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Bayesian Probability Revision and Infection Prevention Behavior in Japan: A Quantitative Analysis of the First Wave of COVID-19

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Abstract: The relationship between cognitive biases and infection prevention behavior remains unexplored in the existing literature. This study uses data from a questionnaire survey conducted in Japan regarding the first wave of coronavirus disease 2019 (COVID-19) from February to May 2020 to investigate the impact of Bayesian probability inference, impact of cognitive biases of PCR test results on infection prevention behavior, and the discrepancy between infection prevention intentions and behaviors. The results showed that the higher probability responses, implying pessimism biases, were more likely to indicate that declaring a state of emergency was necessary and effective, and that they were more health oriented to ensure infection prevention behavior even at the expense of the economy. However, regarding actual behavioral change, it was found that even though they really wanted to reduce the frequency of their outings and the number of people they came in contact with, they actually did not reduce it. It was also found that those affected by pessimism biases showed higher WTP for the vaccine.

JEL Classification Number: I1, D9, C3

Key words: COVID-19, Bayesian inference, cognitive biases

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1. Introduction

The worldwide spread of the novel coronavirus disease 2019 (COVID-19) is not only a medical research problem but also a social science one. People had to make judgments about the probability of infection and adopt infection-preventive actions such as social distancing, restricting outings, and vaccination[1]. In behavioral economics research, humans are said to have cognitive biases because of their limited rationality. Heterogeneity exists in cognitive biases ranging from optimism to pessimism for different individuals. This suggests a correlation between cognitive biases and the degree of infection prevention behavior. Specifically, optimistic thinkers neglect infection prevention behaviors, while pessimistic ones adopt infection prevention actions. Based on a questionnaire survey conducted regarding the first wave of COVID-19 in Japan, which occurred from late February to May 2020, this study aims to determine the correlation between cognitive biases that affect probabilistic judgments about PCR test results and evaluations of policies such as infection prevention behaviors and the declaration of state of emergency.

Determining the infection probability requires high level of numerical processing and cognitive ability. This is because all medical tests, including PCR tests, are complicated in terms of probability calculation because false negatives (negative results in the presence of a disease) and false positives (positive results in the absence of a disease) are inevitable. According to the Bayes' theorem, the posterior probability is proportional to the product of the prior probability and the likelihood. However, humans are known to ignore the base rate, the prior probability of how many of the total population are actually infected, which is the basis of Bayes' inference.[2] For example, suppose a woman has a prior probability of 1% for breast cancer, a sensitivity of 80% for those with cancer who test positive, and a specificity of 90% for those without cancer who do not test positive. At this point, using Bayes' theorem, when the test is positive, the probability that the person has cancer is 8%. However, the correct response rate to this question is less than 5%, and many people give incorrect answers by ignoring the base rate (Eddy 1982).

Two caveats should be pointed out here. First, base rate neglect in Bayesian inference is widely observed not only among ordinal people but also among experts such as physicians

[1] The test to determine whether a person is infected, that is, whether COVID-19 is present in that person's body, is the polymerase chain reaction (PCR) test.

[2] This base rate neglect was noted by Meehl and Rosen (1955) in clinical psychology, Kahneman and Tversky (1980) in social psychology, and others. See Grether (1980) for more details.

(Brase 2002; Hoffrage and Gigerenzer 1995; Hoffrage et al. 2000; Hertwig and Hoffrage 2002). In other words, base rate neglect is not a cognitive bias stemming from mere lack of knowledge or miscalculation. Second, the rate of correct responses can change depending on how the information is given. Probability-type framing lowers the correct response rate, while frequency-type framing increases it (Cosmides and Tooby 1996; Gigerenzer and Hoffrage 1995; Sloman et al. 2003; Barbey et al. 2007).[3]

To prevent the spread of infection, much evidence is needed on the correlation between cognitive biases and infection prevention behaviors. Studies have been conducted on measures to promote social distance, which reduces the frequency of outings and the number of people in contact, to deter the spread of COVID-19.[4] For example, experimental studies have investigated the types of information provision that promote social distance and have found loss aversion and social comparison to be effective nudges. Similarly, nudges that motivate vaccination have been studied[5]. However, few studies have examined the correlation between cognitive biases and infection prevention behavior.

We note two points about these previous studies. First, the cognitive bias of infection risk has a systematic effect on infection prevention behavior (Akesson et al. 2021; Alsan et al. 2020; Barrios and Hochberg 2020; Bordalo et al. 2020; Bundorf et al. 2021; Campos-Mercade 2021; Cori et al. 2020; Dryhurst et al. 2020; Fan et al. 2020; Hamano et al. 2020; Manski and Molinari 2020; Plohl and Musil 2021; Wise et al. 2020). It is currently unclear whether there is an expected relationship between the optimistic or pessimistic tendencies of cognitive biases and infection prevention behavior. Therefore, a quantitative understanding of the relationship between cognitive biases and infection prevention behavior is needed. Second, infection prevention intentions do not always lead to actual behavior (Falcoy and Zaccagniz

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[3] Some studies have shown that Bayesian inference is more correct when probability information is given than when frequency information is given (Evans et al. 2000; Masshi 2000).

[4] Reference papers on social distance include Barari et al. (2020), Cato et al. (2020), Everett et al. (2020), Falcoy and Zaccagniz (2020), Heffner et al. (2020), Jordan et al, Kishishita et al. (2022), Lunn et al. (2020), Luttrell and Petty (2020), Moriwaki et al. (2020), Müller and Rau (2021), Sasaki et al. (2020), Simonov et al. (2020), Stock (2020), and Utych and Fowler (2020).

[5] Reference papers on vaccination include Cerda and Garc (2021), Dai et al. (2021), Daly and Robinson (2021), Garc and Cerda (2020), Harapan et al. (2020), Kadoya et al. (2021), Kawata and Nakabayashi (2021), Latkin et al. (2021), Lin et al. (2021), Moehring et al. (2021), Sasaki et al. (2022), Saidor et al. (2021), and Sallam (2021).

2020; Barari et al. 2020; Everett et al. 2020; Wong et al. 2020; Dai et al. 2021).[6] Examples include essential workers who cannot close their offices during an infection outbreak. Even if they want to take infection prevention actions, they may not be able to actually take ideal infection prevention measures, such as restricting the number of days they can be away from work. Therefore, it is necessary to quantitatively understand intention-to-action gaps.

For the question asking about posterior probabilities as Bayesian inference, we employed the probability and frequency types, and collected responses from 1,000 respondents respectively.[7] For the econometric analysis, a bivariate ordinal probit model was employed in addition to the ordinal probit model. This model is an extension of the seemingly unrelated regression (SUR) model, which is often used as an apparently unrelated regression, to an ordinal probit model. The model analyzes how the Bayesian probabilities of the responses affect the necessity of the declaration of a state of emergency, the evaluation of its effectiveness, and infection prevention behaviors such as going out more often and reducing the number of contacts with persons. Simultaneously, the model considers the relationship between two behaviors that are expected to be correlated, that is, the need for declaring a state of emergency and the evaluation of the effectiveness of the emergency.

The results showed that those who responded with higher Bayesian probabilities, that is, those who were influenced by the *pessimism bias*, were more likely to believe that the declaration of a state of emergency was necessary and effective and more health-conscious to ensure infection prevention behaviors even at the expense of the economy. However, regarding actual behavior change, it was also found that although they really wanted to reduce the frequency of their outings and the number of people they came in contact with, they were not actually able to do so. The higher the Bayesian probability, the higher the willingness to pay (WTP) for vaccines.

Several other policy findings were also obtained in this study. Japan did not use the lockdown approach of punitive and mandatory restrictions on going out, as in other countries. It adopted the less punitive and less legally enforceable measure of requesting people to refrain from going out and having contact with others. For those who actually wanted to

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[6] Some studies have reported that information provision effectively changes behavior, at least in the short term, and accumulating evidence is required (Krpan et al. 2020; Moriwaki et al. 2020; Sasaki et al. 2021a).

[7] The survey was conducted in November 2020; Shibamoto (2020) investigated the probability of infection in June 2020, after the first wave. Using Bayes' theorem as in this paper, the study suggests that most people infected with COVID-19 are asymptomatic and argues that countermeasures based on this assumption are necessary.

reduce the frequency of their outings and the number of people they came in contact with, but were unable to do so, it is conceivable that even stronger curbs on outings, such as the lockdown, were necessary. When a *discrepancy between intention and actio*n occurs, imposing behavioral restrictions is a measure to enhance the welfare of the individual concerned.

The rest of this paper is organized as follows. Section 2 describes the survey. Section 3 describes the results of the Bayesian probability revision, and Section 4 explains the methodology of the econometric analysis. Section 5 discusses the results of the Bayesian probability revision's estimation of individuals' evaluations of government measures to prevent the spread of COVID-19 infections and their effectiveness, as well as their willingness to be vaccinated. Finally, Section 6 discusses the results of the analysis and concludes.

2. Survey Summary

We surveyed individuals living in Japan. The survey was conducted in November 2020 using a web-based questionnaire of My Voice, Inc. We asked respondents to provide probability and frequency information for calculating Bayesian probability and collected 1,000 samples for each. A total of 2,000 samples of probability and frequency were used to show the survey results. Gender was assigned so that there would be 1,000 men and 1,000 women.

Table 1 contains the results of the individual attribute responses. Residents of the seven prefectures[8] where the first wave of the declaration of a state of emergency was first issued (April 7, 2020) accounted for about half of the total respondents. The mean age was 44.9 years with a standard deviation of 13.8 years. About half of the respondents were unmarried. About 70% of the respondents were employed (including part-time workers). About 30% were unemployed, including students and retirees. About 20% of the respondents lived in single-person households, and about 80% lived in family households. Approximately 60% of the respondents had a university degree or higher. The average annual household income was 6.18 million yen (USD 56,678, given USD 1 = JPY), with a standard deviation of 3.43 million yen (USD 31,459, given USD 1 = JPY).

<Insert Table 1>

Table 2 contains the results of the health status responses. First, respondents were asked about their health and efforts and the status of transmission of COVID-19 in the first wave.

[8] The seven prefectures are Tokyo, Saitama, Chiba, Kanagawa, Osaka, Hyogo, and Fukuoka.

Here, we defined the “first wave” as the period of expansion of infection from February 2020 to the lifting of the declaration of the state of emergency in May 2020. While 63.1% of the respondents answered that their "physical" health was "very good" or "rather good" during the first wave of expansion, only 38.5% answered that their "mental" health was good. Differences can be observed between the health status of the body and the mind. As for anxiety about infection, 63.6% of the respondents answered that they "felt rather anxious" or "felt very anxious.” Thus, significant differences in responses can be observed.

