Kyoto University,
Graduate School of Economics
Discussion Paper Series

Subjective Risk Valuation and Behavioral Change:

Evidence from COVID-19 in the U.K. and Japan

Masayuki Sato, Shin Kinoshita, Takanori Ida

Discussion Paper No. E-22-011

Graduate School of Economics
Kyoto University
Yoshida-Hommachi, Sakyo-ku
Kyoto City, 606-8501, Japan

January, 2023

Subjective Risk Valuation and Behavioral Change: Evidence from COVID-19 in the U.K. and Japan

Masayuki Sato[†], Shin Kinoshita[*] and Takanori Ida[**]

Abstract: This study analyzed people's behavioral changes in the early stages of COVID-19 expansion in relation to subjective probability, and clarified the effect of risk perception on behavioral changes, such as outbound restriction. We conducted a social survey using an Internet survey in the U.K. and Japan in the fall of 2020 and found that the percentage of those who evaluated risk optimistically was higher in the U.K. than in Japan. In addition, we applied seemingly unrelated regression (SUR) for the bivariate ordinal probit model to the association between desired and actual infection prevention behavior and found that a pessimistic bias is likely to lead to behavioral change, whereas an optimistic one is not. These results suggest that when pessimistic bias is strong, measures that respect people's rights, such as freedom of action, while leaving people to be autonomous, can be effective to some extent. In contrast, when optimistic bias is strong, the use of a certain degree of coercive force may be unavoidable from the standpoint of public interest.

Keywords: COVID-19, Bayesian Inference, Subjective probability, Seemingly Unrelated Regression

---

[†] Corresponding author, Graduate School of Human Development and Environment, Kobe University
Postal address: 3-11 Tsurukabuto, Nada-ku, Kobe 6578501, Japan
E-mail address: msat@port.kobe-u.ac.jp
[*] Department of Economics, Ryukoku University
Postal address: 67 Fukakusa Tsukamoto cho, Fushimi-ku, Kyoto 6128577, Japan
E-mail address: skinoshita@econ.ryukoku.ac.jp
[**] Graduate School of Economics, Kyoto University
Postal address: Yoshida Honmachi, Sakyo-ku, Kyoto 6068501, Japan
E-mail address: ida@econ.kyoto-u.ac.jp

1. Introduction

This research analyzes people's behavioral changes in the early spring 2020 expansion of COVID-19 in relation to their subjective probabilities, using the United Kingdom (U.K.) and Japan as target cases. COVID-19, which has been spreading since the end of 2019, has caused widespread damage in Europe since February 2020 and has significantly impacted people's lives. Although the spread of the disease was relatively slow in the U.K. compared to other European countries, it rapidly became severe in March, and as a result, the country was one of the hardest-hit in the world. In March 2020 in the U.K., in response to the Imperial College London report, the policy of gradual adaptation was changed to strict measures to prevent the spread of infection, including the closure of public schools. On March 23, a lockdown accompanied by a curfew was implemented amid divided public opinion on the measure. Financial assistance and other guarantees were also implemented simultaneously, but their impact on people's lives was enormous. The originally scheduled lockdown period was extended due to insufficient improvement of the infection and was finally relaxed on May 10 after less than two months. The situation of the infection damage at that time is shown in Figure 1. Considering July 1 as the date when the lockdown was relaxed, a cumulative total of 243,910 cases were reported during this period, peaking at 4,797 on April 22. The British government estimated the number of cases based on antibody tests and other data to be 17% in London and approximately 5% in other areas of the country.[1] As of May 21, the number of confirmed cases amounted to 0.4% of the population.

Figure 1: Number of COVID-19 cases in the U.K. and Japan

Contrastingly, Japan suffered relatively little initial damage, so much so that an unidentified factor "Factor X" was verified, indicating cross-immunity unique to the Japanese and a high BCG intake rate[2]. Since April 7, 2020, a state of emergency was declared in seven prefectures in metropolitan areas, including Tokyo, where the spread of infection was serious. Curfew restrictions were imposed in these areas, although voluntary and without legal enforcement or penalties.

