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Abstract

We examine how information provision affects the public's perceived COVID-19 infection risk after the official end of the pandemic as a public health emergency (PHE). We conducted our survey in Japan in August 2023, a few months after the government reclassified COVID-19 from Category II to Category V and officially ended the PHE. We find that none of the information treatments affected the public's risk perceptions in a statistically significant way, in stark contrast with a similar information-provision experiment conducted right before the reclassification. Our result suggests that the official end of the PHE may influence how the public responds to news about infection.

Keywords: COVID-19, Pandemic, Risk Communication, Risk Perception

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1 Introduction

Throughout the COVID-19 pandemic, the public was exposed to various types of information about infection risk, ranging from official statistics and policy announcements to expert commentary and media reports. Such information likely influenced how people perceived the likelihood and consequences of infection and thereby affected preventive behaviors. Accordingly, a better understanding of risk perceptions can give us insights into behavioral responses during public-health crises and help policymakers design effective public communication strategies in a future pandemic.

In this study, we examine how information provision affects the public's perceived COVID-19 infection risk after the official end of the pandemic as a public health emergency (PHE). We fielded a survey experiment in Japan between August 14 and August 28, 2023 (the orange shaded area in Figure 1), a few months after the government's reclassification of COVID-19 from Category II to Category V on May 8, 2023. The reclassification marked the end of the PHE. We randomized respondents into four treatment groups, each receiving one of four real news items published in Japan in July 2023, or into a control group that received no additional information. All four information treatments are qualitative, as opposed to quantitative. Three of them provided a pessimistic infection outlook, whereas one of them provided an optimistic outlook.

A better understanding of public risk perceptions is important even after the official end of the pandemic as a public health emergency for the following reason. In some countries, normalization from the COVID-19 crisis was slow and prolonged. For example, Barrero et al. (2023) show that even after the pandemic ends, many planned to continue reducing in-person interactions for an extended period. More broadly, the literature documents persistent pandemic effects across a range of outcomes, including sectoral reallocation and labor-market churn (Barrero et al., 2021), distributional impacts and labor-market scarring that disproportionately affect lower-wage workers (Chetty et al., 2024), scarring from disruptions to children's human capital accumulation (Fuchs-Schündeln et al., 2020), and longer-lasting mental-health consequences (Bourmistrova et al., 2022). Because perceived infection risk likely influences precautionary behavior—and therefore social and economic activity—how people perceive the infection risk after the official end of COVID-19 is likely to shape the pace of normalization.

We emphasize two main findings. First, on average, none of the information treatments meaningfully changed respondents' perceived infection risk. This finding is robust to alternative experimental setups and is common across major demographic subgroups. This finding is in stark contrast to Chiba et al. (2026) which conducted a similar exper-

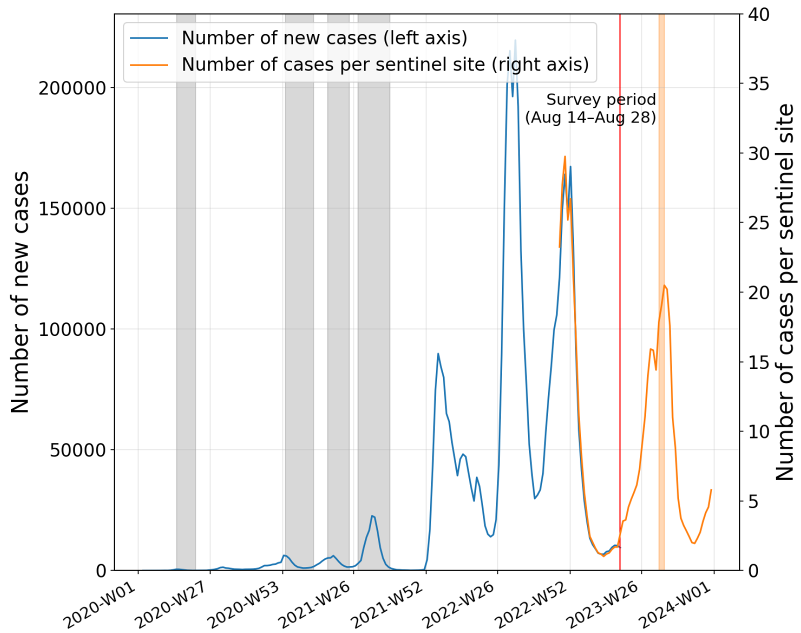

Figure 1: COVID-19 Infections and the Timing of Our Survey

Notes: This figure plots the number of new COVID-19 infections in Japan. The blue line (left y-axis) shows the weekly average of daily new infections from 2020 through May 2023. Following the reclassification of COVID-19 from Category II to Category V on May 8, 2023 (red vertical line), nationwide case counts were replaced by sentinel surveillance (Teiten Kansoku), under which designated medical institutions report new infections. The orange line (right y-axis) shows the weekly number of cases per sentinel site from May 2023 to December 2023. Grey shaded areas indicate periods with a state-of-emergency order in Tokyo, and the orange shaded area marks the survey period (August 14–28, 2023). The data used for the calculations were obtained from the Ministry of Health, Labour and Welfare (MHLW (2023a), MHLW (2023b)) and the Japan Institute for Health Security (JIHS (2023)).

iment in April 2023 and found quantitatively large and statistically significant effects of pessimistic, qualitative information on risk perceptions. Second, though we detect some statistically significant heterogeneous responses for a small number of subgroups, such as respondents with high prior risk perceptions or chronic conditions, these effects are rare and generally not robust across alternative setups.

