{ipt} may be less likely to decrease even further than in prefectures with more cases, regardless of the occurrence of infection spread. As a result, the estimated coefficient of confirmed cases may overestimate the magnitude of actual impact in such a situation.

We conduct two tests for the plausibility of the parallel trend assumption. First, we regress each risky behavior on the monthly fixed effects, the interaction terms between monthly fixed effects and the number of confirmed cases in March in the home prefecture, and the interaction terms between monthly fixed effects and the number of confirmed cases in March in the adjacent prefectures. The parallel trend assumption is more likely to hold, (1) if the coefficients of interaction terms are the same between December 2019 and February 2020 (parallel trend in the pre-treatment period), and (2) if the coefficients of interaction terms during the period are zero (the absence of ceiling effects). Table A2 presents the results. As shown at the bottom of the table, the results mostly provide supporting evidence.

Second, since some prefectures have reported confirmed cases since January, we regress the risky behavior between December and February on the number of confirmed cases in the next month and monthly fixed effects. Table A3 shows that the coefficients of confirmed cases are small and statistically insignificant.

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 A4). 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 the local state of emergency.[15]

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 avoid risky behavior. This is particularly plausible for those who commute to adjacent prefectures for work. To

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

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 an increase in confirmed cases per prefecture is negatively associated with risky behavior. Furthermore, compared to the naïve models (Columns (1) and (5)), the association becomes even larger after controlling for economic conditions (Columns (2) and (6)). The results are also robust to the additional control for confirmed cases in adjacent prefectures (Columns (3) and (7)) and the exclusion of respondents with a schooling-age child (Columns (4) and (8)). Hence, changes in economic conditions or government interventions cannot explain the significantly negative coefficients of confirmed cases.[16] Looking at respondents with no children, Columns (4) and (8) show that a one standard deviation increase in COVID-19 cases (S.D.=1.9 as of March) is associated with a decrease in the likelihood of talking with more than five people per day and dining out at least once a week by 1.5 and 1.0 percentage points, respectively.

We conduct the following robustness checks. First, we estimate the impact of confirmed cases per 1 km^2 of land and per one million people in Table A5. Second, as an alternative measure of infection risk, we re-estimate the model using the accumulated number of confirmed cases over multiple months (Table A6). Third, we alternatively use the daily average confirmed cases between March 15th and 24th for the observations in March, given the rapid increase in the confirmed cases during the period, while the

[16] One may be concerned about potential biases driven by unobserved macro-economic conditions, given that some people may be temporarily placed off-duty (furloughed) while remaining employed. However, this is unlikely to explain our estimation results. The coefficient of confirmed cases increases after controlling for observed economic indicators. Assuming that temporary furloughs are strongly correlated with the observed economic indicators, the estimated impact of confirmed cases should become even larger after controlling for unobserved economic conditions.

average during the whole month is used for the other months (Table A7). Fourth, we re-estimate our models after excluding respondents who do not work, because of differences in the need to have face-to-face conversations and in budget constraints on dining outside (Table A8). Fifth, in Table A9, we use the ordinal variables of face-to-face conversations and dining out as the dependent variables, and re-estimate the models using OLS. The results are robust to these alternative specifications.

One may be concerned that the estimated coefficients are small in magnitude, but it should be emphasized that we examine behavioral changes in the initial phase of the pandemic when people were not aware of the severity of infection risks. In addition, there was no government intervention to encourage social distancing, and therefore these behavioral changes are fully attributed to individuals' voluntary decisions. Finally, there was growing social awareness that the number of confirmed cases was not a good proxy for the extent of infection spread. It is, therefore, valuable to still find significant behavioral changes despite these situations. The small point estimates also suggest the importance of looking further at heterogeneities in sensitivity to the infection spread across respondents.

[Table 1]

5.2. Heterogeneous Effect

Does behavioral sensitivity to infection risk vary across individuals? We address this question by adding interaction terms between confirmed cases and respondent characteristics. Table 2 demonstrates significant differences by educational attainment, particularly for the frequency of conversations. Columns (1) and (2) suggest that the impact of a one standard deviation increase in confirmed cases for university graduates is larger by 1.7 and 2.5 percentage points, respectively, than for high school graduates. The results are robust to controls for month-prefecture fixed effects (Columns (3) and (4)) and the exclusion of interaction terms with characteristics other than education levels (Columns (5) and (6)). Therefore, our result is unlikely to be driven by unobserved heterogeneity at the individual and prefectural levels. The results for dining out are qualitatively the same, while the coefficients become statistically insignificant in the even-numbered columns, where we exclude respondents with children.

A potential issue in this model is the ceiling effects. To test this possibility, we regress the frequency of face-to-face conversations in December 2019 and dining out in January 2020 on the interaction terms between the number of confirmed cases in March and respondent characteristics. Table A10 shows that the coefficient of the interaction term with university degrees is insignificant for all specifications. Therefore, our results in Table 2 cannot be explained by the difference in pre-pandemic risky behavior.

Regarding other characteristics, first, we find a difference in the frequency of dining out by gender. Second, the coefficient of interaction with respondents' age is statistically insignificant for most columns and small in magnitude. 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

6.1. Suitability of Job for Teleworking

First, high school graduates may engage in a job that is not suitable for teleworking or remote work, such as in retail or the restaurant business. To test this channel we construct an industry-level proxy using the survey results of Okubo and NIRA (2020). Based on an online survey in Japan, Okubo and NIRA (2020) show 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. We then regress this proxy on respondent characteristics to examine whether high school graduates actually engage in jobs unsuitable for telework.

Column (1) of Table 3, however, shows that the coefficient for university graduates is negative among the no-child sub-sample, counter to the hypothesis. The observed patterns do not change in the full sample estimation (Table A11). Since the suitability of working at home may vary even within an industry, our proxy may include measurement errors. However, the measurement errors alone are unlikely to explain the negative correlation between the education level and suitability.

[Table 3]

6.2. Economic Status

If the economic status of high school graduates is lower, they may suffer from credit constraints that make the disutility from the income loss caused by staying home larger than for the wealthy. We conduct a polychoric principal component analysis to construct a composite index of economic status from two variables (Kolenikov and Angeles, 2004): annual income, and a binary indicator that takes unity for self-employment, executive, or regular employment.[17] 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.