<Insert Table 2>

Table 3 contains the results of the responses to the familiar infection situation. Respondents were asked whether anyone that they had been in immediate contact with had ever been infected, hospitalized, or died from COVID-19. The results showed that few people, including acquaintances, had been infected: 91.5% of the respondents themselves, 85.1% of family members living with them, and 82.8%, including acquaintances, had not yet been infected.

<Insert Table 3>

Table 4 shows the results of the responses when respondents were asked what actions they took to prevent infection with COVID-19 during the first wave. Washing hands and wearing masks were kept in mind by 90.2% and 93.3% of the respondents, respectively, while 63.6%, 63.1%, and 66.6% kept in mind social distance, going out restriction, and three-closet avoidance, respectively. Only 29.3% were trying to manage their physical condition. Only 3.1% of the respondents did nothing.

<Insert Table 4>

Table 5 contains the results of the responses for regular outings. The questions asked whether the respondents went out regularly in the first wave, such as to work, school, or shopping; if so, how often per week; and the main means of transportation (multiple responses allowed). Regarding the frequency of regular outings, 64.6% of the respondents answered "yes.” In terms of specific frequency type per week, the average was 4 days, indicating that they almost never worked at home, but went to work or school. As for the means of transportation, 52.7% of the respondents indicated that they used their own cars, probably to avoid infection.

<Insert Table 5>

Table 6 lists the percentage reduction in frequency of outings and number of contacts. During the declaration of the state of emergency, the respondents were asked about their wish to reduce the frequency of going out and the number of contacts per outing by what percentage, or about how much they were actually able to reduce the frequency of going out and the number of contacts per outing to prevent the spread of infection. The largest number of respondents (18.1%) actually reduced the number of contacts by about 50%. There were 17.7% and 13% of those who wanted to reduce the number of contacts by 80% and 90%, respectively. The government sought to reduce the number by 80%, but most actually reduced it by about 50%, and few were able to reduce it by more than 80%. The means and standard deviations are listed together, where the realization rate was lower than the desired rate for both the frequency of going out and the reduction in the number of people in contact.

<Insert Table 6>

Table 7 lists the evaluation results for the declaration of the state of emergency. While protecting the health of the general public in measures to prevent the spread of COVID-19, economic activities were restricted through requests to close work and refraining from going out. In other words, a trade-off occurred between health maintenance and economic activities. Therefore, we also asked which should be more important, the health of the general public or economic activities. As a result, 48.9% of the respondents answered that they placed more or less importance on health; only 12.7% of respondents were economically oriented, including somewhat economically oriented. Of the respondents, 72.5% considered the first wave of the declaration of the state of emergency as very necessary or somewhat necessary. Furthermore, 23.3% and 48% responded that the declaration of the state of emergency was very effective and somewhat effective, respectively, in preventing the spread of the disease.

<Insert Table 7>

Table 8 lists the results of the monetary evaluation of the vaccine. Questions were asked regarding vaccines against COVID-19. First, respondents were asked if they would be willing to be vaccinated if a vaccine were developed and available free of charge at the time of the survey. As a result, 73.0% of the respondents answered that they would like to be vaccinated. Next, we asked the respondents how much they would be willing to pay for the vaccine if it were actually available free of charge. In other words, WTP for the vaccine was measured.

Respondents were offered a graduated amount of money and asked to answer whether they would or would not be vaccinated at each amount to determine the maximum amount they would be willing to pay. The results showed that 61.6% of the respondents were willing to pay up to 2,000 yen for the vaccination; the average WTP was over 4,000 yen. The standard deviation was over 7,000 yen, indicating that there is a large variation in WTP.

<Insert Table 8>

3. Bayesian Probability Revision

We gave the respondents data on the infection status and other information about COVID-19 and asked them to calculate the subjective probability of infection, or Bayesian probability. In Bayesian probability, respondents update the prior probability to form the posterior probability. Bayesian probability can be calculated either directly by asking respondents to give a probability such as 10% or by asking them to give a frequency such as 10 out of 100. In Gigerenzer (1996), the event of having breast cancer is H, the event of not having breast cancer is H's complementary-event -H, and the event of a positive test is D. Then, the prior probability p(H) of having breast cancer is 0.01, while the prior probability p(-H) of not having breast cancer is 0.99, the conditional probability p(D|H) of having breast cancer and being positive on the test is 0.8, and the conditional probability p(D|-H) of not having breast cancer but being positive on the test is 0.1. The posterior probability that a person who tests positive actually has breast cancer is then given Bayes' formula:

$$\mathrm{P(H|D)} = \frac{\mathrm{P(D|H)P(H)}}{\mathrm{P(D|H)P(H)+P(D|-H)P(-H)}} = \frac{0.8\times0.01}{0.8\times0.01+0.1\times0.99} = 0.07477\ldots$$

On the other hand, if respondents calculate the probability by frequency, we get that out of 1,000 people, the probability of having breast cancer is 0.1%, that is, 10 people, while the number of people without breast cancer is 990. The probability of a positive test result when breast cancer is present is 80%, that is, 8 people; and when not breast cancer, the probability of a positive test result is 10%, that is, 99 people. The posterior probability that a person with a positive test result actually has breast cancer is $8/(8+99) =$ 0.0747663. Considering the calculation process, the probability type is more complicated and difficult to derive the correct answer, while the frequency type is easier to calculate. As a result, the probability of correct answer is considered higher for the frequency type, which has been confirmed in previous studies.

In the survey of this study, respondents were asked to indicate the probability that a person with a positive PCR test result was actually infected with COVID-19. The sensitivity and specificity were set with reference to previous studies in the medical field (Chan et al. 2020; Kucirka, et al. 2020; Sethuraman et al. 2020). For the probability-type questions, the prior probability was set as 0.1% (1 in 1,000) of the general public being infected in the community based on the first wave of infections in Japan[9]. The conditional probability ("sensitivity") of a positive result when a person infected with COVID-19 is tested by PCR is about 80% (800 in 1,000). Respondents were informed that the conditional probability of a positive result (1-"specificity") is approximately 0.1% (1 in 1,000) for a person not infected with COVID-19 who undergoes a PCR test. After receiving this information, respondents were asked to indicate the probability that they were actually infected with COVID-19 when they received a positive result from a PCR test.

For the frequency-type question, respondents were given the following information as prior probabilities: 10 out of 10,000 members of the general public are currently infected in the community; about 8 out of 10 people who are infected with COVID-19 will test positive if they undergo PCR testing; and about 10 out of 9,990 people who are not infected with COVID-19 will test positive if they undergo PCR testing. When people who are not infected with COVID-19 undergo PCR testing, the number of positive results is about 10 out of 9,990 people.

In this study, the event of being infected with COVID-19 is H, the event of not being infected with COVID-19 is the complementary-event -H, and the event of a positive test result is D. If the prior probability p(H) of being infected with COVID-19 is 0.001 and the prior probability p(-H) of not being infected at the same time is 0.999, the conditional probability p(D|H) of being infected with COVID-19 and being positive on the test is 0.8; and the conditional probability p(D|-H) of not being infected but positive on the test is 0. When the conditional probability of a positive test is 0.001, Bayes' formula gives

$$\mathrm{P(H|D)} = \frac{\mathrm{P(D|H)P(H)}}{\mathrm{P(D|H)P(H)+P(D|-H)P(-H)}} = \frac{0.8\times0.001}{0.8\times0.001+0.001\times0.999} = 0.44469\ldots$$

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[9] The largest number of people requiring hospitalization and treatment (including those on standby) was 12,000 at the peak of the first wave in Japan on May 5. This means that 0.01% of 126 million Japanese population was infected and either receiving treatment or waiting at home. In reality, due to a lack of PCR testing, the community-acquired infection rate is thought to be more than 10 times higher, but details are unknown.

which is the same as the above. On the other hand, the frequency type calculation is 8/ (8+10) = 0.44444 ….

First, we explain the results of the responses to the probability-type questions. Figure 1 shows a histogram of the probability-type responses that were given. The mean is 56% and the median is 75%, indicating that respondents answered a pessimistic probability considerably higher than the correct answer of 44.5%. The histogram shows that the largest number of respondents answered 80%, while a reasonable number of respondents answered lower probabilities, such as 5%. Overall, a pessimistic bias upward from the correct answer is observed.

<Insert Figure 1>

Next, we look at the results of the frequency-type questions. Figure 2 shows the histogram. The mean and median responses are about 43% and 44%, respectively, which is very close to the correct answer of 44.4% as a whole. Frequency-type questions are easier to answer correctly, and this result is consistent with that of Gigerenzer (1996). The histogram shows that, as with the probability-type answers, most of the respondents are in the 80th percentile, while many more are answering in the low 5th percentile. Therefore, the optimism and pessimism biases are likely to cancel each other out, resulting in a value closer to the correct answer on average.

<Insert Figure 2>

In summary, the probability-type questions had a large number of pessimistic respondents who answered higher and a small number of optimistic respondents who answered lower than the correct answer, whereas the frequency-type questions had a nearly equal number of high and low answers.

4. Econometric Model

We employed the ordinal probit model as our basic model, and the Tobit model was used with it to estimate some equations. The ordinal probit model was employed because the responses regarding infection prevention behavior and evaluation of the policy, which are the explained variables, are discrete-valued ordinal data.

Consider the following equation. The explained variable $\boldsymbol{Y_i}$ is represented by an ordinal number. In the ordinal probit model, $\boldsymbol{Y_i}$ corresponds to the continuous latent variable $\boldsymbol{Y_i^*}$.

$\boldsymbol{Y_i}$ is observed, but $\boldsymbol{Y_i^*}$ is not observed.

$$\boldsymbol{Y_i} = j \ \ if \ \ \mu_{j-1} < \boldsymbol{Y_i^*} < \mu_j \ \ j = 0,1,2,\ldots,J \quad (1)$$

The above equation is called the threshold mechanism: the J alternatives divide the real number into J intervals, and their thresholds are $\mu_0 < \mu_1 < \mu_2 < \mu_3 < \cdots < \mu_J$. Their thresholds are defined as

$$\begin{gathered} \boldsymbol{Y_i} = 1, if \ \mu_0 < \boldsymbol{Y_i^*} < \mu_1 \\ \boldsymbol{Y_i} = 2, if \ \mu_1 < \boldsymbol{Y_i^*} < \mu_2 \\ \boldsymbol{Y_i} = 3, if \ \mu_2 < \boldsymbol{Y_i^*} < \mu_3 \\ \cdots \\ \boldsymbol{Y_i} = J, if \ \mu_{J-1} < \boldsymbol{Y_i^*} < \mu_J \ \ (2) \end{gathered}$$

For example, if J=3, the thresholds to be determined are μ_1 and μ_2. The threshold μ_1 is determined as the boundary between $\boldsymbol{Y_i} = 1$ and $\boldsymbol{Y_i} = 2$; and μ_2 is determined as the boundary between $\boldsymbol{Y_i} = 2$ and $\boldsymbol{Y_i} = 3$.