The contrasting findings between this study and Chiba et al. (2026) have important policy implications. Because the two surveys are separated by only a few months, the difference in the findings suggests that the responsiveness of risk beliefs to information can change quickly when the institutional environment changes. A natural explanation is that Japan's widely publicized May 2023 reclassification—the official end of the pandemic as a PHE—served as a salient public signal that reset baseline beliefs and reduced the marginal informational content of subsequent COVID-related news.

Our study contributes to three strands of the literature. First, our paper is related to a set of papers investigating the public's subjective assessments of COVID-19 risks. One line of research compares perceived COVID-19 risks to objective benchmarks (Kowall et al., 2023; Thompson et al., 2024). Another line of research studies how subjective risk beliefs map into preventive behaviors (Bruine de Bruin and Bennett, 2020; Schneider et al., 2021; Dryhurst et al., 2020; Savadori and Lauriola, 2022; Bundorf et al., 2025). Others examine factors associated with subjective risk (He et al., 2021). We differ from this literature in design: Rather than relying primarily on correlational evidence, we implement a randomized information-provision experiment to identify the effect of information exposure causally.

Within this first strand of literature, our paper is most closely related to the analysis of COVID-19 risk perceptions in Japan. See, for example, Adachi et al. (2022), Murakami et al. (2026), Sasaki et al. (2022), Sato et al. (2022), Shiina et al. (2020), Shimamoto and Ibuka (2024), Takemura et al. (2022), Yamagata et al. (2025). None of these papers—except Kato et al. (2022)—conduct information-provision experiments, whereas we do. All papers—except for Murakami et al. (2026)—conduct their surveys in 2020 and 2021, well before the official end of the PHE in 2023. Our paper is unique because we conduct an information-provision experiment in the summer of 2023, after the reclassification of COVID-19 to Category V.

Second, our work is closely related to information-provision experiments in the COVID-19 context. A large experimental literature studies how information affects preventive behaviors, including vaccination intentions (Kerr et al., 2021; Loomba et al., 2021; Motta, 2021; Palm, 2021), social distancing (Lunn et al., 2020; Jordan et al., 2021), mask wearing (Abaluck et al., 2022; Kaplan et al., 2023; Torrente et al., 2022) and other health-protective actions. In contrast to this behavior-focused literature, we study the effect of information provision on people's COVID-19 risk perception.

Third, our paper contributes to the intersection of the above two strands: information treatments that directly target subjective COVID-19 risk perceptions. Existing experiments that link information provision to belief updating about COVID-19 risk provide important evidence during the acute phase of the pandemic (Abel et al., 2021; Akesson et al., 2022; Padilla et al., 2022; Calvo and Ventura, 2021). We differ from this literature by focusing on a dimension that has received limited attention: the post-reclassification period.

The structure of the paper is as follows. Section 2 describes the survey and experimental design. Section 3 presents our main results. Section 4 discusses the implications of our findings. Section 5 concludes.

2 Survey Design

2.1 Setting and Respondents

We conducted a nationally representative online survey of Japanese residents in collaboration with Cross Marketing, Inc., an online marketing firm. The survey was conducted between August 14 and August 28, 2023. This survey period was a few months after the official end of Japan's COVID-19 pandemic response (following the May 2023 reclassification) and around the peak of the ninth infection wave. The survey targeted men and women aged 20 years and older, yielding a valid sample size of 5,000. The survey asked respondents about their perceived risk of COVID-19 infection as well as a range of individual characteristics. To ensure the representativeness of our sample, the proportions of gender (Male, Female), age cohort (20s-30s, 40s-50s, $\geq$60s), and geographic residence (Prefectures) were stratified to match the demographic distribution reported in the 2020 Population Census.

The study was approved by the Ethics Review Board of the University of Tokyo (Approval No. 23-221). All procedures adhered to the relevant guidelines and regulations, and informed consent was obtained from all participants.

2.2 Prior to Information Provision

Our goal was to examine whether providing pessimistic, qualitative information about COVID-19 risk affects individuals' risk perceptions. We first elicited each respondent's prior risk perceptions before any experimental information was provided. Specifically, we elicited the subjective probability of being infected with COVID-19 over the next one month by presenting the following response options to the respondents: (1) less than 0.001%, (2) 0.001% to less than 0.01%, (3) 0.01% to less than 0.1%, (4) 0.1% to less than 1%, (5) 1% to less than 5%, (6) 5% to less than 10%, (7) 10% to less than 20%, and (8) 20% or higher.

Before we elicited these subjective probabilities, we presented two numerical reference points as nominal anchors: (1) the realized infection risk as of July 2022, when infections were spreading rapidly (2.77%), and (2) the realized infection risk as of October 2022, when the spread had slowed (0.83%). Anchors are held constant across arms and are used to reduce extreme entries and improve measurement precision rather than to shift beliefs differentially.