6.3. Information Access

High school graduates may not watch television news or read newspapers, and therefore have poorer knowledge of COVID-19. Existing studies have shown that lack of knowledge is a major cause of risky behaviors (Kenkel, 1991). To test this hypothesis 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 this index and education level in Column (3) of Table 3. The results are consistent with the hypothesis: university graduates follow the mass media more frequently than do high school graduates.

6.4. Risk Perception

The Protection Motivation Theory in psychology proposes that a high risk perception—which is attributed to subjective factors such as expectations of infection probability and the severity of symptoms—is essential if individuals are to take protective actions (Rogers and Prentice-Dunn 1997). Risk perception is formed through exposure to information from the media and peers, the cognitive ability to process the (numeric) information, and engagement in risky behavior (Ferrer and Klein, 2015). When reliable information is scarce and cognitive ability is limited, people suffer from cognitive overload. This causes various cognitive biases in decision-making, including the normalcy bias: the optimistic underestimation of the probability and severity of negative events (Kahneman and Tversky, 1972).

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[17] We use the polychoric principal component analysis to construct composite indices throughout this section. We report the factor loadings of variables in Table A12.

There are reasons to think that high school graduates have lower risk perceptions about COVID-19 infections. First, because the actual number of infected individuals is unobservable, people infer the infection probability from the information available, but news related to COVID-19 frequently includes professional, foreign language terms such as RT-PCR tests. Processing such information may cause them to suffer from cognitive overload, exacerbating the normalcy bias. Second, while mass media reported the severity of the infection spread, a relatively small number of people were actually confirmed to be infected as of March 2020. Therefore, if high school graduates do not rely on or collect information about COVID-19 from the mass media as carefully as do university graduates, they may assess risks based primarily on their peers' experiences with infection. This generates a gap in risk perception based on educational attainment.

To test this hypothesis, we construct a composite index of risk perception using the following two questions: how many infected people that respondents think there actually are in Japan as of the survey period; the extent to which COVID-19 will cause serious problems for themselves. The regression result in Column (4) of Table 3 shows that university graduates are more likely to take the infection risk seriously than are high school graduates, supporting our hypothesis.

6.5. Risk Preference

Given the perceived infection probability and severity, the willingness to take risks may be higher for high school graduates. That is, they may be less risk averse. This predicts lower propensity for them to take precautionary actions (Anderson and Mellor, 2008).

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 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 bring an umbrella when going out*? 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) of Table 3, we estimate the relationship between the composite index of these variables and respondent characteristics, showing that education level is uncorrelated with risk preference.

6.6. Social Capital

Social distancing during the COVID-19 pandemic is a public good, and therefore, people have an incentive to freeride (Cato et al., 2020). This suggests a channel that university graduates may possess more social capital, and so may care more about their reputation or disapproval from neighbors, causing them to follow societal norms of social distancing.

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) of Table 3 demonstrates that social capital is higher for university graduates than for high school graduates, supporting the hypothesis.

6.7. Alternative Protective Measures

High school graduates may take alternative actions to protect themselves, such as wearing masks and washing their hands with disinfectant. 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) of Table 3. The result shows that university graduates are more likely to answer affirmatively than high school graduates, counter to the hypothesis.

6.8. Less Confidence in the Confirmed Cases as a Proxy for Infection Risk

Finally, high school graduates may recognize that the number of confirmed cases underestimates the actual infection risk, and therefore, they may be more sensitive to other types of information, such as the ratio of positive RT-PCR tests. However, this hypothesis assumes that those with lower education have more knowledge about COVID-19 than educated respondents. This assumption contradicts our findings that high school graduates spend less time collecting information on COVID-19 than university graduates (Table 3, Column (3)).

6.9. Association Between Mediating Variables and Risky Behavior

The results so far show that respondents' education levels are associated with economic status, information access, risk perception, and social capital. To further test whether they are also associated with risky 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 estimation results. We find robust evidence that in prefectures with more confirmed cases, those with high risk perception are more likely to reduce the frequency of risky behavior. The table also reports False Discovery Rate q-values (Anderson 2008) to adjust the p-values of the 14 coefficients of each outcome, confirming a robust association between risk perception and frequency of dining out. Among the other three likely mechanisms, the coefficient for economic status is significantly associated with the frequency of conversations, but it does not predict the frequency of dining out. For robustness, we re-estimate the model by controlling for only the interaction term between confirmed cases and risk perception, in addition to the terms included in Table 2. Table A13 shows that the coefficient of risk perception is still statistically significant and comparable in magnitude with that of Table 4.

In Online Appendix 2 we test the validity of this model more carefully, particularly the potential issue of endogeneity of risk perception. Given these arguments, differences in risk perception are the most likely driver of heterogeneity by education level, although we cannot fully rule out the potential role of income opportunity costs.

[Table 4]

7. Conclusion

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 and dining out. However, high school graduates do not respond as much as do university graduates. We provide suggestive evidence that this heterogeneity is driven primarily by the former’s lower perception for infection risk, although we cannot fully rule out the role of income opportunity costs.

The following policy implications can be derived. Some countries have lifted legal regulations before eliminating new COVID-19 infections in order to restart economic activities, but concerns remain about how governments will cope with the concomitant increase in infections (Acemoglu et al., 2020; Inoue and Todo, 2020). Our findings suggest that when the government prioritizes economic activities, socio-economically vulnerable individuals are exposed to higher risk, and thus can 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. One approach is for governments to provide information on the risks of infection transmission in an easily accessible and understandable manner to mitigate cognitive overload and normalcy biases. Another promising approach is interventions that incorporate nudges to elevate risk perceptions, as suggested by Van Bavel et al. (2020). Finally, we should note that our data do not cover those aged over 50 or under 30. Given that their behavioral patterns could differ from our respondents, we should be careful in generalizing our findings to other generations.