In both the U.K. and Japan, the serious outbreak forced people to change their behavior to prevent COVID-19 infection. However, people's perceptions of these social demands varied. Needless to say, people's attitudes toward such behavioral changes are determined by their social circumstances, but this study examined how people perceive the unknown risk of COVID-19

[1] https://metro.co.uk/2020/05/21/17-londoners-5-rest-uk-have-coronavirus-antibodies-12739901/
[2] https://asia.nikkei.com/Business/Science/Yamanaka-on-COVID-19/Uncovering-Japan-s-coronavirus-X-factor-matters-to-the-world

from the perspective of subjective risk assessment. This study contrasted the U.K. and Japan, which have different infection prevention policies, in terms of the subjective risk assessment of how people evaluate the previously unexperienced risk of COVID-19. Although infection is still ongoing, progress has been made in vaccine development and other measures, and a certain level of effectiveness is beginning to be observed. In this context, analysis of the occurrence of and response to the risk of COVID-19 in the early stages of the spread of infection will serve as an important accumulation of empirical knowledge for future reference.

In this study, we empirically analyzed the influence of subjective probability on behavioral changes. First, the existence of a cognitive bias in the subjective probability assessment of COVID-19 risk is noteworthy. Polymerase chain reaction (PCR) tests were performed to determine the presence or absence of infection, but the probability of infection risk can be determined by *false negatives* (negative results in the presence of infection) or *false positives* (positive results in the absence of infection). Advanced numerical processing and cognitive skills are required to correctly determine infection risk in consideration of the probability of false negative and false positive results. However, many people are unable to perform such precise calculations and are likely to ignore the prior probability (base rate) of how much of the total population is actually infected, which is the basis for calculating the risk of infection.[3]

Here is an example. Let us consider a case of a woman who has a prior probability of 1% for breast cancer, a sensitivity of 80% for those with cancer who received a positive test result, and a specificity of 90% for those without cancer who did not receive a positive test result. At this point, using *Bayes Theorem*, when the test is positive, the probability that the person has cancer is 8%. However, the percentage of correct responses to this question is less than 5%, with many people ignoring the base rate and providing answers that are either too high or too low (Eddy 1982). More recent studies have shown that base rate neglect is widely observed among laypeople and professionals alike, such as physicians (Gigerenzer and Hoffrage 1995; Hoffrage et al. 2000; Hertwig and Hoffrage 2002). In other words, base rate neglect is not simply a cognitive bias stemming from a lack of knowledge or miscalculation; a variety of factors can be considered determinants of subjective probability.

Additionally, according to Bundorf et al. (2021) and Hamano et al. (2020), the cognitive bias of infection risk has a systematic influence on infection prevention behavior. In other words, the analysis of the factors that shape subjective probabilities has implications for the practice of infection-prevention behavior. However, it is currently unclear whether there is an expected relationship between cognitive optimistic/pessimistic biases and infection prevention behavior. Therefore, a quantitative understanding of the relationship between cognitive bias and infection

[3] This neglect of base rates was noted by Meehl and Rosen (1955) in clinical psychology, Kahneman and Tversky (1981) in social psychology, and others. See Grether (1980) for details.

prevention behavior is needed. It has also been noted that infection-prevention intentions do not always lead to actual action (Barari et al. 2020; Everett et al. 2020; Falco and Zaccagniz 2020; Wong et al. 2020; Dai et al. 2021).[4] Like essential workers who cannot close their offices during an infection outbreak, even if they want to adopt infection prevention actions, they may not always be able to take ideal infection-prevention measures, such as restricting the number of days they can be away from home. Therefore, it is necessary to quantitatively understand the *intention-to-action gap*.

Nevertheless, measures to promote social distancing, which reduce the frequency of outings and the extent of social contact, have been studied. Experimental studies discussing the types of information provision that promote social distancing have found loss aversion and social comparison to be effective nudges.[5] It has also been shown that people's sociodemographic variables influence their countermeasure behavior (Qian et al. 2020).

In light of previous studies, it is important to accumulate evidence for the effective implementation of infection-spread prevention by simultaneously considering factors that shape subjective probability and influence behavior. Particularly, an analysis of how people perceive infection risk and take action to prevent infection during the lockdowns and declared states of emergency will have significant implications for future infection-prevention policies.

This study compared the U.K. and Japan, which have two different perceptions of COVID-19. The U.K. implemented a lockdown, requiring strict behavioral changes with penalties for going out and contact with others. Contrastingly, Japan took the measure of declaring a state of emergency and requested voluntary restraint in going out and coming in contact with others, a measure without penalties or legal enforceability. As a result, some restaurants and stores remained open without complying with the request for shorter hours or closure, and individuals were still free to go out, meet family members other than those living with them, and travel to other prefectures freely. This differs from other countries, such as the U.K., which implemented so-called lockdowns, such as bans on stores and curfews on individuals, and imposed fines on those who violated them. We analyzed how the difference in the policies between the two countries led to various behavioral changes.