2.3 Information Provision

When providing information about COVID-19, we divided respondents into five groups (each consisting of 1,000 respondents) and randomly assigned respondents to these groups. For all five groups, we first presented the observed infection risk as of April 2023, near the end of the pandemic (0.21%).

We then provided additional COVID-related information that varied by group: one group received no additional information (control group); one group received a comment by a clinic in Tokyo warning about the potential collapse of the medical system; one group received a statement from a hospital in Okinawa made at a press conference, also warning about the potential collapse of the medical system; one group received a comment by a COVID-19 expert stating that the spread of infection will likely continue; and one group received a statement by a government official indicating that Japan is currently not in the middle of the ninth infection wave. The exact wording of the information provided is as follows:

Clinic in Tokyo

> *"In early July, the director of a clinic in Tokyo said that 'the number of patients is on par with the peak of the eighth wave (the number of infections exceeded 20,000 cases per day in Tokyo), and an invisible collapse of the medical system has begun.' "*

Hospital in Okinawa

> *"A hospital in Okinawa held an emergency press conference on July 11 to announce the risk of collapse of the medical system due to a resurgence of infections, urging citizens not to relax basic preventive measures."*

Expert communication

> *"On July 16, Shigeru Omi, the head of the government's COVID-19 countermeasures subcommittee, stated that 'not only the number of new cases but also the number of hospitalized and severe cases are increasing. This could be due to an increase in contact opportunities following the reclassification of COVID-19 and to diminished immunity from natural infections and vaccines over time. We do not know the full extent of the increase in the number of infections, but we should anticipate that this upward trend will continue.' "*

Government Information

> *"At a press conference held in early July, Shigeyuki Goto, the minister in charge of measures for novel coronavirus disease, stated that the number of patients had not increased sharply,*

and it was inappropriate to consider the current period as the ninth wave of infections in Japan."

We interpret the first three information treatments as pessimistic and the last information treatment as optimistic.

To assess the extent of success in randomization, we examine whether the randomization actually generated comparable groups by conducting balance tests on pre-treatment characteristics. Table 1 shows the result. The first five columns report group-specific means for each characteristic, and the remaining columns present p-values from two-sided t-tests that compare each treatment group to the control group. In nearly all cases, the p-values exceed 0.1, indicating that observable characteristics are well balanced across groups.

Table 1: Balance test

	Mean values					*P-values (t-test)*			
	No Info.	Tokyo	Okinawa	Expert	Gov.	Tokyo	Okinawa	Expert	Gov.
Age	50.410	50.482	50.422	50.300	50.419	0.918	0.986	0.875	0.990
Female	0.505	0.505	0.505	0.505	0.505	1.000	1.000	1.000	1.000
College Graduate	0.483	0.484	0.485	0.471	0.485	0.964	0.929	0.591	0.929
High Income	0.505	0.521	0.520	0.497	0.497	0.474	0.502	0.721	0.721
Vaccinated	0.851	0.853	0.851	0.834	0.848	0.900	1.000	0.297	0.851
Chronic Diseases	0.134	0.143	0.146	0.139	0.142	0.560	0.440	0.745	0.604
Infected with COVID-19	0.246	0.240	0.243	0.225	0.248	0.755	0.876	0.269	0.918
Acq. Died from COVID-19	0.085	0.053	0.065	0.068	0.083	0.005	0.090	0.153	0.872

Notes: This table presents the results of covariate balance tests. The first five columns report mean values of each covariate for the control group and the four treatment groups. The last four columns report p-values from two-sided t-tests comparing each treatment group to the control group. "Acq." denotes acquaintance.

2.4 Post Information Provision

After the information provision, we elicited respondents' posterior risk perceptions by asking them again about their subjective probability of becoming infected with COVID-19 within the next one month. We used the same question format and response categories as in the pre-information stage, which allows a direct comparison of beliefs before and after exposure to the assigned information.

At this stage, we also collected respondents' background information, including education, household income in 2022, health conditions, vaccination status (number of vaccine doses), COVID-19 related experiences (the number of times infected and whether the respondent used ECMO/ventilator support), whether any acquaintances died from COVID-19, and the extent of engagement in infection-prevention behaviors over the past month as well as intended engagement over the next month.

Detailed summary statistics regarding individual attributes are presented in Table 2. The respondents' age and gender are distributed closely to those of residents in Japan by construction. The distribution of educational attainment shows a somewhat larger share of college graduates than in official statistics: It is 48.2 percent in our survey, whereas it is 25.7 percent according to the National Census. Income distribution is close to that in the official statistics: 50.8 percent earned more than 4 million yen in our survey, whereas 49.4 percent earned more than 4 million according to the Statistical Survey of Actual Status for Salary in the Private Sector in 2023. Overall, these data suggest that the respondents represent residents in Japan reasonably well.

Table 2: Summary Statistics

	Total
Age	
20-59 years	3,285 (65.7%)
Over 60 years	1,715 (34.3%)
Gender	
Male	2,475 (49.5%)
Female	2,525 (50.5%)
Education Level	
Non-College Graduate	2,592 (51.8%)
College Graduate	2,408 (48.2%)
Income (in ten-thousand yen)	
Less than 400	2,460 (49.2%)
400 or more	2,540 (50.8%)
Vaccination	
Unvaccinated	763 (15.3%)
Vaccinated	4,237 (84.7%)
Chronic Diseases	
Yes	704 (14.1%)
No	4,296 (85.9%)
Infected with COVID-19	
Yes	1,202 (24.0%)
No	3,798 (76.0%)
Acq. Died from COVID-19	
Yes	354 (7.1%)
No	4,646 (92.9%)
N	5,000

Notes: This table reports summary statistics for respondents' individual attributes. Numbers denote counts, and percentages are in parentheses.