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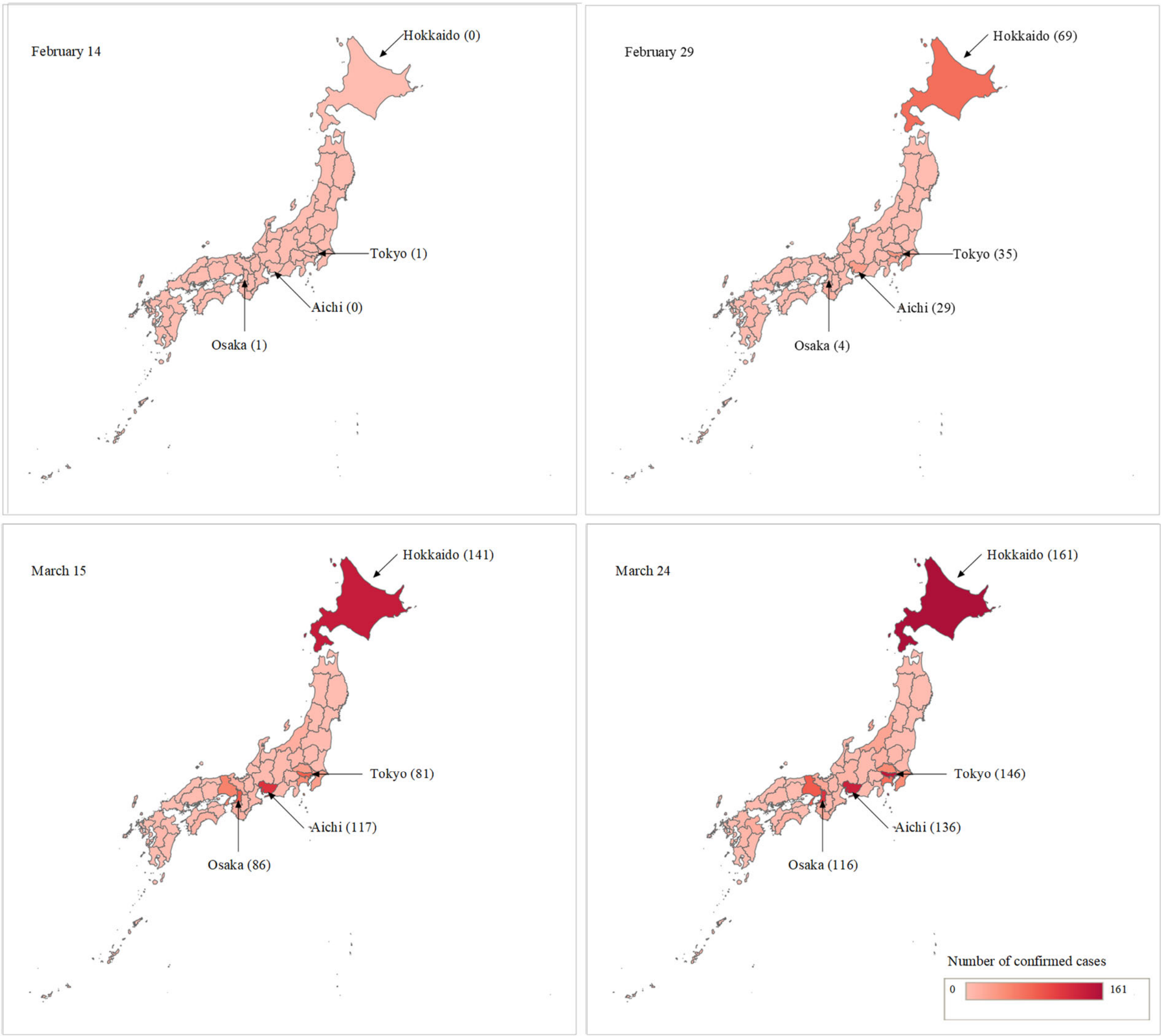

Note: The passengers and crew of the Diamond Princess are not included.
Source: MHLW (https://www.mhlw.go.jp/stf/houdou/index.html)

