



Variations in Early-Stage Responses to Pandemics: Survey Evidence from the COVID-19 Pandemic in Japan

Masahiro Shoji¹ · Susumu Cato¹ · Takashi Iida¹ · Kenji Ishida¹ · Asei Ito¹ · Kenneth Mori McElwain¹

Received: 4 July 2021 / Accepted: 14 November 2021 / Published online: 29 November 2021
© The Author(s), under exclusive licence to Springer Nature Switzerland AG 2021

Abstract

During the initial phase of pandemics, swift behavioral responses by individuals, such as social distancing, can temper the speed and magnitude of further infections. However, individual choices in this period are often made in the absence of reliable knowledge and coordinated policy interventions, producing variation in protective behaviors that cannot be easily deduced from that in later periods. Using unique monthly panel survey data, we examine variations in the association between changes in infections and risky behavior, particularly the frequencies of face-to-face conversations and dining out, between January to March 2020. We find that the increase in confirmed cases is negatively associated with the likelihood of these behaviors. 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 point to the benefits of interventions incorporating nudges to raise individuals' risk perceptions during the initial phase of pandemics. We also discuss the potential efficacy of such interventions in later periods of pandemics.

Keywords COVID-19 · Pandemic · Social distancing · Risky behavior · Risk perception

JEL Codes I12 · I14 · I18

This article is part of the Topical Collection on *Economics of COVID-19*

✉ Masahiro Shoji
shoji@iss.u-tokyo.ac.jp

¹ Institute of Social Science, University of Tokyo, 7-3-1 Hongo, Bunkyo-ku, Tokyo 113-0033, Japan

Introduction

Infectious diseases are one of the leading causes of deaths in the world. Even in the twenty-first century, novel viruses, such as H1N1, SARS, and COVID-19, have posed a great threat to human lives and society. 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; Institute of Medicine 2007; Ipsen 1959).¹ However, it can be difficult to achieve sufficient levels of distancing, because of attendant economic costs, free-riding behavior, and uncertainties about transmission risk. Earlier studies show that individuals' behavioral responses vary across their demographic, socio-economic, and psychological characteristics (Bish and Michie 2010). Evidence from the COVID-19 pandemic in 2020 has also demonstrated similar patterns (Barrios et al. 2021; Brodeur et al. 2021; Dasgupta et al. 2020;).

While insightful, most earlier studies have left an important issue unaddressed. Individuals' behavioral response to the initial phase of a pandemic may differ from that of later periods, due to changes in knowledge about the virus, policy interventions, and socio-economic conditions. However, how they respond in the initial phase of the infection spread is not well understood. This is crucial for two reasons. First, prompt, appropriate initial responses are essential to minimizing later infection spreads. Second, it is even more costly for people to adopt—and justify—protective behavior in early periods, because of poor knowledge about the virus's risks and effective policy interventions. Therefore, it is relevant to identify obstacles that prevent individuals from taking protective behavior, such as social distancing, in this period.

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 of emergency on April 7th, 2020. Japan is suitable for this exercise, because it was one of the earliest countries to confirm COVID-19 cases outside of China, following Thailand (WHO 2020). Therefore, citizens, as well as the government, suffered from a lack of knowledge about the virus. Furthermore, 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. We also examine differences in the magnitude of association by individuals' demographic and socio-economic conditions.

Crucially, this study also uncovers obstacles to voluntary compliance with risk-reducing measures, such as economic conditions, poor access to information, low perceptions of transmission risks, and socio-psychological characteristics. 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

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).

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 and a fixed effect model, we regress 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, even in the early pandemic period and even without legally enforceable policy interventions. 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 in the early phase of pandemics.

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, which is an important predictor of disaster preparedness and resilience. 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.

Our findings are also relevant to understanding individuals' protective behavior in the absence of policy interventions. Governments enforce social distancing through various interventions, such as closing public transportation and workplaces, making viral or antibody tests widely available, and providing financial subsidies (Hale et al. 2020). Existing studies suggest that these domestic regulations can be an effective tool to control the infection spread (Gatto et al. 2020; Hoeben et al. 2021; Jarvis et al. 2020; Katafuchi et al. 2021).² However, an obvious concern regarding these legal interventions is their economic consequences, such as increases in the unemployment rate (Acemoglu et al. 2020; Gharehgozli et al. 2020; Inoue and Todo 2020; Mandel and Veetil 2020; Martin et al. 2020). Mandatory social distancing also affects residents' mental and physical health negatively (Liu et al. 2020; Pfefferbaum and North 2020; Yamamura and Tsustsui 2021) and exacerbates anti-social behavior, including violence and suicide (Dsouza et al. 2020;

² In line with these studies, Nakamura and Managi (2020) examine the impact of restrictions on international air travel on the transmission of the COVID-19 virus across the countries.

Mazza et al. 2020). As a result, governments often lift social distancing requirements to restart social and economic activities even before infections are brought under control. These negative side-effects point to the importance of illuminating how governments can cope with infections without relying on costly regulations. One component is uncovering the obstacles to voluntary social-distancing behavior in the absence of legal regulations.