The estimating equation is then given by

$$\boldsymbol{Y_i^*} = \alpha + \beta \boldsymbol{X_i} + \gamma \boldsymbol{Z_i} + \boldsymbol{u_i} \quad (3)$$

where $\boldsymbol{X_i}$ is the Bayesian probability answered by respondents, and $\boldsymbol{Z_i}$ are the other explanatory variables. α, β, and γ denote parameters. If we assume a normal distribution as the probability distribution function of the error term $\boldsymbol{u_i}$, the model is the ordered probit model.

Now, in this study, the following variables were considered for the explained variable $\boldsymbol{Y_i}$:

1) Importance of health and economy: Respondents were asked whether they placed more importance on health in preventing the spread of COVID-19 by suppressing infection even at the expense of economic activities, or vice versa. Specific items were: "5 = I think health should be much more important at the expense of the economy," "4 = I think health should be important at the expense of the economy," "3 = I am neutral about this," "2 = I think the economy should be important at the expense of health," and "1 = I think that the economy should be much more important at the expense of health."

2) Necessity of issuing the declaration of the state of emergency: The respondents were asked to select one of the following: "5 = I think it was very necessary," "4 = I think it was

rather necessary," "3 = I don't know," "2 = I think it was rather unnecessary," or "1 = I think it was very unnecessary."

3) Evaluation of the effectiveness of the declaration of the state of emergency: The respondents were asked to select one of the following: "5 = It was very effective in preventing the spread of infection," "4 = It was somewhat effective in preventing the spread of infection," "3 = It was neither effective nor ineffective," "2 = It was not very effective in preventing the spread of infection," or "1 = It was not effective at all in preventing the spread of infection."

4) Degree of reduction in frequency of going out (desired value): The respondents were asked what percentage they wanted to reduce the frequency of going out as a desired change in behavior under the declaration of the state of emergency and the numbers were assigned as follows: 1 = 0%, 2 = 10%, 3 = 20%, 4 = 30%, 5 = 40%, 6 = 50%, 7 = 60%, 8 = 70%, 9 = 80%, 10 = 90%, 11 = 100%.

5) The number of contacts (desired value): As with the frequency of outings, the respondents were asked about the number of contacts they wished to reduce by what percentage. The numbers were assigned in the same way as for the frequency of outings.

6) Actual reduction in frequency of going out (actual value): The question asked how many percent reduction in frequency of going out was desired, as well as how many percent reduction was actually achieved. The numbers were assigned in the same way as for the desired value.

7) Actual reduction in the number of contacts (actual value): The question asked how many contacts were actually reduced, as well as how many contacts were desired to be reduced. The numbers were assigned in the same way as for the desired value.

8) Monetary evaluation (WTP) for vaccination[10]

One problem that arises here is that correlations are expected among the above explained variables. For example, a correlation could be expected between 2) the evaluation of the necessity of the declaration of the state of emergency and 3) the evaluation of its effectiveness. Similarly, a correlation can be expected between 4) the degree of reduction in the frequency of going out (desired value) and 5) the degree of reduction in the number of people contacted (desired value), or between 6) the degree of reduction in the frequency of going out (actual value) and 7) the degree of reduction in the number of people contacted (actual value).[11]

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[10] Only the monetary valuation of vaccination was used in the Tobit model, which disconnects at zero.

[11] Other possible correlations, such as 4) and 6) as well as 3) and 5), confirm the robustness

Considering the possibility of such correlations, we employed a bivariate ordinal probit model (Butler and Chatterjee 1997). This model is an extension of the SUR model, which is often used as an apparently unrelated regression, to an ordinal probit model.

Consider the correlation between the error terms (Corr $(u_1, u_2) = \rho$) in the two equations. If ρ is significant, then there is a relationship between the two behaviors. The parameters are estimated using the full information maximum likelihood estimation (FIML) method. Since it is practically difficult to estimate the correlations for more than three simultaneous equations, a single estimation is used for the importance of health and economics and the monetary value of vaccination. For the valuation of health and economic importance and monetary evaluation of vaccination, we use independent estimation.

As the explanatory variables, and the following were employed.

1) Bayesian probability: The probability of a correct answer was subtracted from the Bayesian probability of a response. In other words, a response with a correct response probability is represented by 0, an optimistic bias lower than the correct response probability by a negative value, and a pessimistic bias higher than the correct response probability by a positive value. If respondents answer 80%, since the correct probability is 44.5%, the value is 35.5% (80 - 44.5), and if respondents answer 5%, the value is -39.5% (5 - 44.5). The slope of the regression line may change above and below 0, while it is 0 when the probability of a correct response is answered.
2) Physical health: Respondents were asked to indicate their "physical" health during the first wave of the spread of COVID-19. The options were: 1 = very good, 2 = rather good, 3 = neutral, 4 = rather bad, and 5 = very bad.
3) Mental health: Respondents were asked to indicate their "mental" health during the first wave of the spread of COVID-19. The options were: 1 = very good, 2 = rather good, 3 = neutral, 4 = rather bad, and 5 = very bad.
4) Familiarity with infected persons: Respondents were asked whether anyone in their immediate surroundings of possible contact had been infected with, hospitalized with, or died from COVID-19. Respondents who were infected themselves, family members living with them, or acquaintances (work, school, neighbors, close relatives, etc.) were used as dummy variables, with 1 being the respondent who had infected persons.
5) Seven-prefecture dummies: Dummy variables were defined as respondents living in

of the analysis.

the seven prefectures covered by the declaration of the state of emergency issued on April 7, 2020 (Tokyo, Kanagawa, Saitama, Chiba, Osaka, Hyogo, and Fukuoka prefectures). They were set as 1.

6) Gender dummies: A dummy variable was used with females as 1 and males as 0.
7) Age
8) Marriage dummies: A dummy variable was used with married persons as 1 and unmarried persons as 0.
9) Employed dummy: A dummy variable was used with employed persons as 1 and unemployed persons as 0.
10) Number of family members living together
11) College graduate dummies: A dummy variable was used with 1 for college and graduate degrees and 0 for others.
12) Household income (million yen).

Finally, to account for the possibility that estimates of the slope of the Bayesian probability may differ above and below the probability of a correct answer, we also consider a model in which the explanatory variables include a cross term between the Bayesian probability X and a dummy variable D that takes as 1 those who answered below the probability of a correct answer. In this case, the regression equation would be

$$\boldsymbol{Y_i^*} = \alpha + \beta \boldsymbol{X_i} + \gamma \boldsymbol{D_i} + \boldsymbol{\delta X_i} * \boldsymbol{D_i} + \boldsymbol{\varepsilon Z_i} + \boldsymbol{u_i}. \qquad (4)$$

If the coefficient of the cross term $\boldsymbol{\delta}$ is significant when the person who responded with a probability below the correct response probability is 1, it indicates that the coefficient of the slope of the Bayesian probability is different between respondents with probabilities below the correct response probability and those with probabilities above the correct response probability[12]. The results of the analysis of the cross terms are explained in the text and their estimation results are summarized in Appendix.

5. Estimation Results

5.1 Health and Economic Importance

[12] We hereafter assume $\gamma = 0$ in the following estimation, indicating that straight lines can kink, but they don't jump at $\boldsymbol{X_i} = \boldsymbol{0}$.

An ordinal probit model was used for estimation. The estimation results are shown in Table 9. If the coefficients of the explanatory variables are positive, we can say that people tend to value health more than the economy.

Bayesian probability was significant for the probability-type with a positive sign on the coefficient, but not for the frequency type. In the probability type, those who responded with higher Bayesian probabilities were more concerned with health than with the economy.

As for the other explanatory variables, gender dummies, age, number of family members living together, and household income were significant for the probability type. The signs of the coefficients indicate that men, the elderly, those with more family members living together, and those with lower household income were more likely to value health. For the frequency type, familiar infected persons, seven prefecture dummies, age, and household income were significant. The signs of the coefficients indicate that people who had no familiar infected persons, did not live in the seven prefectures, are older, and had lower household income were more likely to value health.

Next, we considered the estimation results of the model with Bayesian probability and a dummy variable with a cross term of 1 for those who responded below the correct answer. Only the Bayesian probability and cross term results were considered at this point. Only for the probability type, the coefficient on the Bayesian probability was positive and significant. On the other hand, the cross term was not significant. The higher the Bayesian probability, the more health-oriented the respondents were. However, the fact that the cross term was not significant indicates that there was no significant difference in the degree of health-orientation between the respondents who answered lower Bayesian probability and those who answered higher. For the frequency type, neither the Bayesian probability nor the cross term was significant (see Table A1).

<Insert Table 9>

5.2 Need to Issue the Declaration and its Effectiveness

Necessity of "issuing" the declaration of the state of emergency and the evaluation for "effectiveness" were considered to be related. They were estimated with a bivariate ordinal probit model that considers the relatedness. The estimation results are shown in Table 10. If the sign of the coefficient of the explanatory variable is positive, it indicates that the higher the Bayesian probability, the more people thought that the emergency declaration was necessary and effective.

First, we consider the estimation results in the need to "issue" the declaration of the state of emergency. The sign of the coefficients is positive and significant for both the probability and frequency types of Bayesian probability. Those who responded with higher probabilities, that is, pessimistic respondents estimated higher probability of infection and believed that it was necessary to declare a state of emergency.

Next, we consider the other explanatory variables. In the probability type, the sign of the coefficient for those with a familiar infected person is positive, the sign of the coefficient for the employed dummy is negative, and the sign of the coefficient for the college graduate dummy is significantly positive. It indicates that those who had an infected person close to them, those who were unemployed, and those who were college graduates believed that it was necessary to declare a state of emergency. On the other hand, for the frequency type, the mental health, age, and college graduate dummies are significant. The signs of the coefficients indicate that those who had poor mental health, older adults, and those who were not college graduates believed that the declaration of the state of emergency was necessary. The results for education were opposite for the probability and frequency types.

The estimation results are then discussed for the evaluation of the effect of the declaration of the state of emergency. The Bayesian probabilities for both probability and frequency types are significant, with positive signs on the coefficients. The higher the Bayesian probability answered, the more likely the respondent believed that the declaration of the state of emergency was effective.