2.5 Two Alternative Setups

For robustness, we conduct the same information-provision experiment described thus far in two slightly modified setups. The first alternative setup is identical to the baseline setup, except that we do not provide our respondents with nominal anchors before eliciting the prior subjective risk perceptions. This allows us to rule out the possibility that nominal anchors substantially shift beliefs and affect our treatment effects.

The second alternative setup is identical to the first alternative setup, except that we do not elicit prior subjective risk perceptions. This allows us to rule out experimenter-demand effects from eliciting priors—that is, respondents may infer the importance of risk perceptions and adjust their subsequent responses. The key results from the baseline setup described in the following section are robust to these two alternative setups. The robustness results are discussed in the Appendix.

3 Results

3.1 Risk Perceptions Prior to Information Provision

We begin by describing respondents' risk perceptions prior to information provision. Figure 2 plots the distribution of subjective infection risk. The blue vertical lines indicate summary statistics of subjective beliefs (the sample mean and median), while the red vertical line indicates the realized infection risk.[1]

The figure shows substantial risk overestimation relative to the realized risk: A large mass of respondents reports infection probabilities far above the realized risk of 2.72%. In particular, 38.8% (16.6 + 12.8 + 9.4) respondents believed that their likelihood of contracting COVID-19 within the next month was 5% or greater. Setting a higher threshold, we find that 22.2% (12.8 + 9.4) of the respondents assessed the infection risk as 10% or higher. At the same time, a non-negligible share understates the risk: 13.9% report that their infection risk is almost zero (less than 0.001%).

Overall, the distribution is wide and centered well above the realized risk, consistent with our earlier surveys on COVID-19 risk perceptions in Japan (Chiba et al., 2024, 2026).

[1] We estimate the actual infection risk for the one-month period from the survey start date (August 14 – September 13, 2023). Specifically, we use the two COVID-19 infection series shown in Figure 1, based on data from MHLW (2023a), MHLW (2023b), and JIHS (2023). We regress the weekly average number of new infections (left y-axis) on the number of cases per sentinel site (right y-axis) using data from December 2022 to May 2023. The estimated coefficient is then applied to sentinel-site data to compute the weekly average number of new infections during August 14 – September 13, 2023. We aggregate these weekly estimates and divide the total number of infections by the total population reported by the Statistics Bureau of Japan (MIAC (2023)) to obtain the actual infection risk.

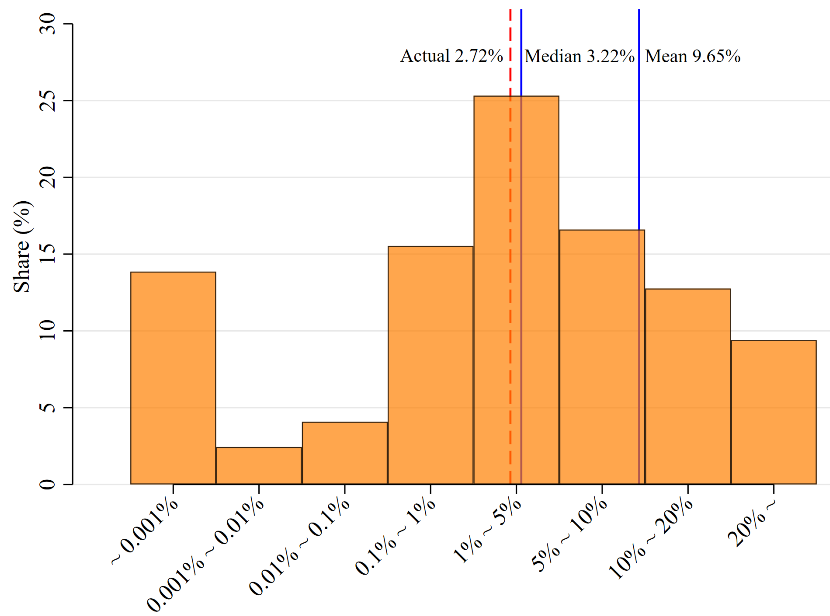

Figure 2: Distribution of Prior Risk Perceptions

Notes: This figure shows the distribution of subjective infection risk. The red vertical line indicates the actual infection risk. The blue vertical lines indicate the mean and median of perceived risk.