Finally, this study also contributes to the extensive 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. Consequently, both scientifically confirmed and unconfirmed information about COVID-19 spread on social media (Cato et al. 2021b). 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.

Background

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

Japan was one of the earliest countries to confirm COVID-19 cases outside of China, following Thailand (WHO 2020). 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 (Fig. 1). 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 the end of February, a total of 239 cases were reported. However, more than half of the 47 prefectures had not yet confirmed any cases, and even populous prefectures, such as Miyagi and Osaka, had found only a few cases Fig. 2 and 3.

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

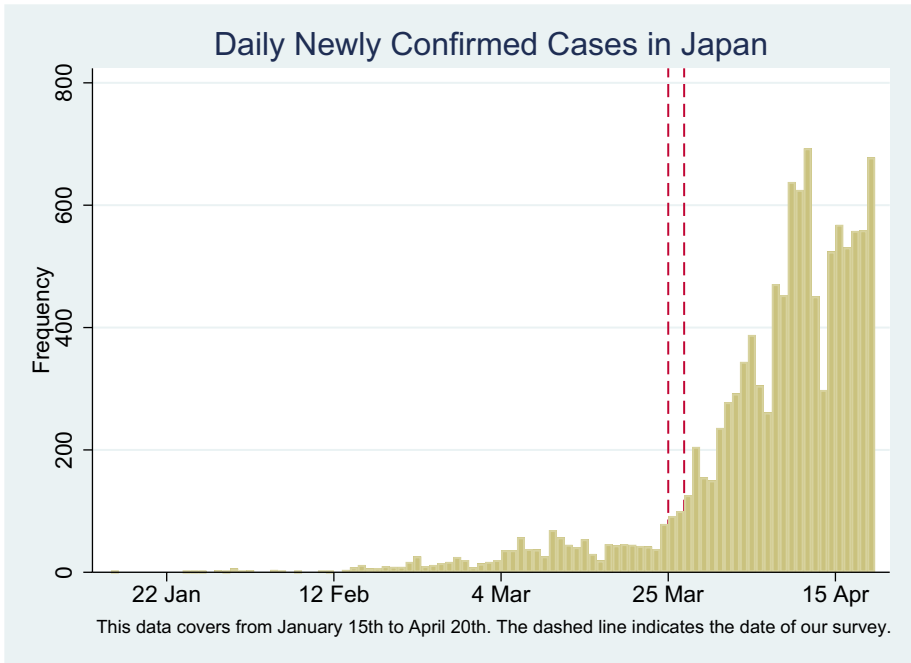


Fig. 1 Infection spread in Japan

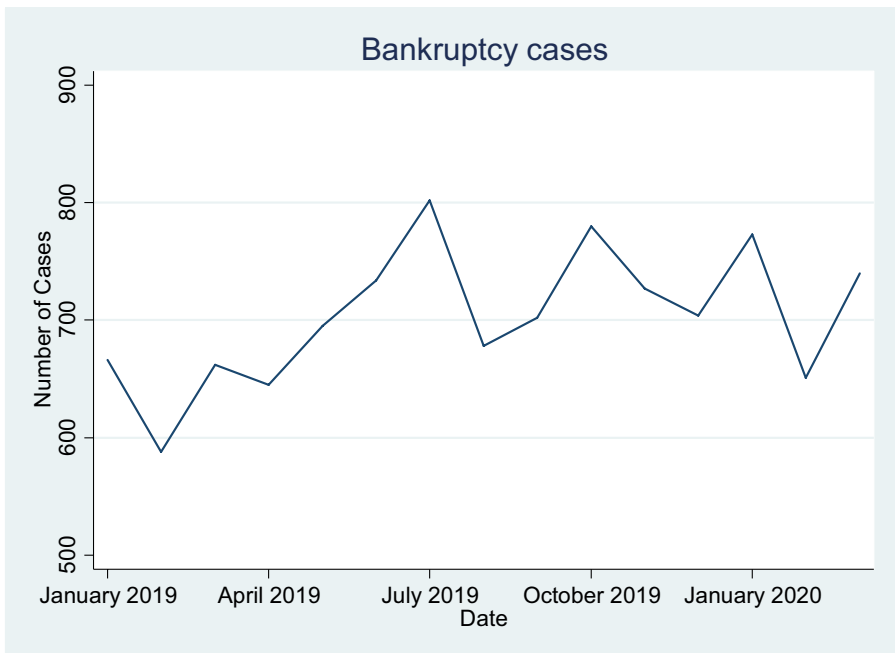


Fig. 2 Infection spread in Japan

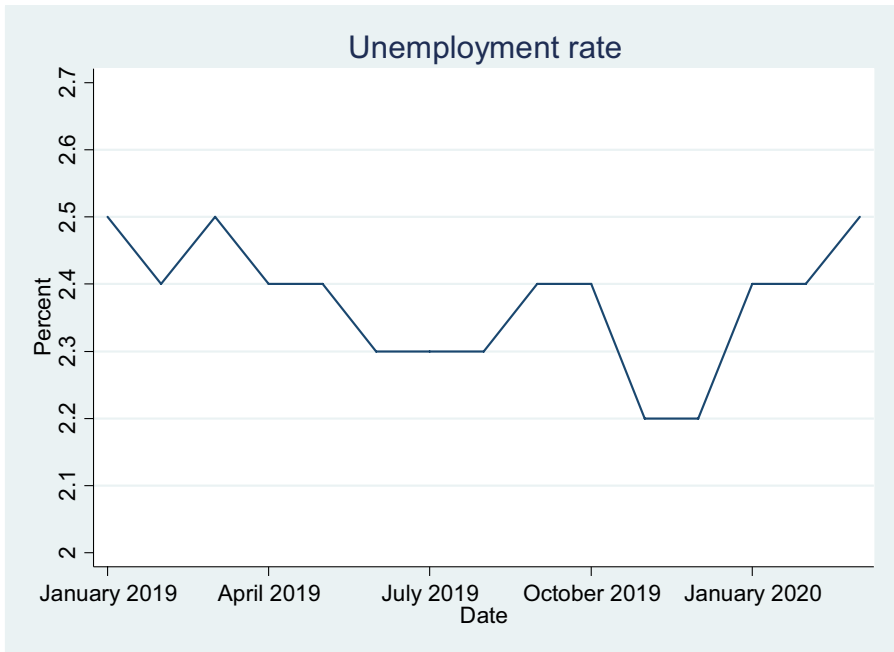


Fig. 3 Infection spread in Japan

occurred on the 10th, when 70 cases were reported. Around the same time, fatalities from COVID-19 started being reported regularly.

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. 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 of emergency, although it had no legal force, and requested that residents avoid leaving their homes

for three weeks. 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.³ 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.⁴ 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 Fig. 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 (Fig. A2).

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 daily confirmed cases between December 2019 and March 2020 (4 periods \times 47 prefectures). 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.

Second, this study uses data from an original, nationwide online panel survey. 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. 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 Affairs and Communications 2018 p156).

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

³ According to a report by the Ministry of Health, Labour, and Welfare (MHLW) 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).

⁴ 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 m (6 ft) or less.

Table 1 Changes in risky behavior

	Obs.	Mean
Face-to-face conversation (1 if talked with five people or more on a typical day)		
December 2019	2609	0.535
January 2020	2609	0.537
February 2020	2609	0.515
March 2020	2612	0.486
Dining out (1 if had dinner outside at least once a typical week)		
January 2020	2620	0.484
February 2020	2616	0.461
March 2020	2619	0.429