A probability type was employed for the questions about the risk evaluation of infection. For 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,

---

[4] Some studies have reported that information provision is effective in changing behavior, at least in the short term, and accumulation of evidence is necessary (Krpan et al. 2020, Moriwaki et al. 2020, Sasaki et al., 2022).

[5] For references on social distance, see Barari et al. (2020), Everett et al. (2020), Falco and Zaccagni (2020), Heffner et al. (2021), Jordan et al. (2020), Lunn et al. (2020), Luttrell and Petty (2021), Moriwaki et al. (2020), Sasaki et al. (2021), and Utych and Fowler (2020).

often used as an apparently unrelated regression, to the ordinal probit model. The model analyzes how the subjective probability of responding affects the necessity and effectiveness of lockdowns and emergency declarations, as well as infection prevention behaviors, such as going out more often and reducing the extent of social contact. At the same time, the model considers the relationship between two behaviors that are expected to be correlated, for example, the need for a lockdown and the evaluation of its effectiveness.

The results of this study confirmed the following: First, in lockdowns and emergency declarations, those with an optimistic bias were more likely to place greater emphasis on economic activity. Second, in the U.K., those with a pessimistic bias rated the necessity and effectiveness of the lockdown lower than those with an optimistic bias. Nonetheless, in the first wave, those with a pessimistic bias rated the necessity and effectiveness of lockdowns higher than those with an optimistic bias in Japan, because the damage caused by infection was less severe than in other countries. Third, we confirmed that perceived infection risk, such as pessimistic and optimistic bias, was related to behavioral changes such as reducing the frequency of outings and the number of contacts. Fourth, a discrepancy between intention and action was observed among Japanese with a pessimistic bias, who were able to reduce the number of contacts even though they had the intention to do so. These results suggest the paternalistic policy can be effective in the case of preventing the spread of Covid-19 infection. Additionally, the findings of this paper indicate that the degree of enforceability of regulations to prevent the spread of infection might depend on the risk attitude of the public.

The remainder of this paper is organized as follows. Section 2 describes the survey. Section 3 reviews the distribution of subjective probabilities, and Section 4 explains the econometric analysis methods. Section 5 presents the estimation results regarding which individuals form which subjective probabilities. Section 6 discusses the results of the analysis and concludes the paper.

2. Survey and data

This study focused on the factors that shape subjective probabilities of the risk of infection with COVID-19 and their impact on people’s behavior in the U.K. and Japan. The U.K. has suffered significant infection damage when compared internationally and has implemented severe lockdown measures, with both legal enforcement and penalties. Contrastingly, Japan faced lesser damage by international comparison, and even during the declaration of a state of emergency, behavioral restrictions were limited to requests from the national and local governments, with no legal enforceability or penalties. Instead, measures were taken to appeal to the autonomous behavioral restraint of the public. We analyzed the acceptability and evaluation of infection control measures based on data on the risk perception and behavioral patterns of people in the U.K. and Japan, which differ in terms of damage and countermeasures.

This study independently conducted social surveys in the U.K. and Japan. For the U.K., we conducted a social survey using an internet-based survey throughout the U.K. from November 25 to December 3, 2020 and collected 1,135 responses. The sample size for each country was determined based on the population composition of England, Scotland, Wales, and Northern Ireland. For England, the number of samples collected for each region was determined based on the population proportions of the nine regions that constitute England. Furthermore, the number of samples collected for each region was equally divided into five age groups and collected at a male-to-female ratio of 1:1. For the U.K. data, the overall sample was equally allocated to the five age groups, and an equal sex ratio was maintained.

In Japan, an Internet survey was conducted from November 19 to 25, 2020, targeting households in Japan, and 1,000 responses were collected. As in the U.K., the overall collection sample was equally allocated to the five age groups from age 20 – over-60s, with an equal number of men and women. They were sampled in proportion to the population distribution of the 47 prefectures in Japan, considering the regional distribution of the population.

To comparatively analyze risk perception and countermeasure behaviors in both countries, we asked questions about socio-demographic characteristics, health status, and other conditions under the spread of COVID-19 infection, risk perception, control behaviors, and policy evaluation. In this study, the data on the following items will be used, particularly for the analysis.