Other explanatory variables are also discussed. In the probability type, physical health, familiar infected persons, gender dummy, age, employed dummy, number of family members living together, and college graduate dummy are significant. The sign of the coefficients indicates that the poorer the physical health, the less the effect was. Since the sign of the coefficient for those infected close to them is positive, the more people who had an infected person close to them, the more they thought the declaration had an effect. Others, such as men, the elderly, those with a large number of family members living with them, college graduates, and the unemployed, indicate that they thought the declaration had an effect. In the frequency type, on the other hand, physical health, infected people close to them, seven-prefecture dummies, gender dummies, age, and income are significant. Except for the seven-prefecture dummies, the results are similar to the probability type. The negative sign of the coefficient for the seven-prefecture dummy indicates that the declaration had no effect for those living in the seven prefectures.

ρ , which represents the correlation between the error terms in the simultaneous equations, is positive and significant. The necessity and effectiveness of issuing the declaration of the state of emergency are positively correlated, indicating that the more people believe that it was necessary, the more effective they believe it was.

In the model with the cross term added, in the probability type, the coefficient of the Bayesian probability is positive and significant for the necessity of issuing the declaration of the state of emergency, while the cross term is not significant. The higher Bayesian probability respondents believed that it was necessary to issue the declaration of the state of emergency, but there is no significant difference in their evaluation compared to those who responded with a probability lower than the correct answer. Neither the Bayesian probability nor the cross term is significant for the evaluation of the effect of declaring a state of emergency (see Table A2).

On the other hand, in the frequency type, the coefficient of the Bayesian probability is positive and significant for the necessity nature of issuing the declaration of the state of emergency, and the coefficient of the cross term is negative and significant. The sum of the coefficients of the Bayesian probability and the coefficient of the cross term is negative, indicating that those who responded with a probability below the correct answer believed that it was not necessary to issue the declaration. While the coefficient of the Bayesian probability is positive and significant for the assessment of the effect of the declaration, the cross term is not significant. Those who responded with higher Bayesian probabilities believed that the declaration was more effective than those who responded with probabilities below the correct answer, but the difference is not significant compared to those who responded with probabilities below the correct answer.

<Insert Table 10>

5.3 Willingness to Reduce Frequency of Outings and Number of Contacts

If the sign of the coefficients of the explanatory variables is positive, it indicates that the higher the Bayesian probability, the more people wanted to reduce the frequency of going out and the number of contacts as desired. The willingness to reduce the frequency of going out and the number of contacts were also estimated in a bivariate ordinal probit model because the two were considered to be related. Table 11 shows the estimation results. For the probability type, the Bayesian probabilities were positive and significant for both going out less and contacting fewer people, but for the frequency type, none of the Bayesian probabilities were significant. This means that for the probability type, the more pessimistic respondents who responded with higher Bayes probabilities were more willing to reduce the frequency of outings and the number of contacts.

Next, we consider other significant explanatory variables. In the probability type, mental health, infected persons close to home, seven-prefecture dummy, gender dummy, and employed person dummy are significant. The signs of the coefficients indicate that the poorer the mental health, having an infected person nearby, living in seven prefectures, male, and unemployed respondents were more willing to reduce the frequency of going out and the number of contacts as a wish. In the frequency type, the mental health, seven-prefecture dummy, gender dummy, and employed dummy are significant. The signs of the coefficients indicate that those with poorer mental health, living in the seven prefectures, male, and unemployed were more willing to reduce the frequency of going out and the number of contacts as a desire. The results are the same as for the probability type, except that the number of people infected close to them was not significant.

Both ρ are positive and significant, indicating that those who wanted to reduce the frequency of outings as a wish also wanted to reduce the number of contacts as well.

In the model with a dummy variable and a Bayesian probability cross term with 1 for those who responded below the correct answer probability, the Bayesian probability was significant for the probability type with a positive sign on the coefficient for both the desired reduction in outing frequency and reduction in the number of contacts. In both cases, the cross terms were not significant. The higher the Bayesian probability, the more respondents wanted to reduce the desired frequency of going out and the number of contacts, but there was no significant difference from those who answered lower probabilities than the correct answer. None of the frequency types were significant (see Table A3).

Prior studies have indicated that willingness to reduce frequency of outings and number of contacts in infection prevention behaviors diverge from the actual behavior (Falcoy and Zaccagniz 2020; Barari et al. 2020; Everett et al. 2020; Wong et al. 2020; Dai et al. 2021). The intention-to-action gaps are analyzed in detail in Section 6.

<Insert Table 11>

5.4 Monetary Evaluation of Vaccination

We measure the impact of Bayesian probability revision on WTP for vaccines. We estimate a single regression equation with WTP as the explained variable, without simultaneous estimation with other behaviors and so on. Table 12 presents the estimation results for the WTP of vaccines. The regression analysis is conducted using the amount of money that respondents responded as the explained variable. Since some people do not want to be vaccinated even if it costs 0 yen, we used a Tobit model that disconnects at 0 yen. The sign of the coefficient of the Bayesian probability is significantly positive and for both the probability and frequency types. Respondents with higher Bayesian probabilities show higher WTP for the vaccine.

The other significant explanatory variables are physical health, college graduation dummy, and household income in the probability type. On the other hand, in the frequency type, they are the seven prefectures dummy, marriage dummy, college graduation dummy, and household income. The coefficient for physical health is negative. The poorer the physical health, the lower the WTP for the vaccine. The coefficients for college graduation dummy and household income are both positive. College graduates and those with higher household income show higher WTP for vaccines. In frequency, the coefficient for the seven-prefecture dummy is negative, so the more people live in the seven prefectures, the lower their WTP for vaccines. The coefficient for the marriage dummy is positive, indicating that married people have a higher WTP for vaccines.

Next, we consider the estimation results of the model with the dummy variable and the Bayesian probability cross term, where the person who responded below the probability of the correct answer is set to 1. In both the probability and frequency models, the sign of the coefficient on the Bayesian probability is positive and significant, but none of the cross terms are significant. We see that those who responded with higher Bayesian probabilities show higher WTP for vaccines but are not significantly different from those who responded below the correct answer (see Table A4).

<Insert Table 12>

6. Discussions and Conclusions

An important objective of this study was to analyze how respondents' Bayesian probability revisions affect their evaluations of policies such as the declaration of the state of emergency, behavior changes such as going out more often or reducing the number of contacts, and vaccination preferences. In doing so, a bivariate ordinal probit model was used for any two possibly correlated behaviors or evaluations.

Table 13 summarizes the estimation results. In both probability and frequency models, those who had a pessimistic bias and responded with a higher Bayesian probability were more health oriented, believing that the declaration of the state of emergency was necessary and effective, and were more thorough in their infection prevention behavior, even at the expense of the economy. Furthermore, they were more willing to take the vaccine if it was free; and even if there was a fee, they valued it highly financially. ρ is positive and significant in the evaluation of the necessity and effectiveness of the emergency declaration using a bivariate ordinal probit model, and in the willingness to reduce the frequency of outings and number of contacts, which was taken up. The two behaviors and evaluations were found to be correlated.

<Insert Table 13>

However, there were significant differences in statistical significance between the probability-type and frequency-type responses for several items. In the probability type, Bayesian probabilities were significant with a positive sign for all items. However, in the frequency type, only the need for the declaration of the state of emergency, evaluation of effectiveness, and WTP for vaccines were statistically significant. Why does this asymmetry exist? There was a pessimistic bias toward responses with higher probability in the probability type. This pessimistic bias may have correlated with the evaluation of infection prevention policies and behavioral restrictions. On the other hand, the frequency type was easier to answer than the probability type, the frequency type was evenly distributed on both the optimistic and pessimistic sides, and the mean was close to the correct answer. It is thought that both those who responded to the low and high Bayesian probabilities were equally likely to have limited their infection-prevention behavior.

In the model that added a dummy variable with 1 below the correct answer and a Bayesian probability cross term, there were many significant items for the Bayesian probability, but no significant items for the cross term. This may be because those who responded with a high Bayesian probability valued health over the economy and thought that there was a need to issue the declaration of the state of emergency and rated it as effective. However, because few responded below the correct answer, the cross term itself was not significant and only the Bayesian probability was significant.

Next, we would like to discuss the discrepancy between the intention and the reality of behavior restrictions for infection prevention. Regarding the reduction of the frequency of outings and the number of contacts, we asked the respondents what percentage of reduction they actually achieved, as well as what percentage of reduction they really wanted to achieve. By asking both the actual reduction and the desired reduction, if there is a difference in the results, we can verify whether there is a gap between the intention and the reality. Japan did not take a strong behavioral restriction called "lockdown," which forcibly restricts people from going out, as in other countries, but took a weak behavioral restriction called "request for self-restraint in going out and contact." Therefore, even if a person wishes to reduce the frequency of going out and the number of contacts, it is up to his/her own will whether he/she actually acts on it or not.

Table 14 shows the results of the estimation of actual frequency of going out and reduction in number of contacts. Again, the two behaviors were considered to be related and were estimated in a bivariate ordinal probit model. First, for the Bayesian probability, neither the probability type nor the frequency type was significant. However, ρ is positive and significant, indicating that those who actually reduced their outings also actually reduced the number of contacts.

For the model that added a dummy variable that takes the number of respondents who answered below the probability of correct as 1 and a Bayesian probability cross term, for the probability type, the Bayesian probability was significant with a positive sign of the coefficient only for the actual reduction in the number of contacts. On the other hand, the cross term was not significant. The higher the Bayesian probability, the more the number of contacts was actually reduced. However, it was not significantly different from those who responded with a probability lower than the correct answer. None of the frequency types were significant (see Table A5).

The results suggest that those who responded with generally high Bayesian probabilities actually wanted to reduce their outings but were unable to do so due to personal or work commitments. For such persons, it is thought that imposing mandatory behavioral restrictions, such as the lockdowns implemented overseas, would curb the gap between intention and reality and improve the welfare of the person in question.[13]

<Insert Table 14>

Considering the above findings, let us also discuss the policy implications. In general, infectious disease control policies are based on a paternalism in which governments and experts decide to restrict citizens' behavior or request self-restraint. In our study, we observed an optimistic bias to respond to lower Bayesian probabilities and a pessimistic bias to respond to higher Bayesian probabilities in the Bayesian probability revision. Should the optimistic and pessimistic biases be corrected from a paternalism perspective? According to our analysis,

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[13] For reference, we also attempted to estimate the bivariate ordinal probit models for reductions in actual and desired outing frequency and number of contacts. First, the correlation coefficient ρ between actual and willingness to reduce frequency of going out is positive and significant for both probability and frequency types. This indicates that those who actually reduced the frequency of going out wanted to reduce the frequency of going out as desired. Next, ρ between actual contact frequency reduction and desired contact frequency reduction is positive and significant. This means that those who actually reduced the number of contacts also wanted to reduce the number of contacts as a wish.

the owners of the optimistic bias are reluctant to change their behavior in infection prevention, while the owners of the pessimistic bias are more willing to change their behavior in infection prevention. Since infection is a kind of negative externality, optimistic bias has a negative social impact and pessimistic bias has a positive social impact.