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. First, we asked respondents to retrospectively report their frequency of face-to-face conversation on a typical day in each month between December 2019 and March 2020 (4 periods). Second, we also asked for the frequency of dining out for dinner in a typical week in each month between January and March 2020 (3 periods), based on recall. 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.” Specifically, for conversations, we asked the following question for each month: “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. After dropping the sample of Hokkaido prefecture, 2624 respondents answered these questions. From this information, a monthly panel dataset was compiled.⁵

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 2293 individuals participated in both surveys, but the sample size in Section 6 becomes even smaller because of missing values.

Table 1 presents the proportion of those who had face-to-face conversations with five people or more (roughly around the median) on a typical day, and the proportion of those who had dinner outside at least once a typical week. It shows reductions of risky behavior over time, particularly in March, but the changes are small, likely due to two reasons. First,

⁵ We 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.

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.

Identification Strategy

This study estimates the following fixed effect model:

$$R_{ipt} - \overline{R_{ip}} = \alpha + \beta \left(Inf_{pt} - \overline{Inf_p} \right) X_{ip} + \gamma \left(AdjInf_{pt} - \overline{AdjInf_p} \right) + \delta \left(Damage_{pt} - \overline{Damage_p} \right) + T_t + \varepsilon_{ipt} \quad (1)$$

where, R_{ipt} denotes the binary indicators of risky behavior of individual i in prefecture p in month t , and $\overline{R_{ip}}$ is the mean of R_{ipt} over the periods. For face-to-face conversations, R_{ipt} takes unity if the individual talks with five people or more per day, and zero otherwise. For dining outside, it takes unity if the individual undertakes the activity at least once a week. X_{ip} includes predetermined respondent characteristics, such as age, gender, and educational attainment, which we use as interaction terms. Inf_{pt} denotes the monthly average of newly confirmed cases per day in the prefecture in which the respondent resides. $AdjInf_{pt}$ denotes the summation of Inf_{pt} 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, T_t denotes monthly fixed effects. The use of fixed effect model controls 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 announcement of school closure, news about the infection spread in other countries, and restrictions on overseas travel. In this model, β is the coefficient of interest.

Our identification strategy relies on four assumptions: no reverse causality, parallel trend assumption, limited impact of economic damage and government intervention, and limited spillover effect. We examine their plausibility in [Appendix](#).