3.2 Effects of Information Provision

To examine the effects of information provision on reported infection risk, we estimate the following regression specification:

$$y_i = \alpha + \sum_{j=1}^{4} \beta_j D_{ji} + \mathbf{x}_i' \gamma + \epsilon_i \tag{1}$$

where the dependent variable (y_i) is subjective infection risk, defined as the midpoints of each response category.[2] The independent variables (D_{1i},D_{2i},D_{3i},D_{4i}) are dummy variables for "Tokyo", "Okinawa", "Expert" and "Government" information group, respectively. The set of control variables ($\mathbf{x}_i$) include dummy variables for high prior risk perceptions (prior risk $\geq$ 10%), age, gender, education, income, chronic diseases, infection history (0 or $\geq$1), acquaintance's COVID-19-related deaths, and vaccination status. We also control for prefecture fixed effects and for the primary type of media respondents used to obtain information about COVID-19, considering that respondents were under different measures and situations of COVID-19 across prefectures and under different accuracy and accessibility to information across media. However, in all tables presenting

[2] For open-ended categories of 20% or higher and less than 0.001%, we top-code at 100% and bottom-code at 0%, assigning midpoints of 60% and 0.0005%, respectively.

regression results, the coefficients on media types and prefectures are omitted for simplicity.

Table 3 reports the estimation results. Two-sided p-values below 0.05 are treated as statistically significant. For each group dummy variable included in the regression, if the estimated coefficient is positive (negative), respondents in that group perceive the risk to be higher (or lower) than those in the control group. According to the table, all treatment coefficients are small in magnitude and not statistically significantly different from zero. This result is robust to alternative experimental setups and remains qualitatively similar across demographic subgroups.

Table 3: Average Effects (Including Prior Risk)

	(1) Infection Risk
Information: Tokyo	0.453
	(0.554)
Information: Okinawa	−0.331
	(0.544)
Information: Expert	0.434
	(0.557)
Information: Government	−0.629
	(0.533)
Prior Risk Above 10%	24.303***
	(0.712)
College Graduate	−0.109
	(0.367)
High Income	−0.155
	(0.361)
Age Over 60 years	−0.703*
	(0.375)
Female	0.640*
	(0.360)
Vaccination	0.263
	(0.491)
Chronic Diseases	0.614
	(0.507)
Infected with COVID-19	0.114
	(0.443)
Acq. Died from COVID-19	0.528
	(0.787)
Constant	3.358***
	(1.021)
Observations	5,000
R-squared	0.416

Notes: This table reports regression results examining the average treatment effects of information provision. The dependent variable is subjective infection risk. The independent variables are dummy variables for information groups. Control variables include dummy variables for prior risk perception, age, gender, education, income, chronic diseases, prior infection, acquaintance's COVID-19-related death, and vaccination status. All regressions also include prefecture fixed effects and dummy variables for primary media type; however, coefficients for these variables are omitted from the table for brevity. Robust standard errors are in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

We now turn to the analysis of heterogeneous treatment effects. For this analysis, we partition the sample by respondents' demographic and socioeconomic characteristics as well as their COVID-19 experiences, and estimate the following equation:

$$y_i = \alpha + \delta H_i + \beta D_i + \eta D_i \times H_i + \mathbf{x}_i' \gamma + \epsilon_i \tag{2}$$

For this analysis, we added to our baseline regressions in (1) (presented in Table 3) the interaction terms between the information group dummy variables and each characteristic of interest (H_i)—prior risk perceptions, age, gender, education, income, health condition, COVID-19-related experiences, and vaccination status. Across a wide range of characteristics, the interaction coefficients are generally small and statistically insignificant, suggesting that most observable characteristics are not associated with systematically different responses to the information treatments.

Nevertheless, we detect statistically significant responses for a small number of subgroups in some specifications. For respondents with high prior risk perceptions (prior risk $\geq$ 10%), the Okinawa treatment is associated with a negative and statistically significant interaction at the 5% level, and the Government treatment yields a negative interaction that is marginally significant at the 10% level. Among respondents with chronic diseases, the Okinawa treatment generates a negative interaction significant at the 5% level, while the Expert treatment produces a positive interaction that is marginally significant at the 10% level. We also find a few additional isolated significant interactions. For example, the Expert treatment interacted with age 60+ is negative and significant at the 5% level, and the Government treatment interacted with female, having an acquaintance who died from COVID-19, or related characteristics is negative and marginally significant at the 10% level. Overall, however, these significant findings are sparse and do not appear robust across alternative experimental setups, so we interpret them cautiously.

Table 4: Heterogeneity - Prior Risk

	(1)	(2)	(3)	(4)
GROUP	Control & Tokyo	Control & Okinawa	Control & Expert	Control & Gov.
VARIABLES	Posterior Risk	Posterior Risk	Posterior Risk	Posterior Risk
Prior Risk Above 10%	26.130***	26.050***	26.182***	26.123***
	(1.512)	(1.516)	(1.506)	(1.513)
Treatment*Prior Risk Above 10%	−0.655	−5.402**	0.245	−3.842*
	(2.246)	(2.205)	(2.183)	(2.145)
Treatment dummy	0.579*	0.857**	0.287	0.229
	(0.313)	(0.333)	(0.301)	(0.255)
Observations	2,000	2,000	2,000	2,000
R-squared	0.457	0.426	0.472	0.453

Notes: This table reports regression results examining heterogeneous treatment effects by prior infection risk. The dependent variable is subjective infection risk. The independent variables are *Prior Risk Above 10%*, the treatment group dummy, and their interaction. All specifications control for individual characteristics, prefecture fixed effects, and primary media type dummies. However, coefficients for these variables are omitted from the table for brevity. In each column, the regression sample consists of respondents in the control group and one treatment group—Tokyo, Okinawa, Expert, and Government, respectively. Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Heterogeneity - Age