Here, the reference is *asymmetric paternalism* proposed by Camerer et al. (2003).[14] According to that idea, A regulation is asymmetrically paternalistic if it creates large benefits for those who make errors while imposing little or no harm on those who are fully rational.

It is important to note that there are two types of bias: optimistic and pessimistic. The optimistic bias has a negative social externality in the case of a COVID-19 spread, so it is desirable to correct this bias through information provision and education. On the other hand, the pessimistic bias has a socially positive externality, so there is no need to correct that bias through information provision or education. Thus, asymmetric conclusions can be drawn for biases with different orientations when there is asymmetry in the perception of infection, where it is recommended to correct the bias on the one hand and not necessarily on the other.

Finally, we would like to point out some limitations of this study. First, although this is a case study focusing on Japan, the damage caused by COVID-19 and infection control policies vary across countries. Therefore, it is important to conduct an international comparative study that addresses countries other than Japan. Second, this study only addresses the first wave, and the subsequent second and third waves caused different damage from the spread of infection. As a result, public awareness and behavior are expected to have changed. Follow-up surveys over time are warranted. Third, this study relies on surveys of past attitudes and behaviors, as well as hypothetical surveys of infection. Direct observation of actual behavior and information on vaccination status are needed. These are issues for future research.

[14] Similar concepts to asymmetric paternalism include *libertarian paternalism* proposed by Sunstein and Thaler (2003) and *light paternalism* proposed by Lowenstein and Haisley (2008).

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Table 1: Personal Attributes

Prefecture (%)	Seven prefectures that have issued the emergency declarations	53.8
	All other prefectures	46.2
Gender (%)	Men	50.0
	Women	50.0
Age (years)	Mean value	44.9
	Standard deviation	13.8
Marriage rate (%)	Not married (including separated and bereaved)	50.9
	Married	49.1
Occupation rate (%)	Employed (including part-timers)	69.7
	Student/Unemployed/Other	30.3
Household status (%)	Single-person household	21.4
	Family household	78.6
Educational status (%)	University graduate (including junior college and technical college)	62.1
	Non-university graduate	37.9
Annual household income (10,000 yen)	Mean value	617.8
	Standard deviation	342.9

N=2,000

Table 2: Health Status During the "First Wave"

Q1. How was your physical health during the first wave of COVID-19 outbreak?	%
Very good	20.7
Good	42.4
Neutral	27.6
Bad	7.3
Very bad	2.2
Q2. How was your mental health during the first wave of COVID-19 outbreak?	%
Very good	10.1
Good	28.4
Neutral	37.0
Bad	18.2
Very bad	6.4
Q3. During the emergency declaration "in force" (April 7 - May 25), how concerned were you about the infection?	%
I didn't feel anxious at all.	5.6
I didn't feel anxious.	12.5
I was neutral about the infection.	18.4
I felt anxious.	43.9
I felt very anxious.	19.7

N=2,000

Table 3: Familiarity with Infected, Hospitalized, or Deceased Persons

Q Has anyone in your immediate vicinity that you may have come in contact with, been infected with COVID-19? Additionally, did anyone get hospitalized or die because of it?					
	Not infected.	Infected	Hospitalized	Death	I don't know.
The respondent	91.5	0.1	0.0	0.0	8.4
Family living together	85.1	0.2	0.05	0.0	14.7
Acquaintances (work, school, neighbors, close relatives, etc.)	82.8	4.5	1.4	0.2	12.8

N=2,000

Table 4: Infection Prevention Measures for the First Wave of COVID-19

Q What actions have you taken to prevent infection of the first wave of COVID-19? Please check all that apply.	%
Water (or basin) for washing one's hands	90.2
Wearing a mask (e.g., face mask)	93.3
Social distancing	63.6
Restrictions on going out	63.1
Voluntary infection control	66.6
Physical condition (no smoking, no drinking, etc.)	29.3
I didn't do anything.	3.1

N=2,000

Table 5: Regular Outings, Frequency, and Means of Transportation

Regular outings or not	%
Regular outings Yes	64.6
Regular outings No	35.4
Frequency per week (days)	
Mean value	4.19
Standard deviation	1.75
Means of transportation	%
Train (including subway)	33.1
Buses and Taxis	10.5
Private automobile	52.7
Bicycles and Motorcycles	25.6
Walking	39.6

N=2,000

Table 6: Percentage Reduction in the Frequency of Outings and Number of the Contacts

	Frequency reduction rate of outings		Contact reduction rate	
	Desired rate (%)	Realized rate (%)	Desired rate (%)	Realized rate (%)
0%	8.6	8.9	8.4	10.2
10%	3.8	6.3	2.5	5.0
20%	5.8	11.0	4.5	9.2
30%	8.2	13.3	7.4	11.7
40%	4.1	4.9	3.9	4.8
50%	21.0	18.1	20.8	19.9
60%	4.8	5.2	5.2	5.6
70%	7.6	9.1	7.3	8.6
80%	16.7	12.6	17.7	12.5
90%	10.7	8.2	13.0	9.2
100%	8.9	2.7	9.6	3.6
Mean value	6.6	5.7	6.9	5.9
Standard deviation	3.0	2.9	3.0	2.9

N=2,000

Table 7: Evaluation of the First Wave of Emergency Declarations

Q1. Which do you think should be more important in preventing the spread of COVID-19, the health of the general public or the economy?	%
I think we should focus on health at the expense of economy.	13.7
I think we should focus on health at the expense of economy.	35.2
I am neutral about this.	38.4
I think we should focus on the economy at the expense of health.	9.7
I think we should focus on economy at the expense of health.	3.0
Q2. Do you think it was necessary to issue the first wave of emergency declarations?	**%**
I think it was very necessary.	34.5
I think it was necessary.	38.0
I don't know.	19.5
I think it was unnecessary.	5.4
I think it was very unnecessary.	2.7
Q3. How would you rate the effectiveness of declaring the state of emergency?	**%**
It was very effective in preventing the spread of infection.	23.3
It was somewhat effective in preventing the spread of infection.	48.0
It was neither effective nor ineffective.	19.1
It was not very effective in preventing the spread of infection.	6.2
It was completely ineffective in preventing the spread of infection.	3.5

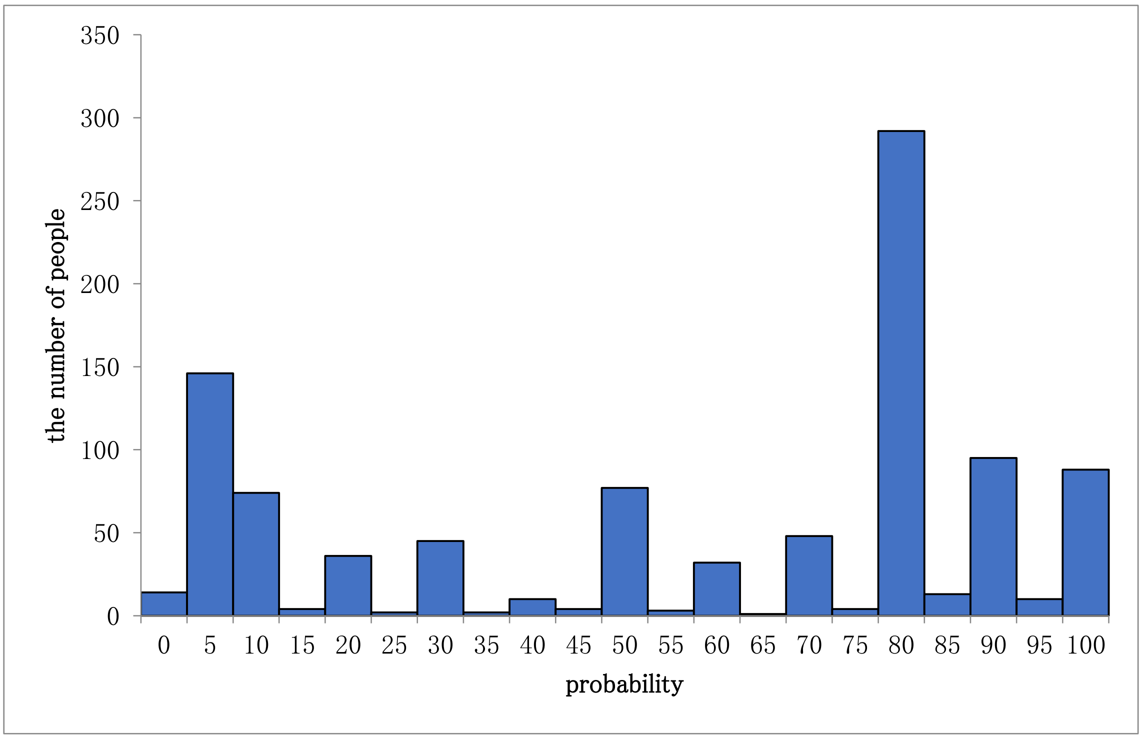
N=2,000

Table 8: Vaccine Monetary Valuation Results

Q If a vaccine were developed and made available free of charge, would you want to be vaccinated?	%	
	I want to be vaccinated.	I don't want to be vaccinated.
	73.0	27.0
Q How much would you be willing to pay out-of-pocket for a vaccine?	%	
Price	I would get vaccinated.	I would not get vaccinated.
0 yen	72.6	27.4
2,000 yen	61.6	38.4
4,000 yen	46.6	53.4
6,000 yen	28.7	71.3
8,000 yen	19.0	79.0
10,000 Yen	13.0	87.0
15,000 yen	5.2	94.8
20,000 yen	3.7	96.3
25,000 yen	2.7	97.3
30,000 yen	2.1	97.9
40,000 yen	1.5	98.5
50,000 yen	1.4	98.6
Mean value	4,349.5 yen	
Standard deviation	7,259.4 yen	