Figure 1: Cumulative Number of Confirmed Cases

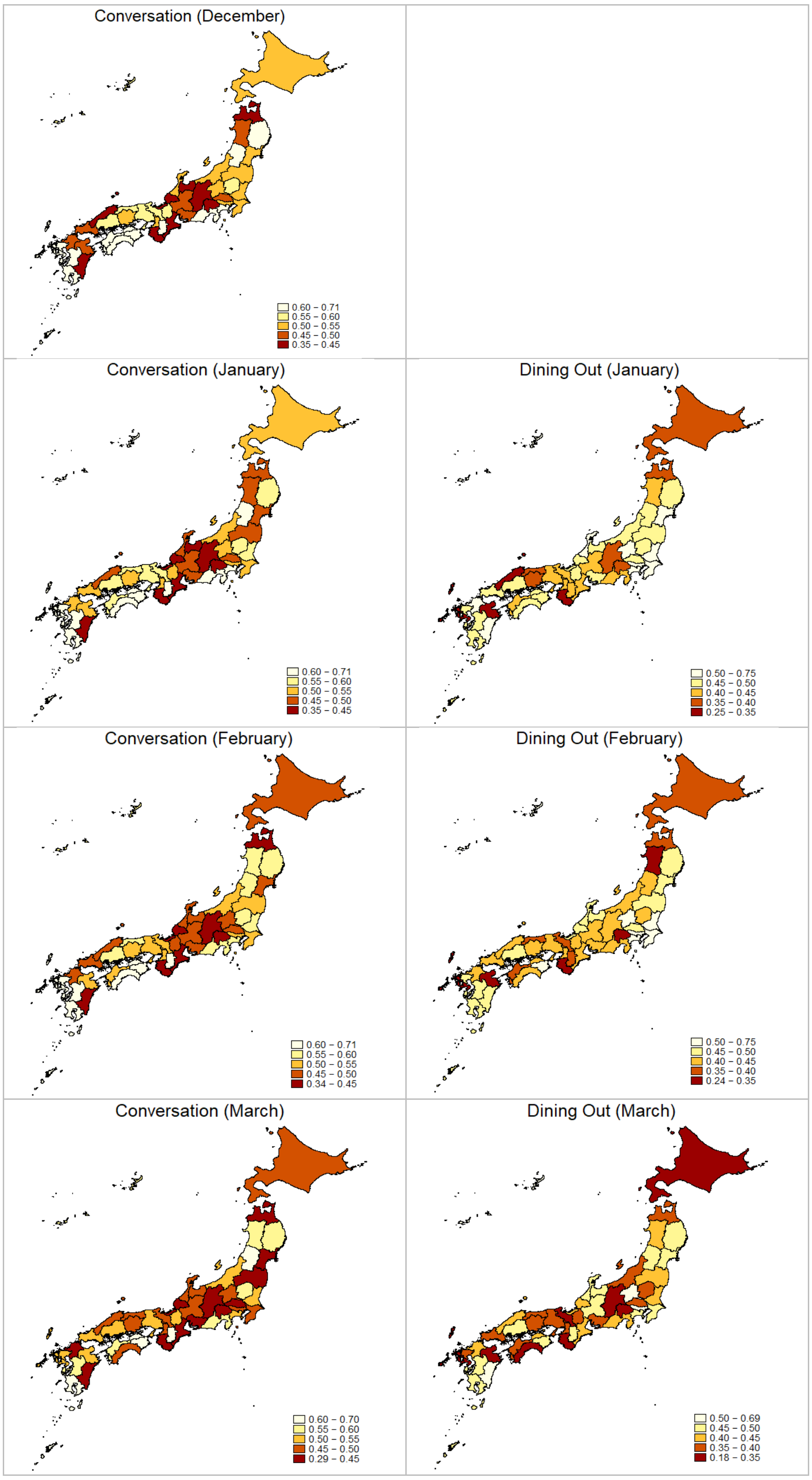

Figure 2: Geographical Distribution of Risky Behavior: Jan 2019 – Mar 2020

Table 1: The Association between Infection Spread and Behavior

	Conversation			
Sample:	All	All	All	No child
	(1)	(2)	(3)	(4)
Confirmed cases	-0.007***	-0.008***	-0.009***	-0.008***
	(0.002)	(0.002)	(0.002)	(0.003)
Confirmed cases			0.001	0.002
in adjacent prefectures			(0.002)	(0.002)
Bankruptcy cases		0.371**	0.370**	0.220
		(0.178)	(0.179)	(0.281)
Job-openings- to-applicants ratio		-0.164***	-0.173***	-0.123
		(0.059)	(0.057)	(0.087)
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
Obs. at the month-prefecture level	184	184	184	184
Number of respondents	2,613	2,613	2,613	1,827
	Dining			
Sample:	All	All	All	No child
	(5)	(6)	(7)	(8)
Confirmed cases	-0.006**	-0.007***	-0.005**	-0.005**
	(0.002)	(0.002)	(0.003)	(0.002)
Confirmed cases			-0.002	-0.003
in adjacent prefectures			(0.002)	(0.002)
Bankruptcy cases		0.457	0.464	0.630*
		(0.391)	(0.372)	(0.334)
Job-openings- to-applicants ratio		-0.009	0.006	-0.032
		(0.084)	(0.087)	(0.095)
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
Obs. at the month-prefecture level	138	138	138	138
Number of respondents	2,624	2,624	2,624	1,835

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 2: Heterogeneous Effect

	Conversation					
Sample:	All	No child	All	No child	All	No child
	(1)	(2)	(3)	(4)	(5)	(6)
Confirmed cases	0.005	0.006				
	(0.016)	(0.017)				
Confirmed cases	-0.009*	-0.013***	-0.009*	-0.013***	-0.009	-0.013***
x University	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)	(0.004)
Confirmed cases	-0.009*	-0.015**	-0.009*	-0.015**	-0.011***	-0.017***
x Vocational	(0.005)	(0.007)	(0.005)	(0.007)	(0.004)	(0.006)
Confirmed cases	-0.004	-0.003	-0.003	0.002		
x Age	(0.040)	(0.042)	(0.040)	(0.041)		
Confirmed cases	-0.007*	-0.005	-0.007*	-0.005		
x Female	(0.004)	(0.005)	(0.004)	(0.005)		
Confirmed cases	-0.005		-0.004			
x Live with schooling-age child	(0.005)		(0.005)			
Monthly Fixed Effect	Yes	Yes	No	No	No	No
Month-Prefecture Fixed Effect	No	No	Yes	Yes	Yes	Yes
Individual Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Other prefecture characteristics	Yes	Yes	No	No	No	No
Observations	10,192	7,203	10,192	7,203	10,339	7,231
Obs. at the month-prefecture level	184	184	184	184	184	184
Number of respondents	2,551	1,803	2,551	1,803	2,588	1,810

	Dining					
Sample:	All	No child	All	No child	All	No child
	(7)	(8)	(9)	(10)	(11)	(12)
Confirmed cases	0.004	0.007				
	(0.014)	(0.024)				
Confirmed cases	-0.011**	-0.003	-0.011**	-0.003	-0.010**	-0.003
x University	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
Confirmed cases	-0.008**	0.001	-0.007**	0.001	-0.012***	-0.002
x Vocational	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)	(0.003)
Confirmed cases	0.027	-0.012	0.023	-0.013		
x Age	(0.029)	(0.055)	(0.029)	(0.055)		
Confirmed cases	-0.016***	-0.010*	-0.017***	-0.011*		
x Female	(0.004)	(0.005)	(0.004)	(0.006)		
Confirmed cases	-0.015*		-0.015*			
x Live with schooling-age child	(0.008)		(0.007)			
Monthly Fixed Effect	Yes	Yes	No	No	No	No
Month-Prefecture Fixed Effect	No	No	Yes	Yes	Yes	Yes
Individual Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Other prefecture characteristics	Yes	Yes	No	No	No	No
Observations	7,665	5,422	7,665	5,422	7,777	5,443
Obs. at the month-prefecture level	138	138	138	138	138	138
Number of respondents	2,559	1,810	2,559	1,810	2,597	1,817

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

	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	-0.101***	0.642***	0.194***	0.199***	0.026	0.500***	0.170***
	(0.024)	(0.054)	(0.061)	(0.058)	(0.041)	(0.064)	(0.048)
Vocational	-0.047	0.258***	0.147***	0.117*	0.038	0.390***	0.214***
	(0.035)	(0.066)	(0.053)	(0.060)	(0.070)	(0.081)	(0.056)
Age	-0.001	-0.005**	0.023***	0.004	-0.002	-0.001	-0.012***
	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.006)	(0.003)
Female	0.157***	-0.427***	-0.124***	-0.073	-0.213***	0.262***	0.387***
	(0.021)	(0.048)	(0.044)	(0.047)	(0.041)	(0.058)	(0.046)
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,465	1,586	1,798	1,785	1,790	1,451	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 Risky Behavior