	(1)	(2)	(3)	(4)
GROUP	Control & Tokyo	Control & Okinawa	Control & Expert	Control & Gov.
VARIABLES	Posterior Risk	Posterior Risk	Posterior Risk	Posterior Risk
Age Over 60 years	−1.814**	−1.890**	−2.041***	−1.821**
	(0.779)	(0.772)	(0.780)	(0.774)
Treatment*Age Over 60 years	0.305	1.024	2.835**	0.766
	(1.098)	(1.102)	(1.125)	(1.090)
Treatment dummy	0.325	−0.668	−0.636	−0.923
	(0.732)	(0.706)	(0.729)	(0.718)
Observations	2,000	2,000	2,000	2,000
R-squared	0.457	0.421	0.473	0.450

Notes: This table reports regression results examining heterogeneous treatment effects by age. The dependent variable is subjective infection risk. The independent variables are *Age Over 60 years*, the treatment group dummy, and their interaction. All specifications control for individual characteristics, prefecture fixed effects, and primary media type dummies. However, coefficients for these variables are omitted from the table for brevity. In each column, the regression sample consists of respondents in the control group and one treatment group—Tokyo, Okinawa, Expert, and Government, respectively. Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Heterogeneity - Gender

	(1)	(2)	(3)	(4)
GROUP	Control & Tokyo	Control & Okinawa	Control & Expert	Control & Gov.
VARIABLES	Posterior Risk	Posterior Risk	Posterior Risk	Posterior Risk
Female	0.979	0.689	1.082	1.008
	(0.794)	(0.802)	(0.797)	(0.799)
Treatment*Female	−0.674	0.182	0.658	−1.844*
	(1.139)	(1.092)	(1.130)	(1.092)
Treatment dummy	0.769	−0.409	0.011	0.271
	(0.754)	(0.739)	(0.740)	(0.714)
Observations	2,000	2,000	2,000	2,000
R-squared	0.457	0.421	0.472	0.451

Notes: This table reports regression results examining heterogeneous treatment effects by gender. The dependent variable is subjective infection risk. The independent variables are *Female*, the treatment group dummy, and their interaction. All specifications control for individual characteristics, prefecture fixed effects, and primary media type dummies. However, coefficients for these variables are omitted from the table for brevity. In each column, the regression sample consists of respondents in the control group and one treatment group—Tokyo, Okinawa, Expert, and Government, respectively. Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Heterogeneity - Acquaintance Death

	(1)	(2)	(3)	(4)
GROUP	Control & Tokyo	Control & Okinawa	Control & Expert	Control & Gov.
VARIABLES	Posterior Risk	Posterior Risk	Posterior Risk	Posterior Risk
Acq. Died from COVID-19	1.602	1.568	1.607	1.325
	(1.386)	(1.402)	(1.362)	(1.384)
Treatment*Acq. Died from COVID-19	−3.430	2.260	−0.556	−3.874*
	(2.240)	(2.455)	(2.508)	(2.015)
Treatment dummy	0.655	−0.482	0.386	−0.339
	(0.578)	(0.559)	(0.570)	(0.557)
Observations	2,000	2,000	2,000	2,000
R-squared	0.457	0.421	0.472	0.451

Notes: This table reports regression results examining heterogeneous treatment effects by COVID-19-related acquaintance death. The dependent variable is subjective infection risk. The independent variables are *Acq. Died from COVID-19*, the treatment group dummy, and their interaction. All specifications control for individual characteristics, prefecture fixed effects, and primary media type dummies. However, coefficients for these variables are omitted from the table for brevity. In each column, the regression sample consists of respondents in the control group and one treatment group—Tokyo, Okinawa, Expert, and Government, respectively. Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4 Discussion

We find that none of the information treatments meaningfully changed respondents' perceived infection risk. This finding is in stark contrast to Chiba et al. (2026), which conducted a similar experiment in April 2023 and found quantitatively large and statistically significant effects of the following pessimistic, qualitative infection outlook on risk perceptions. In Chiba et al. (2026), we provided the following information treatment to our respondents:

"The number of new cases has been gradually increasing, and there is concern about the spread of infection after the holidays in May. On April 19, the expert group mentioned the possibility of a 9th wave, which would be larger than the 8th wave. Compared to the 6th and 7th waves (January-April 2022 and July-September 2022), the 8th wave (November 2022-February 2023) showed an increase in fatality rate."

It is interesting to note that this information treatment had statistically significant and quantitatively large effects on risk perceptions, even though the infection was low and stable at the time of the survey. According to Figure 1, the number of daily new infections was near the trough between two infection waves at the time of the survey.

There are two possible reasons for the difference between Chiba et al. (2026) and our study. The first is that the narrative about the infection outlook in Chiba et al. (2026) was more pessimistic than the three narratives in our study. The second is that the public's perception was more responsive to information before the reclassification of COVID-19 from Category II to Category V on May 8, 2023. Though somewhat conjectural, we believe that the second factor is more likely to be responsible for the divergent results than the first factor.