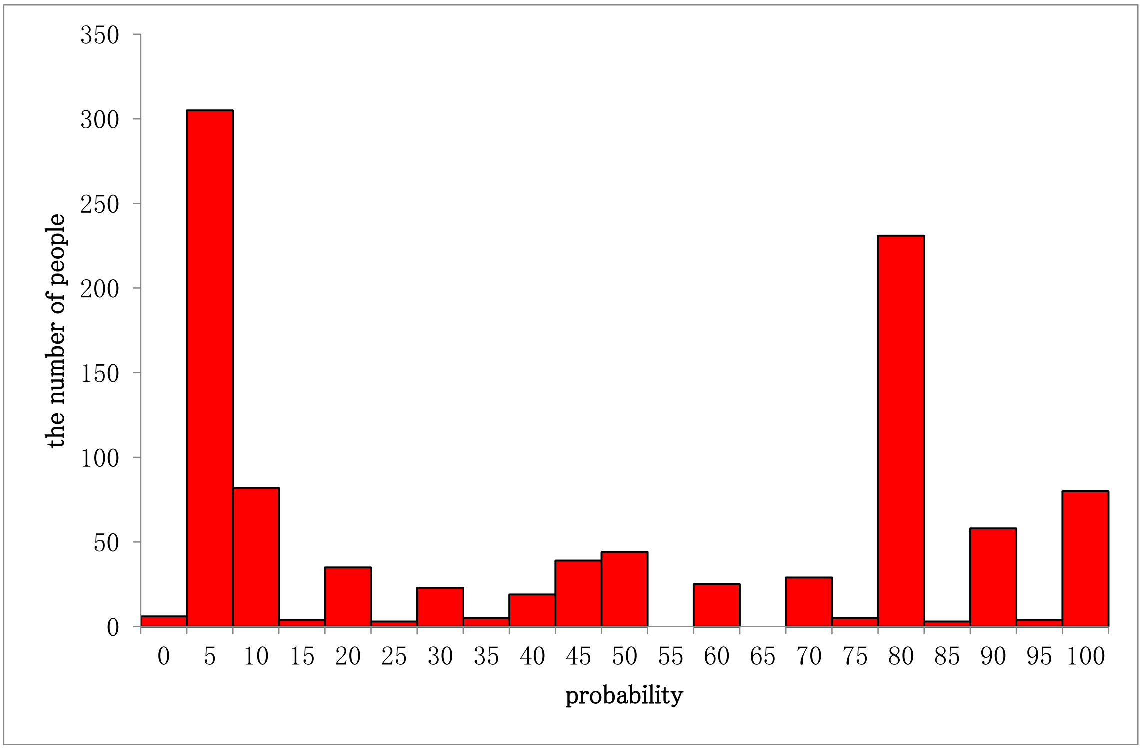
Note: N=2,000

Figure 1: Results of the probability-type responses



Note: Mean 56.168, Median 75, Standard deviation 34.682

Figure 2 Results of the frequency-type responses



Note: Mean 43.562, Median 44.444, Standard deviation 37.778

Table 9: Estimation Results: Health or Economy Focus

	Probability type			Frequency type		
Variable	Coefficient	SE		Coefficient	SE	
Constant term	1.4269	0.2080	***	1.5393	0.2027	***
Bayesian probability	0.0028	0.001	***	0.0004	0.0009	
Physical health	0.0486	0.0432		-0.0035	0.0455	
Mental health	-0.0204	0.0398		0.0205	0.0403	
Familiar infected persons	-0.0745	0.1432		-0.3395	0.1914	*
Seven prefectures dummy	-0.0981	0.0683		-0.1379	0.069	**
Gender dummy	-0.1403	0.0728	*	-0.1138	0.0719	
Age	0.0111	0.0028	***	0.0126	0.0028	***
Marriage dummy	0.0177	0.082		-0.0275	0.0828	
Employed dummy	-0.1253	0.0785		0.0102	0.0768	
Number of family members	0.0705	0.0311	**	0.0134	0.031	
University graduate dummy	0.0898	0.0737		0.0731	0.0725	
Family income	-0.0002	0.0001	**	-0.0002	0.0001	*
Threshold 1	0.8112	0.0459	***	0.7248	0.0486	***
Threshold 2	1.9007	0.0410	***	2.0484	0.0423	***
Threshold 3	2.9871	0.0514	***	3.1355	0.0525	***
McFadden R^2	0.0185			0.0139		
Log-likelihood	-1347.42			-1281.24		

***: 1% level of significance, **: 5% level of significance, *: 10% level of significance

Table 10: Estimation Results: Need to Issue and Effectiveness of Emergency Declarations

	Probability type			Frequency type		
Variable	Coefficient	SE		Coefficient	SE	
(a) Necessity of issuing the declaration of the state of emergency						
Constant term	1.8314	0.2188	***	1.4857	0.2238	***
Bayesian probability	0.0025	0.0010	**	0.0022	0.0010	**
Physical health	-0.0621	0.0441		-0.0606	0.0425	
Mental health	0.0188	0.0400		0.1266	0.0381	***
Familiar infected persons	0.3415	0.1543	**	0.1832	0.2231	
Seven prefectures dummy	-0.0971	0.0723		-0.0898	0.0708	
Gender dummy	-0.0710	0.0760		-0.0591	0.0764	
Age	0.0042	0.0029		0.0082	0.0030	***
Marriage dummy	0.0536	0.0849		-0.0192	0.0868	
Employed dummy	-0.1516	0.0812	*	-0.0373	0.0813	
Number of family members	0.0384	0.0335		0.0135	0.0317	
University graduate dummy	0.1389	0.0773	*	-0.1372	0.0756	*
Family income	0.0000	0.0001		0.0001	0.0001	
Threshold 1	0.5880	0.0785	***	0.5345	0.0795	***
Threshold 2	1.4263	0.0930	***	1.3578	0.0944	***
Threshold 3	2.4042	0.0983	***	2.3895	0.0996	***
(b) Evaluation of the effectiveness of the declaration of the state of emergency						
Constant term	1.8399	0.2246	***	1.7810	0.2125	***
Bayesian probability	0.0030	0.0010	***	0.0033	0.0009	***
Physical health	-0.1294	0.0415	***	-0.0840	0.0436	*
Mental health	-0.0255	0.0390		-0.0119	0.0386	
Familiar infected persons	0.3486	0.1529	**	0.3818	0.1873	**
Seven prefectures dummy	-0.0250	0.0721		-0.1288	0.0704	*

Gender dummy	-0.1746	0.0768	**	-0.1628	0.0771	**
Age	0.0054	0.0029	*	0.0059	0.0031	*
Marriage dummy	0.0980	0.0868		0.1416	0.0871	
Employed dummy	-0.1584	0.0852	*	0.0271	0.0832	
Number of family members	0.0523	0.0309	*	-0.0314	0.0313	
University graduate dummy	0.1642	0.0753	**	-0.0470	0.0762	
Family income	0.0002	0.0001		0.0002	0.0001	**
Threshold 1	0.5027	0.0678	***	0.4926	0.0634	***
Threshold 2	1.2899	0.0866	***	1.2125	0.0785	***
Threshold 3	2.6335	0.0952	***	2.5760	0.0896	***
ρ	0.5712	0.0227	***	0.6322	0.0201	***

***: 1% level of significance, **: 5% level of significance, *: 10% level of significance

Table 11: Estimation Results: Willingness to Reduce Frequency of Going out and number of Contacts

	Probability type			Frequency type		
Variable	Coefficient	SE		Coefficient	SE	
(a) Desire to reduce frequency of outings						
Constant term	1.03343	0.21022	***	1.34653	0.19924	***
Bayesian probability	0.00291	0.00096	***	0.00092	0.00088	
Physical health	0.00037	0.03968		-0.05188	0.04284	
Mental health	0.13594	0.03845	***	0.15511	0.03820	***
Familiar infected persons	0.31704	0.15148	**	0.26119	0.19897	
Seven prefectures dummy	0.15785	0.06817	**	0.11495	0.06632	*
Gender dummy	-0.26980	0.07118	***	-0.28748	0.07062	***
Age	-0.00412	0.00277		-0.00201	0.00271	
Marriage dummy	0.05401	0.08439		-0.02435	0.08214	
Employed dummy	-0.18861	0.07469	**	-0.16672	0.07351	**
Number of family members	0.03511	0.02925		0.02876	0.02990	
University graduate dummy	0.07253	0.07483		0.08544	0.07125	
Family income	0.00013	0.00010		-0.00002	0.00010	
Threshold 1	0.21249	0.03764	***	0.22297	0.03757	***
Threshold 2	0.46263	0.04551	***	0.48908	0.04590	***
Threshold 3	0.71537	0.05124	***	0.80741	0.05289	***
Threshold 4	0.84579	0.05320	***	0.93016	0.05500	***
Threshold 5	1.41729	0.05834	***	1.47809	0.06025	***
Threshold 6	1.53877	0.06011	***	1.60532	0.06250	***
Threshold 7	1.72125	0.06255	***	1.82947	0.06512	***
Threshold 8	2.27376	0.07074	***	2.31745	0.07384	***
Threshold 9	2.71675	0.08102	***	2.87159	0.08150	***
(b) Desire to reduce the number of contacts						
Constant term	0.89310	0.21162	***	1.39764	0.20268	***

Bayesian probability	0.00523	0.00096	***	0.00105	0.00089	
Physical health	-0.01388	0.04008		-0.06580	0.04476	
Mental health	0.11041	0.03791	***	0.13984	0.03942	***
Familiar infected persons	0.32431	0.17079	*	0.23151	0.21520	
Seven prefectures dummy	0.21772	0.06820	***	0.08448	0.06682	
Gender dummy	-0.28363	0.07160	***	-0.32781	0.07123	***
Age	0.00059	0.00284		-0.00087	0.00277	
Marriage dummy	0.12087	0.08473		-0.04082	0.08220	
Employed dummy	-0.22806	0.07459	***	-0.12512	0.07377	*
Number of family members	0.03425	0.02958		0.02937	0.02943	
University graduate dummy	0.13510	0.07453	*	0.11137	0.07194	
Family income	0.00010	0.00011		0.00006	0.00010	
Threshold 1	0.15396	0.03269	***	0.17275	0.03800	***
Threshold 2	0.34716	0.04134	***	0.44387	0.05035	***
Threshold 3	0.59492	0.04893	***	0.77706	0.05773	***
Threshold 4	0.73188	0.05141	***	0.90588	0.06003	***
Threshold 5	1.33361	0.05894	***	1.47711	0.06387	***
Threshold 6	1.46456	0.06023	***	1.61526	0.06506	***
Threshold 7	1.64435	0.06227	***	1.82083	0.06721	***
Threshold 8	2.20573	0.06910	***	2.30834	0.07430	***
Threshold 9	2.76247	0.07924	***	2.83435	0.08278	***
ρ	0.74723	0.01212	***	0.78832	0.01090	***