(1) Physical condition at lockdown/declaration of emergency was measured on a 5-point scale as follows: 1 = very bad, 2 = somewhat bad, 3 = neutral, 4 = somewhat good, and 5 = very good.
(2) Mental status at lockdown/declaration of emergency was measured on a 5-point scale as follows: 1 = very bad, 2 = somewhat bad, 3 = neutral, 4 = somewhat good, and 5 = very good.
(3) Sociodemographic characteristics of respondents (place of residence, gender, age, marital status, number of family members living together, educational background, and employment status): Place of residence was a dummy variable with London/Tokyo = 1 and other = 0. The gender dummy variables were male = 0 and female = 1. Marital status dummy variable: 1 for married and 0 for unmarried. Education dummy variable 1 = graduate degree, 2 = undergraduate degree, 3 = associate degree or vocational school, 4 = technical school, 5 = college/sixth form, 6 = secondary school, and 7 = other.
(4) Infection status of respondents and their surroundings: Respondents answered that they, their family members, and their next of kin had infections that did not require

hospitalization, had infections that required hospitalization, died, or were not infected.

(5) Subjective probability assessment of infection risk: Answers to the infection risk assuming sensitivity and specificity (explained in detail in Section 3).

(6) Evaluation of COVID-19 countermeasures and actions (balance with economic measures, necessity and effectiveness of lockdown and emergency declaration, desired and actual reduction of outings, and desired and actual reduction of contacts): To balance economic measures, respondents were asked to choose between the risk of COVID-19 infection and economic activities on a 5-level scale. The higher the value, the greater the importance of COVID-19 control measures. The respondents were asked to rate the necessity and effectiveness of lockdowns and emergency declarations on a 5-point scale, with higher scores indicating greater importance placed on these measures. Respondents answered on an 11-point scale from 0–10% regarding going out and reducing the number of people in contact with the public, respectively.

This section outlines the status of the data. Figure 2 summarizes the physical condition of the respondents during the lockdown/emergency declaration. Most respondents in both countries were in good condition, as indicated by the fact that most respondents in both countries answered "Generally good" or better; 81.9% of respondents in the U.K. answered that their condition was good, whereas only 61.5% of respondents in Japan answered so. In addition, 6.9% of the respondents in the U.K. answered that their physical condition was either "Generally bad" or "Very bad," whereas a larger number (10.2%) of the respondents in Japan reported that their physical condition was not good. Interestingly, the percentage of people reporting poor physical condition was higher in the U.K. than in Japan, even though the infection was more severe in the U.K. than in Japan. These differences in perceptions of physical condition may affect the evaluation of infection countermeasures and will be analyzed in Section 3.

Figure 2: Physical condition during lockdown

Figure 3 shows the mental status of both countries. Since curbs on leaving the house under lockdown/declaration of a state of emergency directly lead to stress in people, there is a concern that their mental condition may deteriorate, and not only their physical health but also their mental health status may affect their risk perception. The figure suggests that a larger proportion of people in both countries report being unwell with regard to their mental state than their physical state and that there are more unwell people in Japan than in the U.K. The percentage of those who answered "Very good" or "Generally good" was 68.5% in the U.K. and 36.6% in Japan, indicating that mental health was worse than physical health in both countries. In addition, 15.5% in the U.K.

and 26.1% in Japan answered "Very bad" or "Generally bad," indicating that more people complained of mental health problems than physical health problems. The higher rate of ill health in Japan than in the U.K. is similar to that of physical health. This suggests that the Japanese people live under stress due to autonomous compliance, such as wearing masks and washing hands thoroughly, which may also be a result of the greater efforts made by the Japanese people to prevent infection.

Figure 3: Mental state during lockdown

Figure 4 shows the actual experience of COVID-19 infection by the respondents or their close relatives. Consistent with the actual number of infected persons, more respondents in the U.K. had close relatives who were infected, with 6.2% of the U.K. respondents having been infected without requiring hospitalization, and 3.2% of the U.K. respondents having observed COVID-19 requiring hospitalization. In contrast, 0% of Japanese respondents were infected. In the U.K., 14.2% of family members were infected without hospitalization, 5.1% required hospitalization, and 4% died. In Japan, however, there were no cases of infection among family members. If we extend the sample to acquaintances, we find that the situation in the U.K. is worse, with 30.5% of infections not requiring hospitalization, 8.5% requiring hospitalization, and 7.6% being cases of deaths reported. In contrast, in Japan, where there were fewer infections in the early years, the rates were much lower than in the U.K., with 5.7% of infections not requiring hospitalization, 1.8% requiring hospitalization, and only 0.3% of deaths. We introduce this factor in the subsequent econometric model as this infection experience is thought to influence the evaluation of infection control measures and changes in people's behavior. Figure 4 clearly shows that the infection status is worse in the U.K. than in Japan, but the physical and mental health status is reported to be worse in Japan than in the U.K. These differences are likely because people in both countries are more likely to be infected than those in the UK. We will analyze how these differences affect the evaluation of infection risk measures and behavioral change of people in both countries in the next section.