	Conversation				Dining			
Sample:	All		No child		All		No child	
	(1)		(2)		(3)		(4)	
Confirmed cases	-0.010	[0.828]	-0.017*	[0.319]	-0.010	[0.524]	-0.003	[0.868]
x Suitability of job for teleworking	(0.013)		(0.009)		(0.009)		(0.008)	
Confirmed cases	-0.004*	[0.319]	-0.005***	[0.183]	-0.006	[0.364]	-0.003	[0.364]
x Economic status	(0.002)		(0.002)		(0.004)		(0.002)	
Confirmed cases	-0.000	[1.000]	-0.002	[0.664]	-0.003	[0.596]	-0.004	[0.596]
x Information access	(0.002)		(0.002)		(0.003)		(0.005)	
Confirmed cases	-0.005**	[0.319]	-0.006*	[0.319]	-0.009***	[0.001]	-0.007**	[0.069]
x Risk perception	(0.002)		(0.003)		(0.002)		(0.003)	
Confirmed cases	-0.002	[0.828]	-0.001	[1.000]	-0.006***	[0.007]	-0.006**	[0.090]
x Risk preference	(0.002)		(0.002)		(0.002)		(0.002)	
Confirmed cases	-0.002	[0.828]	-0.002	[0.828]	-0.001	[0.868]	-0.002	[0.524]
x Social capital	(0.002)		(0.003)		(0.002)		(0.002)	
Confirmed cases	-0.001	[1.000]	0.001	[1.000]	-0.000	[0.928]	0.000	[0.928]
x Alternative protective measures	(0.004)		(0.005)		(0.004)		(0.004)	
Confirmed cases	-0.009		-0.012***		-0.001		0.006	
x University	(0.006)		(0.003)		(0.004)		(0.004)	
Confirmed cases	-0.015**		-0.020**		-0.003		0.006	
x Vocational	(0.007)		(0.009)		(0.005)		(0.006)	
Confirmed cases	-0.000		-0.000		0.000		-0.000	
x Age	(0.001)		(0.001)		(0.001)		(0.001)	
Confirmed cases	-0.007		-0.003		-0.024***		-0.014*	
x Female	(0.007)		(0.006)		(0.005)		(0.008)	
Confirmed cases	-0.011**				-0.017			
x Live with schooling-age child	(0.005)				(0.011)			
Month-Prefecture Fixed Effect	Yes		Yes		Yes		Yes	
Individual Fixed Effect	Yes		Yes		Yes		Yes	
Observations	6,918		4,901		5,197		3,685	
Obs. at the month-prefecture level	184		184		138		138	
Number of respondents	1,738		1,230		1,740		1,233	

The OLS coefficients are reported. Standard errors clustered at the prefecture level are in parentheses. Anderson's (2008) q-values that adjust the p-values of 14 coefficients in each outcome are in brackets. 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 was designed to collect data from around 2,500 people in their 30s and 40s. Respondents were recruited by Rakuten Insight, which is one of the largest survey companies in Japan (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 was comparable to that of the Japanese population. In collecting the data, Rakuten Insight invited approximately 50,000 randomly selected registrants who matched the sampling criteria by email on March 25th, 2020. They were informed that the online survey would be open until the required sample size was obtained, and that participants would receive 25 points of tokens (equivalent to around 0.23 USD as of March 2020) for shopping at Rakuten.com. The first wave was closed on the 27th, fifty hours after sending the invitation. Out of those who received the invitation, 3,336 browsed the survey website and 2,822 indeed participated. After dropping the sample of Hokkaido prefecture (161 respondents) and those with missing/invalid values in the risky behavior (37 respondents), the data from 2,624 respondents are obtained. On April 27th to May 7th, we re-surveyed the first-wave participants to collect further information on their social and psychological traits, of whom 2,293 participated in both rounds. The attrition in the second wave is 13%.

Table A1 presents the summary statistics of respondent characteristics. Since all questions include the answer option of “do not want to answer,” the sample size varies across variables. In particular, the income data contain many missing values. Female respondents account for 49.8% and the average age is 40.6 years old. 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%. These patterns support 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.

Appendix 2: Threat to Identification in the Estimation of Underlying Mechanism

A potential concern in Table 4 is that the risk perception index may be influenced by the observed severity of risk exposure, such as the number of confirmed cases in the prefecture.[18] Specifically, the number of confirmed cases may be nonlinearly (e.g., quadratically) associated with the frequency of conversations and dining out. In that case, if we control for only the linear term of confirmed cases in Table 4, then the coefficient of the interaction term between the confirmed cases and risk perception, which itself is correlated with risk exposure, may capture the effect of nonlinearity.

We assess the severity of this issue by testing whether the coefficient of risk perception changes when controlling for the measures of risk exposure and the quadratic term of confirmed cases. First, we use the result of Table A13 again. Since this specification does not control for respondents' risk exposure, such as the availability of telework, employment status, and usage of alternative protective measures, the comparability of the coefficient between Table A13 and Table 4 suggests that any unobserved heterogeneity in risk exposure across respondents is unlikely to explain the association between risk perception and risky behavior fully.

Second, we re-estimate the model of Table 4 by controlling for monthly fixed effects, the number of confirmed cases, and its quadratic term, rather than the month-prefecture fixed effects. Table A14 shows that the coefficients of the quadratic term are statistically insignificant in all specifications (even-numbered columns), and the coefficients of risk perception do not change regardless of the control for the quadratic term. Therefore, it is not plausible to interpret our result as an artifact of the nonlinear association between the number of confirmed cases and risky behavior.