Results

Benchmark Results

Before showing the main results of Eq. (1), Table 2 presents the results of models that do not incorporate any interaction terms. 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

Table 2 The association between infection spread and behavior

Sample:	Conversation			
	All (1)	All (2)	All (3)	No child (4)
Confirmed cases	-0.007*** (0.002)	-0.008*** (0.002)	-0.009*** (0.002)	-0.008*** (0.003)
Confirmed cases in adjacent prefectures			0.001 (0.002)	0.002 (0.002)
Bankruptcy cases		0.371** (0.178)	0.370** (0.179)	0.220 (0.281)
Job-openings- to-applicants ratio		-0.164*** (0.059)	-0.173*** (0.057)	-0.123 (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	7299
Obs. at the month-prefecture level	184	184	184	184
R-squared	0.0174	0.0185	0.0186	0.0183
Number of respondents	2613	2613	2613	1827
	Dining			
Sample:	All (5)	All (6)	All (7)	No child (8)
Confirmed cases	-0.006** (0.002)	-0.007*** (0.002)	-0.005** (0.003)	-0.005** (0.002)
Confirmed cases in adjacent prefectures			-0.002 (0.002)	-0.003 (0.002)
Bankruptcy cases		0.457 (0.391)	0.464 (0.372)	0.630* (0.334)
Job-openings- to-applicants ratio		-0.009 (0.084)	0.006 (0.087)	-0.032 (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	7855	7855	7855	5494
Obs. at the month-prefecture level	138	138	138	138
R-squared	0.0199	0.0202	0.0204	0.0140
Number of respondents	2624	2624	2624	1835

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

cannot explain the significantly negative coefficients of confirmed cases.⁶ Looking at respondents with no children, Columns (4) and (8) show that a one standard deviation

⁶ The robustness to the exclusion of respondents with a schooling-age child may suggest that the increase in parents' time for childcare during the school closure had minimal impact on their propensity to engage in risky behavior. Although this is intriguing, our dataset does not allow us to evaluate the policy impact more rigorously.

Table 3 Heterogeneous effect

Sample:	Conversation					
	All (1)	No child (2)	All (3)	No child (4)	All (5)	No child (6)
Confirmed cases	0.005 (0.016)	0.006 (0.017)				
Confirmed cases x University	-0.009* (0.005)	-0.013*** (0.003)	-0.009* (0.005)	-0.013*** (0.003)	-0.009 (0.005)	-0.013*** (0.004)
Confirmed cases x Vocational	-0.009* (0.005)	-0.015** (0.007)	-0.009* (0.005)	-0.015** (0.007)	-0.011*** (0.004)	-0.017*** (0.006)
Confirmed cases x Age	-0.004 (0.040)	-0.003 (0.042)	-0.003 (0.040)	0.002 (0.041)		
Confirmed cases x Female	-0.007* (0.004)	-0.005 (0.005)	-0.007* (0.004)	-0.005 (0.005)		
Confirmed cases x Live with schooling-age child	-0.005 (0.005)		-0.004 (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 character- istics	Yes	Yes	No	No	No	No
Observations	10,192	7203	10,192	7203	10,339	7231
Obs. at the month-prefecture level	184	184	184	184	184	184
R-squared	0.0198	0.0194	0.0331	0.0412	0.0322	0.0415
Number of respondents	2551	1803	2551	1803	2588	1810
Sample:	Dining					
	All (7)	No child (8)	All (9)	No child (10)	All (11)	No child (12)
Confirmed cases	0.004 (0.014)	0.007 (0.024)				
Confirmed cases x University	-0.011** (0.005)	-0.003 (0.005)	-0.011** (0.005)	-0.003 (0.005)	-0.010** (0.005)	-0.003 (0.004)
Confirmed cases x Vocational	-0.008** (0.003)	0.001 (0.005)	-0.007** (0.003)	0.001 (0.005)	-0.012*** (0.003)	-0.002 (0.003)
Confirmed cases x Age	0.027 (0.029)	-0.012 (0.055)	0.023 (0.029)	-0.013 (0.055)		
Confirmed cases x Female	-0.016*** (0.004)	-0.010* (0.005)	-0.017*** (0.004)	-0.011* (0.006)		
Confirmed cases x Live with schooling-age child	-0.015* (0.008)		-0.015* (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

Table 3 (continued)

Other prefecture characteristics	Yes	Yes	No	No	No	No
Observations	7665	5422	7665	5422	7777	5443
Obs. at the month-prefecture level	138	138	138	138	138	138
R-squared	0.0272	0.0168	0.0427	0.0406	0.0380	0.0391
Number of respondents	2559	1810	2559	1810	2597	1817

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

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 present the robustness of the results in Online Appendix A2.1.

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, because of asymptomatic transmissions. 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.

Main Results: Variations in the Responses to Infection Spread

Does behavioral sensitivity to infection risk vary across individuals according to demographic and socioeconomic characteristics? We address this question by estimating Eq. (1). Table 3 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. We address the possibility of ceiling effects in Online Appendix A2.2.

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.