Figure 4: COVID-19 infection status of the respondents

Regarding the distribution of opinions on COVID-19 countermeasures in Japan and the U.K., this survey asked respondents whether they would place more importance on COVID-19 countermeasures or economic countermeasures during the spread of COVID-19. The results are shown in Figure 5. The result shows that only a small number of respondents in both Japan and the U.K. thought that the economy should take priority. In the U.K. (65.9 %) and Japan (50.4 %), respondents supported proceeding with COVID-19 countermeasures even if the economy was affected, indicating overall support for the implementation of COVID-19 countermeasures. In Japan, a higher proportion of respondents hesitated between COVID-19 infection and the economy, whereas support for COVID-19 measures appeared to be stronger in the U.K. This may be due to a worsening infection.

Figure 5: Balance between the Economy and COVID-19 control in the U.K. and Japan

Respondents were then asked about the necessity and effectiveness of such measures to control infections, such as a lockdown in the U.K. and the state of emergency in Japan. Figure 6 shows that more than 80% of the respondents in the U.K. agreed that a lockdown was necessary, and more than 70% of the respondents in Japan agreed that declaring a state of emergency was necessary, indicating that the U.K. had more support for hardline measures. This may be due to differences in the magnitude of damage. However, the effectiveness of the measures is approximately 70% in both countries, with more than 10% of respondents in the U.K. rating them as ineffective, indicating that the effectiveness of the measures is relatively low compared to their necessity. This is an indication of dissatisfaction with the implementation, and it can be inferred that some people consider the actual behavior restrictions during the lockdown to be inadequate.

Figure 6: Evaluation of Lockdown (UK) and Declaration of Emergency (Japan)

Figure 7 shows the desired and actual reductions in the number of outings in the U.K. and Japan as a change in people's behavior under the lockdown/emergency declaration. In terms of the reduction in going out, the U.K. shows a considerably higher awareness of the need to reduce the number of outings than Japan, as indicated by the fact that a higher percentage (90% or 100%) of respondents in the UK want to reduce their outings and have actually reduced them. In contrast, in Japan, a large percentage of respondents answered that their actual reduction rate was between 0–50%. This indicates that the desire to reduce going out is not manifested in the actual behavior in Japan. This difference may be due to the difference in the restrictive power of the emergency declaration in Japan compared to the U.K.

Figure 7: Desired and actual reduction of outings

A similar trend was observed for the number of contacts (Figure 8). In the U.K., the lockdown resulted in stricter reductions in the number of contacts than in the number of outings. The number of contacts was reduced by 90% or 100%, a high percentage that people desired and achieved. However, in Japan, desired and actual reductions are low. In Japan, most respondents reduced the number of contacts by approximately 50%.

Figure 8: Desired and actual reduction in the number of contacts with persons

In the following sections, we will analyze how people's subjective risk assessment influences their evaluation and behavioral change toward lockdown and emergency declaration, as observed in Figures 6, 7, and 8, paying attention to the differences between Japan and the U.K.

3. Subjective probability of infection risk

As one of the main survey items, we measured the subjective probability of COVID-19 infection for respondents in the U.K. and Japan. The resulting subjective probabilities are shown in Figure 9. The subjective probabilities in Figure 9 represent the extent to which the respondents correctly estimated the risk of infection based on Bayesian inference. In this survey, we made the following assumptions: i) the risk of community-acquired infection is 0.1%; ii) the probability that a person with COVID-19 infection will correctly test positive when tested by PCR (sensitivity) is 80%; and iii) the probability that a person without infection will correctly test negative (specificity) is 99.9%[6]. We then asked respondents to answer the following questions.

One person has taken a PCR test and tested positive. What do you think is the probability that the person who tested positive is actually infected with COVID-19?

Many studies have used this question format, including Gigerenzer (1996), who used breast cancer risk as an example. In this study, the standard question format was followed and the probability of infection was calculated as follows: Event *H* was PCR-positive, complementary-event-*H* was PCR-negative, Event *D* was infected, and complementary-event-*D* was non-infected.

$$P(D|H) = \frac{P(D) * P(H|D)}{P(D) * P(H|D) + P(-D) * P(H|-D)}$$

$$= \frac{0.001 \times 0.8}{0.001 \times 0.8 + 0.999 \times 0.001} \doteqdot 0.445$$

[6] 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).