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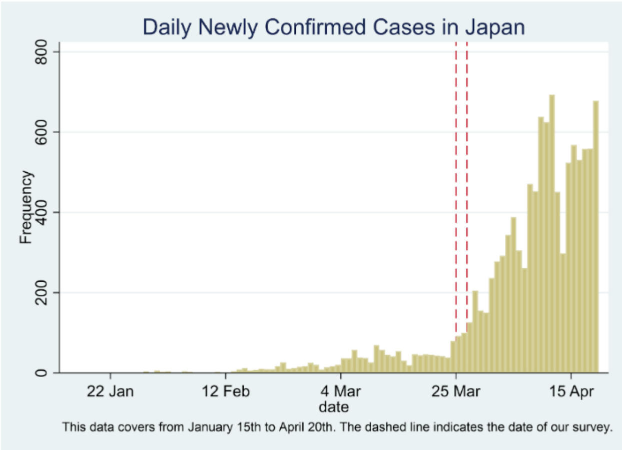
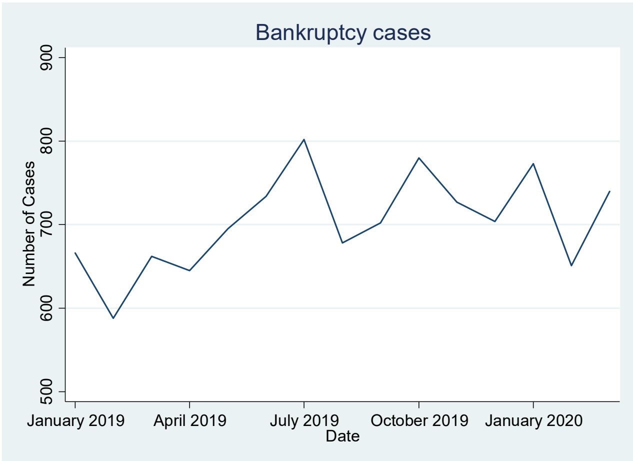
[18] In addition to the exposure to infection risk, the infection experiences of respondents or their peers may also affect their risk perception. However, the effect of omitted variable biases should be small, because relatively few people were confirmed to be COVID-19 positive as of the end of March 2020. Separately, reverse causality also fails to explain our results, because those who take protective measures have lower risk exposure, and therefore should perceive less personal risk.



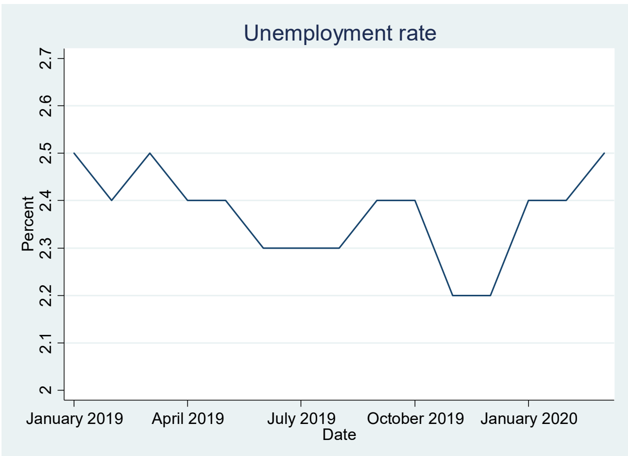
Note: The passengers and crew of the Diamond Princess are not included.
Source: MHLW (https://www.mhlw.go.jp/stf/houdou/index.html, accessed on May 6th, 2020)

Figure A1: Infection Spread in Japan



Source: https://www.tsr-net.co.jp/news/status/monthly/index.html, accessed on May 6th, 2020

Figure A2: The Trend in Bankruptcy Cases: Jan 2019 – Mar 2020



Source: https://www.stat.go.jp/data/roudou/sokuhou/tsuki/index.html, accessed on May 6th, 2020

Figure A3: 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			
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: Test for Parallel Trend Assumption

	Conversation		Dining	
Sample:	Full	No child	Full	No child
	(1)	(2)	(3)	(4)
January	0.007	0.007		
	(0.007)	(0.010)		
February	-0.014*	-0.024***	-0.036***	-0.029**
	(0.007)	(0.009)	(0.010)	(0.012)
March	-0.034***	-0.035**	-0.046***	-0.029*
	(0.010)	(0.014)	(0.011)	(0.015)
December x	-0.001	0.006		
Confirmed cases in March	(0.005)	(0.007)		
January x	-0.002	0.005	0.007	0.008
Confirmed cases in March	(0.004)	(0.006)	(0.009)	(0.010)
February x	-0.002	0.006	0.008	0.011
Confirmed cases in March	(0.004)	(0.006)	(0.009)	(0.010)
March x	-0.009*	-0.002	0.003	0.006
Confirmed cases in March	(0.005)	(0.007)	(0.009)	(0.011)
December x	0.000	-0.006		
Confirmed cases in adjacent prefectures in March	(0.004)	(0.006)		
January x	-0.000	-0.007	-0.000	-0.002
Confirmed cases in adjacent prefectures in March	(0.004)	(0.005)	(0.004)	(0.005)
February x	-0.001	-0.007	0.003	-0.001
Confirmed cases in adjacent prefectures in March	(0.004)	(0.005)	(0.004)	(0.005)
March x	0.000	-0.005	-0.001	-0.005
Confirmed cases in adjacent prefectures in March	(0.004)	(0.005)	(0.004)	(0.005)
Constant	0.535***	0.514***	0.474***	0.477***
	(0.017)	(0.024)	(0.015)	(0.019)
Mean Dep. Var.	0.518	0.486	0.458	0.464
Individual FE	No	No	No	No
Test for pre-pandemic parallel trend (p-values)				
Confirmed cases in the home prefecture	0.6648	0.9083	0.4116	0.0684
Confirmed cases in the adjacent prefectures	0.8475	0.6041	0.0588	0.7538
Test for pre-pandemic behavioral difference (p-values)				
Confirmed cases in the home prefecture	0.4734	0.8023	0.5762	0.1182
Confirmed cases in the adjacent prefectures	0.9120	0.0949	0.1453	0.9189
Observations	10,439	7,299	7,855	5,494
Obs. at the month-prefecture level	184	184	138	138
Number of respondents	2,613	1,827	2,624	1,835

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

This pre-pandemic parallel trend tests the null that the coefficients of interaction terms are the same between December 2019 and February 2020. Pre-pandemic behavioral difference tests the null that the coefficients of interaction terms are zero between December 2019 and February 2020.