***: 1% level of significance, **: 5% level of significance, *: 10% level of significance

Table 12: Estimation Results: Monetary Valuation of Vaccination

	Probability type			Frequency type		
Variable	Coefficient	SE		Coefficient	SE	
Bayesian probability	22.5505	10.2175	**	18.6320	8.9026	**
Physical health	-808.6608	447.1545	*	-99.3027	450.7902	
Mental health	565.3929	411.7579		100.9622	398.5159	
Familiar infected persons	-269.4187	1468.3600		2091.0190	1892.7850	
Seven prefectures dummy	217.7167	707.1799		-1585.6620	680.3894	**
Gender dummy	775.9474	755.7790		441.9409	710.1480	
Age	-19.0001	28.5801		2.6678	27.8088	
Marriage dummy	609.5035	848.6996		1640.3220	820.1941	**
Employed dummy	437.0141	819.8568		184.6203	762.5505	
Number of family members	-67.5000	317.7940		-360.6974	308.6277	
University graduate dummy	1628.4400	763.0223	**	1639.4570	715.3422	**
Family income	5.6644	1.0733	***	3.2504	0.9812	***
Constant term	-2641.2160	2139.1180		-1070.5080	2008.3590	
McFadden R^2	0.0047			0.0032		
Log-likelihood	-6867.9030			-6784.0939		

***: 1% level of significance, **: 5% level of significance, *: 10% level of significance

Table 13: Summary of the Estimation Results

(a) Model with no cross term

<table>
<tr><td rowspan="3"></td><td colspan="4">Probability type</td><td colspan="4">Frequency type</td></tr>
<tr><td colspan="2">Bayesian probability</td><td colspan="2">ρ</td><td colspan="2">Bayesian probability</td><td colspan="2">ρ</td></tr>
<tr><td>Sign</td><td>Significance</td><td>Sign</td><td>Significance</td><td>Sign</td><td>Significance</td><td>Sign</td><td>Significance</td></tr>
<tr><td>Health or economy?</td><td>+</td><td>○</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Necessity of the issue</td><td>+</td><td>○</td><td rowspan="2">+</td><td rowspan="2">○</td><td>+</td><td>○</td><td rowspan="2">+</td><td rowspan="2">○</td></tr>
<tr><td>Effectiveness evaluation</td><td>+</td><td>○</td><td>+</td><td>○</td></tr>
<tr><td>Outing reduction request</td><td>+</td><td>○</td><td rowspan="2">+</td><td rowspan="2">○</td><td></td><td></td><td rowspan="2">+</td><td rowspan="2">○</td></tr>
<tr><td>Contact reduction desired</td><td>+</td><td>○</td><td></td><td></td></tr>
<tr><td>WTP for vaccination</td><td>+</td><td>○</td><td></td><td></td><td>+</td><td>○</td><td></td><td></td></tr>
</table>

○: significant

(b) Model with cross terms

<table>
<tr><th rowspan="3"></th><th colspan="6">Probability type</th><th colspan="6">Frequency type</th></tr>
<tr><th colspan="2">Bayesian probability</th><th colspan="2">Cross term</th><th colspan="2">ρ</th><th colspan="2">Bayesian probability</th><th colspan="2">Cross term</th><th colspan="2">ρ</th></tr>
<tr><th>Sign</th><th>Significance</th><th>Sign</th><th>Significance</th><th>Sign</th><th>Significance</th><th>Sign</th><th>Significance</th><th>Sign</th><th>Significance</th><th>Sign</th><th>Significance</th></tr>
<tr><td>Health or economy?</td><td>+</td><td>○</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Necessity of the issue</td><td>+</td><td>○</td><td></td><td></td><td rowspan="2">+</td><td rowspan="2">○</td><td>+</td><td>○</td><td>-</td><td>○</td><td rowspan="2">+</td><td rowspan="2">○</td></tr>
<tr><td>Effectiveness evaluation</td><td></td><td></td><td></td><td></td><td>+</td><td>○</td><td></td><td></td></tr>
<tr><td>Outing reduction request</td><td>+</td><td>○</td><td></td><td></td><td rowspan="2">+</td><td rowspan="2">○</td><td></td><td></td><td></td><td></td><td rowspan="2">+</td><td rowspan="2">○</td></tr>
<tr><td>Contact reduction desired</td><td>+</td><td>○</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>WTP for vaccination</td><td>+</td><td>○</td><td></td><td></td><td></td><td></td><td>+</td><td>○</td><td></td><td></td><td></td><td></td></tr>
</table>

○: significant

Table 14: Actual Reduction in Frequency of Outings and in Number of Contacts

	Probability type			Frequency type		
Variable	Coefficient	SE		Coefficient	SE	
(a) Actual reduction in frequency of outings						
Constant term	1.2180	0.1963	***	1.6319	0.1987	***
Bayesian probability	0.0005	0.0010		0.0006	0.0009	
Physical health	-0.0170	0.0416		-0.0845	0.0449	*
Mental health	0.1355	0.0401	***	0.1161	0.0391	***
Familiar infected persons	0.2807	0.1507	*	0.4587	0.2744	*
Seven prefectures dummy	0.1571	0.0684	**	0.0602	0.0661	
Gender dummy	-0.1898	0.0700	***	-0.3004	0.0718	***
Age	-0.0033	0.0027		-0.0025	0.0027	
Marriage dummy	0.0541	0.0834		-0.0548	0.0842	
Employed dummy	-0.3162	0.0773	***	-0.3205	0.0738	***
Number of family members	0.0048	0.0283		0.0214	0.0302	
University graduate dummy	0.0790	0.0745		0.0462	0.0716	
Family income	0.0001	0.0001		0.0001	0.0001	
Threshold 1	0.3278	0.0423	***	0.3425	0.0418	***
Threshold 2	0.7611	0.0543	***	0.7109	0.0528	***
Threshold 3	1.1389	0.0592	***	1.1075	0.0596	***
Threshold 4	1.2518	0.0609	***	1.2584	0.0613	***
Threshold 5	1.7196	0.0641	***	1.7529	0.0661	***
Threshold 6	1.8550	0.0655	***	1.9108	0.0681	***
Threshold 7	2.1128	0.0686	***	2.2014	0.0713	***
Threshold 8	2.6091	0.0785	***	2.7113	0.0792	***
Threshold 9	3.2772	0.1078	***	3.3939	0.1052	***
(b) Reduction in actual number of contacts						
Constant term	0.9502	0.2039	***	1.5786	0.1992	***

Bayesian probability	0.0015	0.0010		0.0002	0.0009	
Physical health	-0.0410	0.0414		-0.0478	0.0441	
Mental health	0.1364	0.0372	***	0.0495	0.0400	
Familiar infected persons	0.3328	0.1686	**	0.3476	0.2145	
Seven prefectures dummy	0.1859	0.0689	***	0.0767	0.0671	
Gender dummy	-0.1894	0.0714	***	-0.3366	0.0713	***
Age	-0.0013	0.0028		-0.0020	0.0028	
Marriage dummy	0.0735	0.0812		-0.0429	0.0835	
Employed dummy	-0.3232	0.0753	***	-0.2844	0.0721	***
Number of family members	0.0141	0.0285		0.0337	0.0293	
University graduate dummy	0.1423	0.0744	*	0.0913	0.0712	
Family income	0.0001	0.0001		0.0002	0.0001	*
Threshold 1	0.2087	0.0317	***	0.3191	0.0422	***
Threshold 2	0.5635	0.0456	***	0.6631	0.0520	***
Threshold 3	0.8878	0.0516	***	1.0372	0.0577	***
Threshold 4	1.0051	0.0533	***	1.1832	0.0592	***
Threshold 5	1.5180	0.0585	***	1.7109	0.0630	***
Threshold 6	1.6742	0.0604	***	1.8591	0.0648	***
Threshold 7	1.9363	0.0644	***	2.1111	0.0674	***
Threshold 8	2.4469	0.0733	***	2.5551	0.0748	***
Threshold 9	3.0842	0.0961	***	3.2000	0.0930	***
ρ	0.7291	0.0132	***	0.7507	0.0125	***

***: 1% level of significance, **: 5% level of significance, *: 10% level of significance

APPENDIX Estimation results (Model with Cross Terms)

Table A1: Health or Economy Focus (Model with Cross Terms)

	Probability type			Frequency type		
Variable	Coefficient	SE		Coefficient	SE	
Constant term	1.3119	0.2213	***	1.5305	0.2173	
Bayesian probability	0.0065	0.0026	**	0.0007	0.0026	
Cross term	-0.008	0.0052		-0.0006	0.0048	
Physical health	0.0483	0.0432		-0.0036	0.0455	
Mental health	-0.0215	0.0398		0.0206	0.0403	
Familiar infected persons	-0.0699	0.1432		-0.3394	0.1914	*
Seven prefectures dummy	-0.0927	0.0684		-0.1379	0.069	**
Gender dummy	-0.1359	0.0729	*	-0.1137	0.0719	
Age	0.0108	0.0028	***	0.0126	0.0028	***
Marriage dummy	0.0219	0.0821		-0.0273	0.0828	
Employed dummy	-0.1185	0.0787		0.0104	0.0768	
Number of family members	0.0702	0.0311	**	0.0133	0.031	
University graduate dummy	0.0821	0.0739		0.0733	0.0725	
Family income	-0.0002	0.0001	**	-0.0002	0.0001	*
Threshold 1	0.8119	0.0460	***	0.7248	0.0486	***
Threshold 2	1.9020	0.0410	***	2.0486	0.0424	***
Threshold 3	2.9903	0.0515	***	3.1356	0.0525	***
McFadden R^2	0.0193			0.0139		
Log-likelihood	-1346.23			-1281.23		

***: 1% level of significance, **: 5% level of significance, *: 10% level of significance

Table A2 Necessity to Issue and Evaluation of Effectiveness of Emergency Declaration (Model with Cross Terms)

	Probability type			Frequency type		
Variable	Coefficient	SE		Coefficient	SE	
(a) Necessity of issuing a declaration of state of emergency						
Constant term	1.71330	0.23516	***	1.32396	0.23951	***
Bayesian probability	0.00639	0.00257	**	0.00720	0.00263	***
Cross term	-0.00837	0.00523		-0.01005	0.00496	**
Physical health	-0.06274	0.04425		-0.06304	0.04267	
Mental health	0.01705	0.04013		0.12936	0.03844	***
Familiar infected persons	0.34575	0.15528	**	0.17768	0.21711	
Seven prefectures dummy	-0.09128	0.07245		-0.08984	0.07106	
Gender dummy	-0.06635	0.07626		-0.05644	0.07649	
Age	0.00390	0.00286		0.00771	0.00302	**
Marriage dummy	0.05809	0.08507		-0.01717	0.08694	
Employed dummy	-0.14335	0.08126	*	-0.03567	0.08159	
Number of family members	0.03825	0.03348		0.01259	0.03165	
University graduate dummy	0.13102	0.07775	*	-0.13466	0.07576	*
Family income	0.00002	0.00011		0.00012	0.00010	
Threshold 1	0.58787	0.07867	***	0.53533	0.08012	***
Threshold 2	1.42673	0.09295	***	1.36057	0.09534	***
Threshold 3	2.40679	0.09828	***	2.39511	0.10065	***
(b) Assessing the Effectiveness of Declaring a State of Emergency						
Constant term	1.82987	0.23962	***	1.66831	0.23111	***
Bayesian probability	0.00330	0.00256		0.00673	0.00263	**
Cross term	-0.00069	0.00519		-0.00696	0.00502	
Physical health	-0.12949	0.04156	***	-0.08560	0.04365	**