As with this inference, a reasonable Bayesian estimate should be 44.5%; however, past studies have shown that people do not always estimate correctly when actually surveyed. This study focuses on whether there is a structural trend in such estimation errors between the U.K. and Japan. Figure 9 shows that the subjective probability responses are biased downward in the U.K. and upward in Japan. The mean value was 31.3% for the U.K. and 56.2% for Japan. The skewness, which indicates the distributional asymmetry, is 0.73 in the U.K., skewed to the left, whereas it is -0.49 in Japan, skewed to the right. These differences in the distribution of responses indicate an optimistic tendency to underestimate the risk of COVID-19 in the U.K., whereas there is a pessimistic tendency to overestimate the risk in Japan.

Figure 9: Subjective Probability Response Distributions for the U.K. and Japan

In Japan, the government did not implement as severe a lockdown as that in the U.K. in the form of an emergency declaration, but most of the population voluntarily curbed outdoor activities. They also actively wore masks and washed their hands, and both the number of infected people and the infection rate were among the lowest in the world during the first wave in the spring of 2020. In contrast, the U.K. was one of the countries that suffered a major blow in the early stages of the COVID-19 outbreak. It is noteworthy that there were differences in the public's assessment of the risk of infection between these two countries. In the next section, we quantitatively analyze how each nation's citizens' subjective probability and socioeconomic attributes affect their assessment of countermeasures and behavioral change.

4. Estimation model

In this section, we conduct an econometric analysis using data from the U.K. and Japan to analyze how differences in the evaluation of subjective probability led to behavioral change. Since the data on evaluations and behavioral change are ordinal, we employ an ordinal probit model (1) in which the error term ε is assumed to follow a normal distribution. We use the following equation:

$$y_i^* = const + \beta_{SP}SP + \beta_{Pess}SP * Pess + \beta_1 X_1 + \cdots + \beta_{11} X_{11} + \varepsilon \quad (1)$$

where y_i^* is a latent continuous variable corresponding to response data y_i to measure evaluation and behavioral change. The ordinal probit includes and estimates a threshold.

$$y_i = j \leftrightarrow \mu_{j-1} < y_i^* < \mu_j$$

The explained variables to be analyzed are as follows.

a) Focus on the economy or COVID-19 control

b) Evaluation of necessity and effectiveness of lockdown/state of emergency

c) Behavioral changes during lockdown/state of emergency

c1) Desired and actual reduction of outings

c2) Desired and actual reduction in the extent of interpersonal contact

Equation (1) introduces subjective probability (SP) as an explanatory variable. Furthermore, to analyze the effect of pessimistic/optimistic bias, a pessimistic bias dummy, $Pess$, is introduced in the econometric model, and a cross term is taken with SP as a variable that takes 1 only when the subjective probability is estimated to be higher than 44.5%. This allows us to analyze the refraction of the regression line at y_1 = 44.5%, where β_{SP} is the coefficient of subjectivity probability at values lower than 44.5% (the slope when we have an optimistic bias), and $(\beta_{SP}+\beta_{Pess})$ is the coefficient of subjective probability at values higher than 44.5% (the slope when we have a pessimistic bias).

In Tables 1–4, the coefficient of SP (β_{sp}) and the cross term (β_{pess}) are listed, with the former indicating the effect of the probability perception of those with optimistic bias and the latter $(\beta_{SP}+\beta_{Pess})$ indicating the effect of the probability perception of those with pessimistic bias. Table 5 contains a summary of the estimation results from Tables 1–4 for optimistic and pessimistic biases. As for the significance of the sum of the coefficients, the Wald test can be applied for H_0: $(\beta_{SP}+\beta_{Pess})$ = 0 to verify the significance level (Hensher et al., 2015).

The other explanatory variables to be examined were: X_1 -the place of residence (London / Tokyo dummy), X_2 -physical health at the first lockdown, X_3 -mental health at the first lockdown, X_4 -gender (female = 1), X_5 -age, X_6 -marital status (married = 1), X_7 -family size, X_8 -the presence of children (with children = 1), X_9 -education, X_{10} -employment status (earning = 1), and X_{11} -infection experience (own and acquaintances, yes = 1).

For the evaluation items considered to be strongly related, such as the need for and effectiveness of lockdowns and emergency declarations, as well as the desired and actual reduction in the number of outings and contacts, a seemingly unrelated regression (SUR) was applied to account for their associations. In both regression equations, a bivariate ordinal probit model was employed because the explained variables were ordinal (Butler and Chatterjee, 1997). Here, we consider the correlation $Cor(u_1, u_2) = \rho$ between the error terms of 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 (FIML) estimation method, which is used for two related explained variables, such as COVID-19 control and economic importance.