Table A3: Falsification Test

	Conversation		Dining	
Sample:	Full	No child	Full	No child
	(1)	(2)	(3)	(4)
Confirmed cases in the next month	-0.002	0.007	0.011	0.014
	(0.005)	(0.007)	(0.010)	(0.011)
Confirmed cases in adjacent prefectures in the next month	-0.001	-0.008	0.003	-0.000
	(0.004)	(0.006)	(0.005)	(0.005)
January	0.003	0.002		
	(0.004)	(0.005)		
February	-0.014	-0.018	-0.048**	-0.039*
	(0.013)	(0.020)	(0.018)	(0.021)
Constant	0.535***	0.505***	0.479***	0.480***
	(0.010)	(0.014)	(0.011)	(0.013)
Mean Dep. Var.	0.529	0.496	0.472	0.474
Individual FE	No	No	No	No
Observations	7,827	5,472	5,236	3,663
Obs. at the month-prefecture level	184	184	138	138
Number of respondents	2,613	1,827	2,624	1,835

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: The Association between Infection Spread and Economic Conditions

	Bankruptcies (1)	Job-openings- to-applicants ratio (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 A5: Estimation Using the Confirmed Cases Adjusted by Area and Population Size

	Conversation		Dining	
Sample:	All	No child	All	No child
	(1)	(2)	(3)	(4)
Confirmed cases per 1 km^2 of land	-14.710***	-18.989***	-11.561**	-13.338***
	(4.611)	(6.881)	(5.534)	(4.195)
Monthly FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Other prefecture characteristics	Yes	Yes	Yes	Yes
Observations	10,375	7,247	7,807	5,455
Obs. at the month-prefecture level	184	184	138	138
Number of respondents	2,597	1,814	2,608	1,822

	Conversation		Dining	
Sample:	All	No child	All	No child
	(5)	(6)	(7)	(8)
Confirmed cases per a million people	-0.063***	-0.044	-0.066***	-0.059**
	(0.021)	(0.032)	(0.024)	(0.026)
Monthly FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Other prefecture characteristics	Yes	Yes	Yes	Yes
Observations	10,375	7,247	7,807	5,455
Obs. at the month-prefecture level	184	184	138	138
Number of respondents	2,597	1,814	2,608	1,822

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 A6: Estimation Using the Cumulative Number of Confirmed Cases

	Conversation		Dining	
Sample:	All	No child	All	No child
	(1)	(2)	(3)	(4)
Cumulative number of confirmed cases	-0.423***	-0.441***	-0.225*	-0.223*
	(0.074)	(0.100)	(0.115)	(0.118)
Monthly FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Other prefecture characteristics	Yes	Yes	Yes	Yes
Observations	10,439	7,299	7,855	5,494
Obs. at the month-prefecture level	184	184	138	138
Number of respondents	2,613	1,827	2,624	1,835

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 A7: Nonlinear Increase in Confirmed Cases

	Conversation		Dining	
Sample:	All	No child	All	No child
	(1)	(2)	(3)	(4)
Confirmed cases	-0.006***	-0.006**	-0.003	-0.003
	(0.002)	(0.003)	(0.003)	(0.003)
Monthly FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Other prefecture characteristics	Yes	Yes	Yes	Yes
Observations	10,439	7,299	7,855	5,494
Obs. at the month-prefecture level	184	184	138	138
Number of respondents	2,613	1,827	2,624	1,835

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 A8: Estimation Excluding Unemployed Respondents

	Conversation		Dining	
Sample:	All	No child	All	No child
	(1)	(2)	(3)	(4)
Confirmed cases	-0.008***	-0.008***	-0.004	-0.004
	(0.002)	(0.003)	(0.002)	(0.003)
Monthly FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Other prefecture characteristics	Yes	Yes	Yes	Yes
Observations	8,829	6,134	6,647	4,615
Obs. at the month-prefecture level	184	184	138	138
Number of respondents	2,209	1,535	2,220	1,541

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 A9: Estimation Using Ordinal Dependent Variables

OLS	Conversation		Dining	
Sample:	All	No child	All	No child
	(1)	(2)	(3)	(4)
Confirmed cases	-0.027***	-0.029***	-0.008**	-0.010***
	(0.008)	(0.009)	(0.003)	(0.003)
Monthly FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Other prefecture characteristics	Yes	Yes	Yes	Yes
Observations	10,439	7,299	7,855	5,494
Obs. at the month-prefecture level	184	184	138	138
Number of respondents	2,613	1,827	2,624	1,835

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 A10: Test for Baseline Difference in Heterogeneous Effect Model

	Conversation				Dining			
Sample:	All		No child		All		No child	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Confirmed cases in March	0.032		0.034		0.001		0.041	
	(0.027)		(0.044)		(0.038)		(0.041)	
Confirmed cases in March	0.009	0.011	0.006	0.004	0.019	0.020	0.024	0.024
x University	(0.012)	(0.012)	(0.011)	(0.012)	(0.014)	(0.015)	(0.018)	(0.018)
Confirmed cases in March	-0.003	-0.001	-0.008	-0.009	-0.002	-0.005	-0.003	-0.008
x Vocational	(0.010)	(0.010)	(0.013)	(0.014)	(0.019)	(0.019)	(0.021)	(0.021)
Confirmed cases in March	-0.001	-0.001	-0.001	-0.001	-0.000	0.000	-0.001	-0.001
x Age	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Confirmed cases in March	-0.004	-0.004	-0.003	-0.004	-0.007	-0.008	-0.024***	-0.025***
x Female	(0.007)	(0.007)	(0.011)	(0.010)	(0.006)	(0.006)	(0.008)	(0.009)
Confirmed cases in March	-0.008	-0.005			-0.002	0.002		
x Live with schooling-age child	(0.010)	(0.010)			(0.008)	(0.009)		
University	0.078***	0.072**	0.083**	0.086**	0.054*	0.044	0.063*	0.055
	(0.028)	(0.030)	(0.036)	(0.038)	(0.030)	(0.031)	(0.037)	(0.038)
Vocational	0.047	0.043	0.047	0.051	0.063*	0.066**	0.080*	0.087**
	(0.039)	(0.040)	(0.043)	(0.047)	(0.032)	(0.031)	(0.040)	(0.040)
Age	-0.001	-0.000	-0.002	-0.001	-0.005**	-0.005***	-0.002	-0.003
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Female	-0.064**	-0.067**	-0.030	-0.031	-0.105***	-0.106***	-0.066**	-0.066**
	(0.026)	(0.026)	(0.028)	(0.030)	(0.022)	(0.023)	(0.030)	(0.032)
Live with schooling-age child	0.119***	0.117***			0.021	0.020		
	(0.031)	(0.031)			(0.028)	(0.029)		
Prefecture Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	2,547	2,547	1,799	1,799	2,557	2,557	1,808	1,808