5 Conclusion

We examined how information provision affects the public's perceived COVID-19 infection risk in August 2023, a few months after the Japanese government reclassified COVID-19 from Category II to Category V and officially ended the PHE. We found that none of the information treatments affected the public's risk perceptions in a statistically significant way, in stark contrast with a similar information-provision experiment conducted right before the reclassification (see Chiba et al. (2026)). Our result suggests that the official declaration regarding the PHE may be a key factor determining how the public responds to news about infection during a pandemic.

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Appendix

A Questionnaire

Introduction

This survey is an academic research project conducted by the Laboratory of Taisuke Nakata, Graduate School of Economics, The University of Tokyo, and commissioned to Cross Marketing Inc.

The purpose of this survey is to understand people's perceptions of COVID-19 risks. It includes questions about past COVID-19 infection experiences, vaccination history, pre-existing medical conditions, income, and other related factors.

All responses will be statistically processed and anonymized so that no individual can be identified. Summary data or raw data may be made public, but never in a way that allows personal identification. Your data will never be used for any purpose other than this research. Please answer each question as you think.

Estimated time to complete: 10 minutes.

Participation is voluntary. You may stop at any time by closing your browser. In that case, no incentive points will be awarded.

If you agree with the above and wish to participate, please select "Next." If you do not wish to participate, you may end the survey here (no incentive points will be given).

Screening Survey

Respondent criteria

- Men and women aged 20–79 who are registered panel members.
- Sampling will match national representative ratios for age and gender.

Questions

S1. Please indicate your gender. (Single Answer)

  - Male

- Female

S2. Please indicate your age. (Pre-coded Data)
S3. Please indicate the prefecture where you currently live. (Pre-coded Data)
S4. After reading the above information, would you be willing to participate in this survey? (Single Answer)

- Proceed to Next (Participate in the survey)
- Stop answering (Do not participate in the survey)

Main Survey

Q1. Are you currently receiving treatment or under medical observation for any of the following conditions? Please select all that apply. (Multiple Answer)

- Malignant neoplasm (cancer)
- Cerebrovascular disease (e.g., cerebral hemorrhage, cerebral infarction)
- Respiratory disease
- Cardiovascular disease (e.g., angina, myocardial infarction)
- Digestive system disease (stomach, intestines, liver, spleen, etc.)
- Endocrine disease (e.g., diabetes)
- Kidney disease
- Blood disorders (e.g., anemia)
- None

Q2. How many times in total have you received a COVID-19 vaccine so far? (Single Answer)

- 0 times
- 1 time
- 2 times
- 3 times
- 4 time
- 5 times or more

Q3. How many times in total have you been infected with COVID-19? (Single Answer)

- 0 times
- 1 time
- 2 times
- 3 times or more

Q4. (**For respondents who answered "1 time or more" to Q3**) When you were infected, did your condition become severe enough to require a ventilator or ECMO (Extracorporeal Membrane Oxygenation)? (Single Answer)

- Became severe
- Did not become severe

Q5. Do you know anyone who died after being infected with COVID-19? (Single Answer)

- Yes
- No

Q6. To what extent did you practice infection prevention measures over the past month, such as handwashing and hand sanitizing, wearing masks, ventilation, and avoiding the "Three Cs" (closed spaces, crowded places, and close-contact settings)? (Single Answer)

- Frequently
- Sometimes
- Rarely
- Almost never
- Never

Instructions for the Survey Company

- For 33% of respondents, skip Q7 and proceed directly to Q8.
- For 67% of respondents, ask Q7 and then proceed to Q8.

Information Provided Before Q7

- No information provided **(50% of those assigned to Question 7; 33% of all respondents**)
- In July 2022, the number of newly confirmed cases was 3,463,299 (account for 2.77% of the total population), while in October 2022, infection was relatively calm with 1,031,436 newly confirmed cases (0.83% of the total population) reported. (**50% of those assigned to Question 7; 33% of all respondents**)

Q7. What do you think is the probability (in percent) that you will become infected with COVID-19 within the next month? Please give your own assessment. (Single Answer)

- 20% or higher
- 10% or higher but less than 20%
- 5% or higher but less than 10%
- 1% or higher but less than 5%
- 0.1% or higher but less than 1%
- 0.01% or higher but less than 0.1%
- 0.001% or higher but less than 0.01%
- Less than 0.001%

Q8. Which of the following media do you rely on most as a source of information? (Single Answer)

- Television
- Newspapers
- Internet
- Social media (SNS)
- Radio
- Other

Q9. What is the highest level of education you have completed? (Single Answer)

- Junior high school or elementary school
- High school
- Junior college (including technical colleges)
- University
- Graduate school (master's degree)
- Graduate school (doctoral degree)

Q10. What was your household's total annual gross income in 2022, including bonuses? Please select one. (Single Answer)

- No income
- Under 1 million yen
- 1–2 million yen
- 2–4 million yen
- 4–6 million yen
- 6–8 million yen
- 8–10 million yen
- 10–12 million yen
- 12–14 million yen
- 14 million yen or more

Instructions for the Survey Company

At this point, there are three groups:

- 33%: Proceeded to Q8 without being asked Q7
- 33%: Asked Q7 without being provided infection statistics for July/October 2022
- 33%: Asked Question 7 and provided infection statistics for July/October 2022

Information Provided Before Q11

Information Provided to All Respondents

- COVID-19 has been reclassified to Category V Infectious Disease on May 8, 2023. At the same time, the system has been changed from recording the number of daily new infections ("notifiable disease surveillance") to recording the number of new infections in certain medical institutions ("sentinel surveillance").