5. Estimation results

5.1 Economy vs infection control

This section analyzes the correlation between the evaluation of the balance between economic measures and COVID-19 countermeasures, and the perception of infection risk. The implementation of COVID-19 control measures in any country is accompanied by significant negative economic impact. In the U.K., the implementation of the lockdown was met with considerable public consternation and shocks. In particular, the closure of schools, pubs, and restaurants was a definite constraint on daily life in the U.K., and both advantages and disadvantages were raised. In Japan, the timing of the resumption of economic activity was debated, while the public autonomously tried to prevent the spread of infection. Here, we analyzed how subjective perceptions of infection risk contributed to the formation of opinions on COVID-19 control measures.

Table 1: Infection control vs economy

The results in Table 1 show that in both the U.K. and Japan, there is a significant positive effect of the subjective probability of infection as a determinant of the distribution of importance of COVID-19 countermeasures, that is, those who estimate a higher risk of infection place more importance on COVID-19 countermeasures. In the U.K., furthermore, the cross term is statistically significant, and the magnitude of the coefficient, namely the slope of the regression line, changes with the positive response of 44.5% as the boundary point.

In Table 5, the coefficients of the subjective probability of infection and the chi-square value (χ^2) from the Wald test are listed for each of the optimistic bias ($-\beta_{SP}$) and pessimistic bias ($\beta_{SP}+\beta_{Pess}$). For both optimistic and pessimistic biases, their coefficients are measured by the difference from 44.5%, which is the correct response to Bayesian inference. In the UK, the coefficient for optimistic bias is -0.017, whereas the coefficient for pessimistic bias is 0.005. The greater the optimistic bias, the more statistically significant (χ^2 = 23.47, 1% significant) the emphasis on the economy is. However, a greater pessimistic bias is statistically and significantly associated with a greater emphasis on COVID-19 measures (χ^2= 20.93, 1% significant).

In Japan, the coefficient for optimistic bias is -0.008, whereas the coefficient for pessimistic bias is 0.003. On the one hand, a larger optimistic bias is associated with a statistically significant greater emphasis on the economy (χ^2 = 2.92, 10% significant). Contrastingly, a greater pessimistic bias is statistically and significantly associated with a greater emphasis on COVID-19 measures (χ^2 = 9.56, 1% significant)[7].

Comparing the correlation between the subjective probability of infection and the importance of COVID-19 measures in Japan and the U.K., the two countries share the same tendency to place more emphasis on the economy when the tendency toward an optimistic bias increases, and more emphasis on COVID-19 when the tendency toward a pessimistic bias increases. The absolute magnitudes of the coefficients are larger in the U.K. than in Japan for both pessimistic and optimistic biases. In the U.K., where the infection was most severely affected, there may be evidence of a wide divergence of opinion between economic and COVID-19 countermeasures, between optimistic bias, which accounts for the majority, and pessimistic bias, which accounts for only a small minority.

Regarding the influence of other variables, it was observed with statistical significance that in the U.K., the elderly and those who had experienced infection placed greater importance on COVID-19, while in Japan, women, the elderly, and those with larger family sizes placed greater importance on COVID-19 control, while those who were employed placed greater importance on the economy (Table 1).

5.2 Evaluation of lockdown/state of emergency

In this subsection, we analyzed the correlation between the evaluation of lockdown and the perception of infection risk. As public reactions to the necessity and effectiveness of lockdowns and emergency declarations varied in both the UK and Japan, we conducted a bivariate SUR probit model analysis with variables, including the subjective probability of infection as a factor defining the distribution of these opinions (Table 2). The necessity and effectiveness of the lockdown/emergency declaration were set up as simultaneous equations, and the correlation of the error terms is reported as ρ. Both are estimated to be significant, indicating that the assessments of necessity and effectiveness are linked.

Table 2: Evaluation of lockdown/state of emergency

Necessity of lockdown/state of emergency

Table 5 shows that in the U.K., the coefficient for optimistic bias is 0.007, whereas the coefficient for pessimistic bias is -0.006. A larger optimistic bias statistically and significantly

[7] In Japan, despite the small absolute value of the coefficient for pessimistic bias, the high level of statistical significance can be attributed to the large sample size of those with a pessimistic bias, which in turn led to smaller standard errors and higher power.

increases the need for lockdown ($\chi^2 = 3.34$, 10% significance). However, a greater pessimistic bias statistically and significantly reduces the need for lockdown ($\chi^2 = 29.32$, 1% significant).