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 A11: The Association Between Education and Socio-Economic Characteristics (Full Sample)

	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	-0.084***	0.597***	0.216***	0.263***	-0.080**	0.400***	0.124***
	(0.020)	(0.040)	(0.045)	(0.052)	(0.037)	(0.052)	(0.040)
Vocational	-0.047*	0.199***	0.140***	0.129**	-0.035	0.350***	0.155***
	(0.026)	(0.040)	(0.045)	(0.055)	(0.046)	(0.071)	(0.047)
Age	-0.001	-0.001	0.022***	0.002	-0.004	0.002	-0.015***
	(0.001)	(0.002)	(0.003)	(0.003)	(0.003)	(0.006)	(0.003)
Female	0.170***	-0.579***	-0.137***	-0.125***	-0.214***	0.192***	0.364***
	(0.019)	(0.046)	(0.049)	(0.036)	(0.031)	(0.051)	(0.038)
Live with	-0.023	0.205***	0.175***	0.024	0.059	0.271***	0.169***
schooling-age child	(0.017)	(0.046)	(0.036)	(0.035)	(0.050)	(0.072)	(0.029)
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,054	2,256	2,543	2,527	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 A12: Factor Loadings

Variables	Factor Loadings
Economic Status	
Employment status	0.497
Income level	0.497
Information Access	
Frequency of reading paper newspapers	0.543
Frequency of reading newspaper websites	0.445
Frequency of watching television news	0.406
Risk Perception	
Expectation about the number of infected people in Japan	0.236
Expected impact of COVID-19	0.236
Risk Preference	
Choose “Nothing ventured, nothing gained” or “A wise man never courts danger”	0.184
The lowest precipitation probability to bring an umbrella when going out	0.184
Social Capital	
Most people can be trusted	0.532
Important to do something for the good of society	0.774
Important to help people nearby and care for their well-being	0.784
Important to always behave properly	0.580
Important to avoid doing anything people would say is wrong	0.331
Whether the respondent often donates	0.358
Alternative Protective Measures	
Whether the respondents wished to buy facemasks more than usual	0.829
Whether the respondents wished to buy disinfectant soap more than usual	0.829

Table A13: Coefficient Stability of Risk Perception

	Conversation		Dining	
Sample:	All	No child	All	No child
	(1)	(2)	(3)	(4)
Confirmed cases	-0.006**	-0.006**	-0.010***	-0.008***
x Risk perception	(0.002)	(0.003)	(0.002)	(0.003)
Confirmed cases	-0.012*	-0.016***	-0.004	0.002
x University	(0.006)	(0.004)	(0.005)	(0.005)
Confirmed cases	-0.017**	-0.022**	-0.003	0.005
x Vocational	(0.007)	(0.009)	(0.005)	(0.006)
Confirmed cases	-0.000	-0.000	0.000	-0.000
x Age	(0.001)	(0.001)	(0.000)	(0.001)
Confirmed cases	-0.007	-0.003	-0.021***	-0.012
x Female	(0.006)	(0.005)	(0.005)	(0.009)
Confirmed cases	-0.012**		-0.020*	
x Live with schooling-age child	(0.005)		(0.011)	
Month-Prefecture Fixed Effect	Yes	Yes	Yes	Yes
Individual Fixed Effect	Yes	Yes	Yes	Yes
Observations	6,912	4,895	5,195	3,680
Obs. at the month-prefecture level	184	184	138	138
Number of respondents	1,738	1,230	1,741	1,232

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 A14: Nonlinear Association between Infection Spread and Behavior

	Conversation				Dining			
Sample:	All		No child		All		No child	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Confirmed cases	0.016	0.007	0.015	0.024	-0.002	-0.015	0.000	-0.000
	(0.024)	(0.024)	(0.032)	(0.030)	(0.020)	(0.022)	(0.029)	(0.033)
Confirmed cases squared		0.002		-0.002		0.003		0.000
		(0.002)		(0.003)		(0.003)		(0.003)
Confirmed cases	-0.010	-0.010	-0.018*	-0.018*	-0.010	-0.010	-0.003	-0.003
x Suitability of job for teleworking	(0.013)	(0.013)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)
Confirmed cases	-0.003	-0.003	-0.005**	-0.005**	-0.005	-0.005	-0.001	-0.001
x Economic status	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.002)	(0.002)
Confirmed cases	-0.000	-0.000	-0.002	-0.002	-0.004	-0.004	-0.005	-0.005
x Information access	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)
Confirmed cases	-0.005**	-0.005**	-0.006*	-0.006*	-0.009***	-0.009***	-0.007**	-0.007**
x Risk perception	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Confirmed cases	-0.001	-0.001	-0.001	-0.001	-0.006***	-0.006***	-0.006**	-0.006**
x Risk preference	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Confirmed cases	-0.002	-0.002	-0.002	-0.002	-0.001	-0.001	-0.002	-0.002
x Social capital	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Confirmed cases	-0.001	-0.001	0.001	0.001	-0.001	-0.001	-0.000	-0.000
x Alternative protective measures	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Confirmed cases	-0.009	-0.009	-0.012***	-0.012***	-0.001	-0.001	0.006	0.006
x University	(0.006)	(0.006)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Confirmed cases	-0.016**	-0.016**	-0.020**	-0.020**	-0.003	-0.002	0.006	0.006
x Vocational	(0.007)	(0.007)	(0.009)	(0.009)	(0.005)	(0.005)	(0.006)	(0.006)
Confirmed cases	-0.000	-0.000	-0.000	-0.000	0.000	0.000	-0.000	-0.000
x Age	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Confirmed cases	-0.008	-0.008	-0.004	-0.004	-0.023***	-0.023***	-0.013*	-0.013*
x Female	(0.007)	(0.007)	(0.007)	(0.006)	(0.004)	(0.004)	(0.007)	(0.008)
Confirmed cases	-0.012**	-0.012**			-0.019*	-0.019*		
x Live with schooling-age child	(0.005)	(0.005)			(0.011)	(0.011)		
Monthly FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other prefecture characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,914	6,914	4,895	4,895	5,197	5,197	3,680	3,680
Obs. at the month-prefecture level	184	184	184	184	138	138	138	138
Number of respondents	1,738	1,738	1,230	1,230	1,741	1,741	1,232	1,232

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