Suggestive Evidence on the Mechanisms of Heterogeneous Impact

Why are less educated individuals less responsive to the infection spread? This section tests eight potential mechanisms relating to differences in their economic circumstances, knowledge and perception about the transmission risk, socio-psychological characteristics, and other factors. Our identification strategy relies on two analyses. First, we test the association between education levels and potential mediating variables in Subsections 6.1 to 6.4. Second, we test the association between the mediating variables and risky behavior in Subsection 6.5. In the main text, we discuss the results of analyses using the sub-sample of respondents who have no children, as child-rearing responsibilities may have complicated interactive effects with the mediating variables. The estimation results based on the full sample are reported in the Appendix.

Economic Conditions

Individuals' educational attainment may be associated with their occupation and economic status, which may be drivers of heterogeneous effects. We test these channels in this subsection.

Occupational Suitability for Teleworking

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 4, 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 for remote work.

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.⁷ We examine the correlation between this index and education level in

⁷ We use the polychoric principal component analysis to construct composite indices throughout this section. We report the factor loadings of variables in Table A12.

Table 4 The relationship between education and socio-economic indices (sample 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*** (0.024)	0.642*** (0.054)	0.194*** (0.061)	0.199*** (0.058)	0.026 (0.041)	0.500*** (0.064)	0.170*** (0.048)
Vocational	-0.047 (0.035)	0.258*** (0.066)	0.147*** (0.053)	0.117* (0.060)	0.038 (0.070)	0.390*** (0.081)	0.214*** (0.056)
Age	-0.001 (0.002)	-0.005** (0.002)	0.023*** (0.004)	0.004 (0.004)	-0.002 (0.004)	-0.001 (0.006)	-0.012*** (0.003)
Female	0.157*** (0.021)	-0.427*** (0.048)	-0.124*** (0.044)	-0.073 (0.047)	-0.213*** (0.041)	0.262*** (0.058)	0.387*** (0.046)
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.1069	0.1954	0.0556	0.0362	0.0506	0.0629	0.0769
Observations	1465	1586	1798	1785	1790	1451	1787

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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Column (2) of Table 4. It confirms that the economic status of university graduates is significantly higher than that for high school graduates, in line with our hypothesis.

Knowledge and Perception of Transmission Risk

Poor information access and low risk perception are major causes of risky behaviors (Kenkel 1991), suggesting that the maladapted behavioral response of high school graduates may be due to these issues.

Information Access

To test the channel through poor 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 this index and education level in Column (3) of Table 4. The results are consistent with the hypothesis: university graduates follow mass media more frequently than do high school graduates.

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 from their 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).

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 channel, 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 4 shows that university graduates are more likely to take the infection risk seriously than are high school graduates, supporting our hypothesis.

Socio-Psychological Characteristics

The heterogeneous impact of educational attainment may also reflect variations in individuals' risk preference and social capital. This subsection tests these possibilities.

Risk Preference

High school graduates may be less likely to take precautionary actions, because they are less risk averse (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 4, we estimate the relationship between the composite index of these variables and respondent characteristics. We find that education level is uncorrelated with risk preference.

Social Capital

Social distancing during the COVID-19 pandemic is a public good, and therefore, people have an incentive to freeride (Brodeur et al. 2021; Cato et al. 2020; Cato et al. 2021a). 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 4 demonstrates that social capital is higher for university graduates than for high school graduates, supporting the hypothesis.

Alternative Interpretations

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 4. The result shows that university graduates are more likely to answer affirmatively than high school graduates, counter to the hypothesis.

Less Confidence in Confirmed Cases as a Proxy for Infection Risk

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

Table 5 The relationship between socio-economic indices and risky behavior

Sample:	Conversation		Dining			
	All	No child	All	No child		
	(1)	(2)	(3)	(4)		
Confirmed cases	-0.010 (0.013)	[0.828]	-0.010 (0.009)	[0.524]	-0.003 (0.008)	[0.868]
x Suitability of job for teleworking						
Confirmed cases	-0.004* (0.002)	[0.319]	-0.006 (0.004)	[0.364]	-0.003 (0.002)	[0.364]
x Economic status						
Confirmed cases	-0.000 (0.002)	[1.000]	-0.003 (0.003)	[0.596]	-0.004 (0.005)	[0.596]
x Information access						
Confirmed cases	-0.005** (0.002)	[0.319]	-0.009*** (0.002)	[0.001]	-0.007** (0.003)	[0.069]
x Risk perception						
Confirmed cases	-0.002 (0.002)	[0.828]	-0.006*** (0.002)	[0.007]	-0.006** (0.002)	[0.090]
x Risk preference						
Confirmed cases	-0.002 (0.002)	[0.828]	-0.001 (0.002)	[0.868]	-0.002 (0.002)	[0.524]
x Social capital						
Confirmed cases	-0.001 (0.004)	[1.000]	-0.000 (0.004)	[0.928]	0.000 (0.004)	[0.928]
x Alternative protective measures						
Confirmed cases	-0.009 (0.006)		-0.001 (0.004)		0.006 (0.004)	
x University						
Confirmed cases	-0.015** (0.007)		-0.003 (0.005)		0.006 (0.006)	
x Vocational						
Confirmed cases	-0.000 (0.001)		0.000 (0.001)		-0.000 (0.001)	
x Age						
Confirmed cases	-0.007 (0.007)		-0.024*** (0.005)		-0.014* (0.008)	
x Female						
Confirmed cases	-0.011** (0.005)		-0.017 (0.011)			
x Live with schooling-age child						