Mental health	-0.02540	0.03910		-0.01022	0.03884	
Familiar infected persons	0.34887	0.15324	**	0.38062	0.18470	**
Seven prefectures dummy	-0.02457	0.07237		-0.12894	0.07060	*
Gender dummy	-0.17422	0.07692	**	-0.16138	0.07731	**
Age	0.00533	0.00289	*	0.00557	0.00309	*
Marriage dummy	0.09841	0.08677		0.14345	0.08739	
Employed dummy	-0.15794	0.08536	*	0.02852	0.08341	
Number of family members	0.05223	0.03096	*	-0.03200	0.03134	
University graduate dummy	0.16350	0.07580	**	-0.04495	0.07662	
Family income	0.00015	0.00010		0.00022	0.00010	**
Threshold 1	0.50297	0.06793	***	0.49302	0.06394	***
Threshold 2	1.29009	0.08685	***	1.21369	0.07908	***
Threshold 3	2.63374	0.09534	***	2.57893	0.09037	***
ρ	0.57185	0.02278	***	0.63108	0.02015	***

***: 1% level of significance, **: 5% level of significance, *: 10% level of significance

Table A3 Desired Reduction in Outing Frequency and in Number of Contacts (Model with Cross Terms)

	Probability type			Frequency type		
Variable	Coefficient	SE		Coefficient	SE	
(a) Desire to reduce frequency of outings						
Constant term	0.97660	0.22241	***	1.33559	0.22270	***
Bayesian probability	0.00473	0.00255	*	0.00124	0.00245	
Cross term	-0.00395	0.00511		-0.00065	0.00463	
Physical health	0.00021	0.03983		-0.05204	0.04298	
Mental health	0.13538	0.03868	***	0.15516	0.03826	***
Familiar infected persons	0.31969	0.15144	**	0.26040	0.19974	
Seven prefectures dummy	0.16081	0.06834	**	0.11505	0.06635	*
Gender dummy	-0.26752	0.07133	***	-0.28747	0.07084	***
Age	-0.00428	0.00278		-0.00203	0.00271	
Marriage dummy	0.05638	0.08436		-0.02403	0.08240	
Employed dummy	-0.18529	0.07523	**	-0.16633	0.07373	**
Number of family members	0.03497	0.02929		0.02875	0.02995	
University graduate dummy	0.06856	0.07517		0.08600	0.07163	
Family income	0.00013	0.00010		0.00010	-0.22000	
Threshold 1	0.21250	0.03767	***	0.22329	0.03763	***
Threshold 2	0.46269	0.04570	***	0.48981	0.04595	***
Threshold 3	0.71546	0.05151	***	0.80852	0.05293	***
Threshold 4	0.84589	0.05345	***	0.93128	0.05503	***
Threshold 5	1.41775	0.05871	***	1.47891	0.06030	***
Threshold 6	1.53934	0.06046	***	1.60588	0.06252	***
Threshold 7	1.72194	0.06295	***	1.82945	0.06519	***
Threshold 8	2.27470	0.07106	***	2.31722	0.07399	***

Threshold 9	2.71781	0.08124	***	2.87154	0.08185	***
(b) Desire to reduce the number of contacts						
Constant term	0.83279	0.22138	***	1.31425	0.22315	***
Bayesian probability	0.00715	0.00247	***	0.00368	0.00245	
Cross term	-0.00419	0.00499		-0.00530	0.00458	
Physical health	-0.01403	0.04019		-0.06703	0.04483	
Mental health	0.10979	0.03810	***	0.14137	0.03954	***
Familiar infected persons	0.32710	0.17178	*	0.23361	0.21746	
Seven prefectures dummy	0.22093	0.06828	***	0.08468	0.06675	
Gender dummy	-0.28116	0.07188	***	-0.32671	0.07129	***
Age	0.00042	0.00286		-0.00117	0.00277	
Marriage dummy	0.12343	0.08466		-0.03947	0.08222	
Employed dummy	-0.22462	0.07502	***	-0.12458	0.07392	*
Number of family members	0.03412	0.02962		0.02880	0.02953	
University graduate dummy	0.13092	0.07557	*	0.11258	0.07229	
Family income	0.00009	0.00011		0.00007	0.00010	
Threshold 1	0.15397	0.03274	***	0.17277	0.03802	***
Threshold 2	0.34722	0.04155	***	0.44438	0.05067	***
Threshold 3	0.59510	0.04943	***	0.77818	0.05828	***
Threshold 4	0.73214	0.05188	***	0.90716	0.06058	***
Threshold 5	1.33427	0.05949	***	1.47874	0.06431	***
Threshold 6	1.46528	0.06070	***	1.61696	0.06551	***
Threshold 7	1.64514	0.06281	***	1.82283	0.06770	***
Threshold 8	2.20659	0.06937	***	2.31096	0.07473	***
Threshold 9	2.76367	0.07974	***	2.83786	0.08368	***
ρ	0.74701	0.01215	***	0.78858	0.01091	***

***: 1% level of significance, **: 5% level of significance, *: 10% level of significance

Table A4: Monetary Valuation of Vaccination (Model with Cross Terms)

	Probability type			Frequency type		
Variable	Coefficient	SE		Coefficient	SE	
Bayesian probability	51.1618	26.7956	*	42.7357	25.3006	*
Cross term	-62.5424	54.1319		-48.6785	47.8263	
Physical health	-811.7358	446.7702	**	-107.6084	450.8178	
Mental health	554.9867	411.5154		114.9018	398.7339	
Familiar infected persons	-229.6242	1467.8230		2104.8130	1891.8400	
Seven prefectures dummy	265.4183	707.9140		-1593.0180	680.3027	**
Gender dummy	797.0216	755.5308		462.3735	710.2816	
Age	-21.4813	28.6362		0.2107	27.9043	
Marriage dummy	637.6731	848.4728		1650.2890	820.1212	**
Employed dummy	500.0757	821.2251		192.0869	762.4226	
Number of family members	-70.2815	317.6175		-364.2332	308.6136	
University graduate dummy	1571.8060	764.0530	**	1654.1960	715.2844	**
Family income	5.5802	1.0751	***	3.2990	0.9822	***
Constant term	-3538.2690	2276.5600		-1879.2480	2161.4320	
McFadden R^2	0.0048			0.0032		
Log-likelihood	-6867.2348			-6783.5751		

***: 1% level of significance, **: 5% level of significance, *: 10% level of significance

Table A5 Actual Outing Frequency Reduction and Actual Number of Contacts Reduction (Model with Cross Terms)

	Probability type			Frequency type		
Variable	Coefficient	SE		Coefficient	SE	
(a) Actual reduction in frequency of outings						
Constant term	1.19043	0.20746	***	1.73271	0.22087	***
Bayesian probability	0.00137	0.00250		-0.00248	0.00237	
Cross term	-0.00192	0.00504		0.00611	0.00451	
Physical health	-0.01720	0.04180		-0.08307	0.04488	*
Mental health	0.13538	0.04023	***	0.11466	0.03915	***
Familiar infected persons	0.28138	0.15059	*	0.45866	0.26645	*
Seven prefectures dummy	0.15852	0.06849	**	0.06024	0.06621	
Gender dummy	-0.18882	0.07006	***	-0.30234	0.07200	***
Age	-0.00337	0.00271		-0.00213	0.00272	
Marriage dummy	0.05510	0.08347		-0.05666	0.08409	
Employed dummy	-0.31451	0.07756	***	-0.32207	0.07373	***
Number of family members	0.00464	0.02834		0.02195	0.03023	
University graduate dummy	0.07712	0.07497		0.04477	0.07212	
Family income	0.00011	0.00011		0.00009	0.00011	
Threshold 1	0.32786	0.04242	***	0.34329	0.04189	***
Threshold 2	0.76157	0.05439	***	0.71256	0.05297	***
Threshold 3	1.13950	0.05927	***	1.11015	0.05972	***
Threshold 4	1.25229	0.06095	***	1.26126	0.06148	***
Threshold 5	1.71992	0.06412	***	1.75536	0.06620	***
Threshold 6	1.85535	0.06558	***	1.91291	0.06828	***
Threshold 7	2.11309	0.06876	***	2.20298	0.07148	***
Threshold 8	2.60940	0.07877	***	2.71274	0.07957	***

Threshold 9	3.27734	0.10830	***	3.39635	0.10581	***
(b) Actual reduction in number of contacts						
Constant term	0.85856	0.21531	***	1.57335	0.21933	***
Bayesian probability	0.00436	0.00246	*	0.00037	0.00246	
Cross term	-0.00630	0.00500		-0.00042	0.00463	
Physical health	-0.04127	0.04168		-0.04804	0.04411	
Mental health	0.13564	0.03734	***	0.04959	0.04007	
Familiar infected persons	0.33642	0.16868	**	0.34856	0.21444	
Seven prefectures dummy	0.19041	0.06902	***	0.07678	0.06712	
Gender dummy	-0.18541	0.07149	***	-0.33592	0.07153	***
Age	-0.00158	0.00279		-0.00205	0.00279	
Marriage dummy	0.07744	0.08119		-0.04273	0.08349	
Employed dummy	-0.31826	0.07553	***	-0.28461	0.07212	***
Number of family members	0.01396	0.02844		0.03358	0.02935	
University graduate dummy	0.13632	0.07486	*	0.09092	0.07181	
Family income	0.00012	0.00011		0.00019	0.00010	*
Threshold 1	0.20879	0.03190	***	0.31894	0.04222	***
Threshold 2	0.56314	0.04577	***	0.66310	0.05207	***
Threshold 3	0.88761	0.05173	***	1.03697	0.05778	***
Threshold 4	1.00508	0.05343	***	1.18302	0.05925	***
Threshold 5	1.51859	0.05865	***	1.71097	0.06304	***
Threshold 6	1.67475	0.06064	***	1.85922	0.06488	***
Threshold 7	1.93732	0.06463	***	2.11154	0.06748	***
Threshold 8	2.44909	0.07373	***	2.55572	0.07489	***
Threshold 9	3.08708	0.09653	***	3.20091	0.09322	***
ρ	0.72923	0.01316	***	0.75153	0.01252	***

***: 1% level of significance, **: 5% level of significance, *: 10% level of significance