  Before changing to the sentinel surveillance system, **265,404 new infections (0.21% of the total population) were reported in April 2023**. According to the weekly sentinel surveillance records after May 8, the number of new infections has been increasing after the reclassification of COVID-19 to Category V, and the number of new infections in the third week of July is approximately **4.2 times** that in the second week of May.

Additional Information (randomly assigned)

- No additional information **(20% of each group)**
- In early July, the director of a clinic in Tokyo said that "the number of patients is on par with the peak of the eighth wave (the number of infections exceeded 20,000 cases per day in Tokyo), and an invisible collapse of the medical system has begun." **(20% of each group)**
- A hospital in Okinawa held an emergency press conference on July 11 to announce the risk of collapse of the medical system due to a resurgence of infections, urging citizens not to relax basic preventive measures. **(20% of each group)**
- On July 16, Shigeru Omi, the head of the government's COVID-19 countermeasures subcommittee, stated that "not only the number of new cases but also the number of hospitalized and severe cases are increasing. This could be due to

an increase in contact opportunities following the reclassification of COVID-19 and to diminished immunity from natural infections and vaccines over time. We do not know the full extent of the increase in the number of infections, but we should anticipate that this upward trend will continue". **(20% of each group)**

- At a press conference held in early July, Shigeyuki Goto, the minister in charge of measures for novel coronavirus disease, stated that the number of patients had not increased sharply, and it was inappropriate to consider the current period as the ninth wave of infections in Japan. **(20% of each group)**

Q11. Taking into account the recent infection trends just described, please answer again: What do you think is the probability (in percent) that you will become infected with COVID-19 within the next month? Please give your own assessment. (Single Answer)
(Same options as Q7)

Q12. How much do you plan to engage in infection prevention measures over the next month, such as handwashing and hand sanitizing, wearing masks, ventilation, and avoiding the "Three Cs"? (Single Answer)

- I plan to do so frequently
- I plan to do so sometimes
- I plan to do so rarely
- I plan to almost never do so
- I do not plan to do so at all

B Results from Two Alternative Setups

Table A1 and Table A1 show the effect of information provision in the two alternative setups discussed at the end of Section 2. These two tables demonstrate the robustness of the key result in our paper—none of the information treatments has statistically significant effects on the public's risk perceptions.

We also conduct the heterogeneity analysis in these two alternative setups. For all of the four information treatments and for any individual attribute, we find no statistically significant heterogeneity across sub-groups. The results are not show for the sake of brevity, but available upon request.

Table A1: Average Effects: No Anchor - Prior Group

	(1)
	Infection Risk
Information: Tokyo	0.725
	(0.622)
Information: Okinawa	−0.178
	(0.618)
Information: Expert	0.605
	(0.625)
Information: Government	0.317
	(0.637)
Prior Risk Above 10%	25.526***
	(0.710)
College Graduate	−1.176***
	(0.419)
High Income	−0.614
	(0.413)
Age Over 60 years	−1.006**
	(0.424)
Female	0.659
	(0.412)
Vaccination	0.352
	(0.566)
Chronic Diseases	0.097
	(0.578)
Infected with COVID-19	−0.577
	(0.497)
Acq. Died from COVID-19	0.608
	(0.846)
Constant	4.881***
	(1.212)
Observations	5,000
R-squared	0.398

Notes: This table reports regression results examining the average treatment effects of information provision. The regression sample includes respondents in the no nominal anchor and prior elicitation group. The dependent variable is subjective infection risk. The independent variables are dummy variables for information groups. Control variables include dummy variables for prior risk perception, age, gender, education, income, chronic diseases, prior infection, acquaintance's COVID-19-related death, and vaccination status. All regressions also include prefecture fixed effects and dummy variables for primary media type; however, coefficients for these variables are omitted from the table for brevity. Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: No Anchor - No Prior Group: Average Effects

	(1)
	Infection Risk
Information: Tokyo	−0.788
	(0.763)
Information: Okinawa	−0.171
	(0.775)
Information: Expert	−0.044
	(0.777)
Information: Government	0.137
	(0.777)
College Graduate	−1.928***
	(0.503)
High Income	−0.527
	(0.497)
Age Over 60 years	−1.981***
	(0.548)
Female	1.335***
	(0.501)
Vaccination	2.062***
	(0.703)
Chronic Diseases	−0.560
	(0.669)
Infected with COVID-19	2.454***
	(0.622)
Acq. Died from COVID-19	2.965***
	(1.064)
Constant	9.210***
	(1.393)
Observations	5,000
R-squared	0.030

Notes: This table reports regression results examining the average treatment effects of information provision. The regression sample includes respondents in the no nominal anchor and no prior elicitation group. The dependent variable is subjective infection risk. The independent variables are dummy variables for information groups. Control variables include dummy variables for age, gender, education, income, chronic diseases, prior infection, acquaintance's COVID-19-related death, and vaccination status. All regressions also include prefecture fixed effects and dummy variables for primary media type; however, coefficients for these variables are omitted from the table for brevity. Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.