Table 5 (continued)

Sample:	Conversation		Dining	
	All	No child	All	No child
	(1)	(2)	(3)	(4)
Month-Prefecture Fixed Effect	Yes	Yes	Yes	Yes
Individual Fixed Effect	Yes	Yes	Yes	Yes
Observations	6918	4901	5197	3685
Obs. at the month-prefecture level	184	184	138	138
R-squared	0.0491	0.0526	0.0646	0.0657
Number of respondents	1738	1230	1740	1233

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 3, 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

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 4, Column (3)).

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 3.

Table 5 presents 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 and Mellor 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 3. Table A13 shows that the coefficient of risk perception is still statistically significant and comparable in magnitude with that of Table 5. In Online Appendix A3 we test the validity of this model more carefully, particularly the potential issue of endogeneity of risk perception and multicollinearity.

Given these arguments in this section, 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.

Conclusion

Using unique survey data collected in the initial phase of the COVID-19 pandemic 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 for the initial phase of pandemics. Our findings suggest that socio-economically vulnerable individuals are exposed to higher infection risk in this period, 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 prompt, 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).

Our findings also have implications for later pandemic periods. Infection risks change with the community diffusion of the virus, as well as mutations of the virus itself. Various information shocks may also influence individuals' risk perception. For example,

governments often lift legal regulations before the infection spread is brought under control in order to restart economic activities. This may provide a wrong message to some citizens and cause them to lower their risk perception excessively. Individuals must interpret such information and update their risk perception in a measured way, but this may be difficult given cognitive overload and risk biases. The importance of voluntary social distancing remains high until herd immunity can be achieved through large-scale vaccinations. However, access to vaccines is still limited, particularly in developing countries with poor national/local governance (Aida and Shoji 2021). Vaccine hesitancy is another issue that can reduce vaccination coverage among the population (Kawata and Nakabayashi 2021; Miyachi et al. 2020). Therefore, the policy interventions suggested above should be effective even in later periods of pandemics.

Finally, potential limitations of this study may include the usage of retrospective data (errors in recall), the relatively low explanatory power of estimation models, and low factor loadings of composite indices, although these are not uncommon in survey-based research. In addition, we should note that our data does not cover those aged over 50 or under 30. Given that their behavioral patterns could differ from our respondents (Shoji et al. 2021), we should be careful in generalizing our findings to other generations.

Appendix: Underlying Assumptions in the Econometric Analysis

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 (β_{pf}), 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.⁸ 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).⁹ The risky behavior of most respondents should have played a negligible role in the actual increase in confirmed cases.

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, the number of

⁸ 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).

⁹ As of the end of February 2020, only 206 cases were confirmed, compared to the national population of 126 million.

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.

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. Such an announcement may also have changed all citizens' perception about the infection risk and severity of COVID-19, regardless of having a child. To rule out the former impact, we re-estimate the model after excluding respondents with a schooling-age child. The latter can be partly captured by the monthly fixed effects, although we need to be cautious about the validity of this approach because the reaction to the request varied across prefectures.

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

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 address this potential issue, we control for the number of confirmed cases in the adjacent prefectures, $AdjInf_{p,t}$, in the model.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s41885-021-00103-5>.

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

Data and Code Availability Data and code will be made available upon reasonable request subject to compliance with IRB guidelines.

References

- Acemoglu D, Chernozhukov V, Werning I, Whinston MD (2020) A multi-risk SIR model with optimally targeted lockdown, (no. w27102). Research, National Bureau of Economic
- Ahmed F, Ahmed NE, Pissarides C, Stiglitz J (2020) Why inequality could spread COVID-19. *Lancet Public Health* 5(5):e240
- Aida T, Shoji M (2021) Does good National Governance Boost COVID-19 vaccination? Cross-Country Evidence. <https://www.researchsquare.com/article/rs-888069/v1>. Accessed 31 Oct 2021
- Anderson LR, Mellor JM (2008) Predicting health behaviors with an experimental measure of risk preference. *J Health Econ* 27(5):1260–1274
- Barrios JM, Hochberg Y (2020) Risk perception through the lens of politics in the time of the COVID-19 pandemic (no. w27008). National Bureau of Economic Research
- Barrios JM, Benmelech E, Hochberg YV, Sapienza P, Zingales L (2021) Civic capital and social distancing during the Covid-19 pandemic. *J Public Econ* 193:104310
- Bennett D, Chiang CF, Malani A (2015) Learning during a crisis: the SARS epidemic in Taiwan. *J Dev Econ* 112:1–18
- Bish A, Michie S (2010) Demographic and attitudinal determinants of protective behaviours during a pandemic: a review. *Br J Health Psychol* 15(4):797–824
- Brewer NT, Chapman GB, Gibbons FX, Gerrard M, McCaul KD, Weinstein ND (2007) Meta-analysis of the relationship between risk perception and health behavior: the example of vaccination. *Health Psychol* 26(2):136–145

- Brodeur A, Grigoryeva I, Kattan L (2021) Stay-at-home orders, social distancing, and trust. *J Popul Econ* 34:1321–1354
- Cato S, Iida T, Ishida K, Ito A, McElwain KM, Shoji M (2020) Social distancing as a public good under the COVID-19 pandemic. *Public Health* 188:51–53
- Cato S, Iida T, Ishida K, Ito A, Katsumata H, McElwain KM, Shoji M (2021a) Infodemic in social media and social distancing in the COVID-19 pandemic: public good provisions under uncertainty. *Glob Health Action* 14(1):1995958
- Cato S, Iida T, Ishida K, Ito A, Katsumata H, McElwain KM, Shoji M (2021b) The bright and dark sides of social media usage during the COVID-19 pandemic: survey evidence from Japan. *International Journal of Disaster Risk Reduction* 54:102034
- Center for Disease Control and Prevention (2020) Social Distancing. <https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/social-distancing.html>. Accessed 22 May 2020
- Dasgupta N, Jonsson Funk M, Lazard A, White BE, Marshall SW (2020) Quantifying the social distancing privilege gap: a longitudinal study of smartphone movement. Available at SSRN 3588585
- Dsouza DD, Quadros S, Hyderabadwala ZJ, Mamun MA (2020) Aggregated COVID-19 suicide incidences in India: fear of COVID-19 infection is the prominent causative factor. *Psychiatry Res* 290:113145
- Fenichel EP (2013) Economic considerations for social distancing and behavioral based policies during an epidemic. *J Health Econ* 32(2):440–451
- Fenichel EP, Castillo-Chavez C, Ceddia MG, Chowell G, Parra PAG, Hickling GJ et al (2011) Adaptive human behavior in epidemiological models. *Proc Natl Acad Sci* 108(15):6306–6311
- Ferrer RA, Klein WM (2015) Risk perceptions and health behavior. *Curr Opin Psychol* 5:85–89
- Gatto M, Bertuzzo E, Mari L, Miccoli S, Carraro L, Casagrandi R, Rinaldo A (2020) Spread and dynamics of the COVID-19 epidemic in Italy: effects of emergency containment measures. *Proc Natl Acad Sci* 117(19):10484–10491
- Gharehgozli O, Nayebvali P, Gharehgozli A, Zamanian Z (2020) Impact of COVID-19 on the economic output of the US Outbreak's epicenter. *Econ Disast Clim Chang* 4(3):561–573
- Gidengil CA, Parker AM, Zikmund-Fisher BJ (2012) Trends in risk perceptions and vaccination intentions: a longitudinal study of the first year of the H1N1 pandemic. *Am J Public Health* 102(4):672–679
- Glaeser EL, Laibson DI, Scheinkman JA, Soutter CL (2000) Measuring Trust. *Q J Econ* 115:811–846
- Gupta S, Nguyen TD, Rojas FL, Raman S, Lee B, Bento A et al (2020) Tracking public and private response to the covid-19 epidemic: evidence from state and local government actions (no. w27027). Research, National Bureau of Economic
- Hale T, Petherick A, Phillips T, Webster S (2020) Variation in government responses to COVID-19. Blavatnik School of Government Working Paper, 31
- Hoeben EM, Bernasco W, Suonperä Liebšt L, Van Baak C, Rosenkrantz Lindegaard M (2021) Social distancing compliance: a video observational analysis. *PLoS One* 16(3):e0248221
- Iida, T. (2016). *Yukensha no Risuku Taido to Tōhyōkōdō*. Bokutakusha
- Ikeda S, Kato HK, Ohtake F, Tsutsui, Y. (Eds.). (2016) Behavioral economics of preferences, choices, and happiness. Springer
- Inoue H, Todo Y (2020) The propagation of the economic impact through supply chains: the case of a mega-city lockdown against the spread of COVID-19. Available at SSRN 3564898
- Institute of Medicine (2007) Ethical and legal considerations in mitigating pandemic disease: workshop summary. The National Academies Press, Washington, DC. <https://doi.org/10.17226/11917>
- Ipsen J (1959) Social distance in epidemiology: age of susceptible siblings as the determining factor in household infectivity of measles. *Hum Biol* 31(2):162–179
- Jarvis CI, Van Zandvoort K, Gimma A, Prem K, Klepac P, Rubin GJ, Edmunds WJ (2020) Quantifying the impact of physical distance measures on the transmission of COVID-19 in the UK. *BMC Med* 18:1–10
- Kahneman D, Tversky A (1972) Subjective probability: a judgment of representativeness. *Cogn Psychol* 3(3):430–454
- Katafuchi Y, Kurita K, Managi S (2021) COVID-19 with stigma: theory and evidence from mobility data. *Econ Disast Clim Chang* 5(1):71–95
- Kawata K, Nakabayashi M (2021) Determinants of COVID-19 vaccine preference: a survey study in Japan. *SSM-Population Health* 15:100902
- Kenkel DS (1991) Health behavior, health knowledge, and schooling. *J Polit Econ* 99(2):287–305
- Kolenikov S, Angeles G (2004) The use of discrete data in PCA: theory, simulations, and applications to socioeconomic indices, vol 20. Carolina Population Center, University of North Carolina, Chapel Hill, pp 1–59
- Lakdawalla D, Sood N, Goldman D (2006) HIV breakthroughs and risky sexual behavior. *Q J Econ* 121(3):1063–1102

- Lin W, Sloan F (2015) Risk perceptions and smoking decisions of adult Chinese men. *J Health Econ* 39:60–73
- Liu JJ, Bao Y, Huang X, Shi J, Lu L (2020) Mental health considerations for children quarantined because of COVID-19. *The Lancet Child & Adolescent Health* 4(5):347–349
- Lowcock EC, Rosella LC, Foisy J, McGeer A, Crowcroft N (2012) The social determinants of health and pandemic h1n1 2009 influenza severity. *Am J Public Health* 102(8):51–59
- Machida M, Nakamura I, Saito R, Nakaya T, Hanibuchi T, Takamiya T, Odagiri Y, Fukushima N, Kikuchi H, Kojima T, Watanabe H (2020) Adoption of personal protective measures by ordinary citizens during the COVID-19 outbreak in Japan. *Int J Infect Dis* 94:139–144
- Mandel A, Veetil V (2020) The economic cost of COVID lockdowns: an out-of-equilibrium analysis. *Economics of Disasters and Climate Change* 4(3):431–451
- Martin A, Markhvida M, Hallegatte S, Walsh B (2020) Socio-economic impacts of COVID-19 on household consumption and poverty. *Economics of Disasters and Climate Change* 4(3):453–479
- Maurer J (2009) Who has a clue to preventing the flu? Unravelling supply and demand effects on the take-up of influenza vaccinations. *J Health Econ* 28(3):704–717
- Mazza M, Marano G, Lai C, Janiri L, Sani G (2020) Danger in danger: interpersonal violence during COVID-19 quarantine. *Psychiatry Res* 289:113046
- Ministry of Internal Affairs and Communication (2018) The White paper on information and Communications in Japan. Ministry of Internal Affairs and Communication
- Miyachi T, Takita M, Senoo Y, Yamamoto K (2020) Lower trust in national government links to no history of vaccination. *Lancet* 395(10217):31–32
- Muto K, Yamamoto I, Nagasu M, Tanaka M, Wada K (2020) Japanese citizens' behavioral changes and preparedness against COVID-19: how effective is Japan's approach of self-restraint?. medRxiv
- Nakamura H, Managi S (2020) Airport risk of importation and exportation of the COVID-19 pandemic. *Transp Policy* 96:40–47
- Okubo T, NIRA (2020) Shingata Corona Virus no Kansen Kakudai ga Telework wo Katsuyoshita Hata-rakikata, Seikatsu, Seikatsu, Ishiki nado ni Oyobosu Eikyo ni Kansuru Chosa Kekka ni kansuru Houkoukusho. <https://www.nira.or.jp/pdf/NIRA20200430-telemigration1.pdf>. Accessed 14 May 2020
- Pfefferbaum B, North CS (2020) Mental health and the Covid-19 pandemic. *N Engl J Med* 383:510–512
- Rogers, R. W., & Prentice-Dunn, S. (1997). Protection motivation theory
- Schaller J, Schulkind L, Shapiro T (2019) Disease outbreaks, healthcare utilization, and on-time immunization in the first year of life. *J Health Econ* 67:102212
- Shoji M, Ito A, Cato S, Iida T, Ishida K, Katsumata H, McElwain KM (2021) Prosociality and the uptake of COVID-19 contact tracing apps: survey analysis of intergenerational differences in Japan. *JMIR mHealth uHealth* 9(8):e29923
- The Statistics Bureau of Japan (2020) Service Sangyo Doko Chosa. <http://www.stat.go.jp/data/mssi/kekka/pdf/m2002.pdf>. Accessed 14 May 2020
- Tokyo Shoko Research (2020) Getsuji Zenkoku Kigyo Tosan Jokyō. <https://www.tsr-net.co.jp/news/status/monthly/202003.html>. Accessed 9 May 2020
- Van Bavel JJ, Baicker K, Boggio PS, Capraro V, Cichocka A, Cikara M et al (2020) Using social and behavioural science to support COVID-19 pandemic response. *Nat Hum Behav* 4(5):460–471
- WHO (2020) “Novel Coronavirus (2019-nCoV) Situation Report 1,” <https://www.who.int/emergencies/diseases/novel-coronavirus-2019/situation-reports>. Accessed 25 April 2020
- Yamamura E, Tsutsui Y (2021) School closures and mental health during the COVID-19 pandemic in Japan. *J Popul Econ* 34:1261–1298
- Zhou-Richter T, Browne MJ, Gründl H (2010) Don't they care? Or, are they just unaware? Risk perception and the demand for long-term care insurance. *Journal of Risk and Insurance* 77(4):715–747