In Japan, the coefficient for optimistic bias is -0.002, whereas the coefficient for pessimism bias is 0.003. A larger optimistic bias does not statistically or significantly reduce the need for declaring a state of emergency ($\chi^2 = 0.22$, non-significant). Nonetheless, a greater pessimistic bias statistically and significantly increases the need for declaring a state of emergency ($\chi^2 = 5.69$, 5% significant).

Comparing the correlation between subjective probability of infection and the need for lockdown/declaration of emergency in Japan and the U.K., the impact of optimistic and pessimistic biases on the need for lockdown oppose each other. The reasons are difficult to interpret. Significant infection damage had occurred in the U.K. despite the implementation of a strict lockdown. Optimistic bias holders may reflect that the skeptical lockdown was still necessary, whereas holders of the pessimistic bias may be dissatisfied that the lockdown did not help much. Contrarily, in Japan, despite the lax emergency declaration, only a small amount of damage was caused by the infection. The optimistic bias holder may feel that the infection damage could have been prevented even without the emergency declaration, whereas the pessimistic bias holder may feel that stronger measures than the emergency declaration were necessary. In any case, more detailed investigation will be needed to elucidate the reasons.

Regarding the effects of other variables, in the UK, the older the respondents and those who had experienced an infection, the lower their evaluation for the need of a lockdown (Table 2). Contrastingly, in Japan, the more educated and employed individuals were less likely to prefer the declaring a state of emergency and were more likely to avoid declaring a state of emergency. In Japan, however, those who had experienced infection also rated the necessity of declaring a state of emergency higher.

Effectiveness of lockdown/state of emergency

In both the U.K. and Japan, the estimation results of the effectiveness valuation of the actual COVID-19 measures were similar to those of the necessity valuation. Table 5 shows that in the UK, the coefficient for optimistic bias is 0.007, whereas the coefficient for pessimistic bias is -0.004. When the optimistic bias increases, the effectiveness of the lockdown is statistically and significantly higher ($\chi^2 = 4.56$, 5% significant). However, a greater pessimistic bias statistically and significantly reduces the effectiveness of lockdown ($\chi^2 = 14.65$, 1% significant).

In Japan, the coefficient for optimistic bias is -0.001, whereas the coefficient for pessimistic bias is 0.003. A larger optimistic bias does not statistically or significantly reduce the effectiveness of emergency declarations (χ^2=0.11, non-significant). However, a larger pessimistic bias statistically and significantly increases the effectiveness of emergency declarations ($\chi^2 = 7.00$, 1% significant).

As with the case of necessity, a comparison of the correlation between the subjective probability of infection and the effectiveness of lockdown/emergency declaration in Japan and the U.K. shows the opposite effects of optimistic and pessimistic biases on effectiveness. The difference in signs in the U.K. and Japan, as in the case for the need for countermeasures, may be due to the formation of complex infection risk perceptions with reference to the damage results.

Regarding the influence of other variables, in both countries, the elderly tend to rate the effectiveness of lockdown more highly. In addition, in the U.K., those who felt mentally unwell rated the effectiveness of lockdown more highly, while the elderly and those with large family sizes did not rate it as effective. In Japan, however, those who felt physically unwell rated the effectiveness of lockdown less highly, while the elderly, women, and those who experienced infection rated the effectiveness more highly. In Japan, the more educated and employed people were less likely to rate the effectiveness of the lockdown, which is similar to the result of the analysis on necessity.

5.3 Behavioral changes

5.3.1 Desired and actual reduction of outings during lockdown/state of emergency

In this subsection, we analyzed the subjective probability of infection and the reduction in outing opportunities. The results of the analysis are summarized in Table 3. The upper table in Table 3 lists how the subjective probability of infection affected the desired reduction efforts with respect to the outing reductions required during lockdown. Table 3 below lists how the subjective probability of infection affected the actual reduction in outings.

Table 3: Reduction of outings

Desired reduction

Table 5 shows that in the UK, the coefficient for optimistic bias is -0.003, whereas the coefficient for pessimistic bias is 0.002. A larger optimistic bias does not statistically or significantly reduce the desired level of furlough reduction ($\chi^2 = 0.68$, non-significant). However, a greater pessimistic bias does statistically and significantly increase the desired level of furlough reduction ($\chi^2 = 7.02$, 1% significant).

In Japan, the coefficient for optimistic bias is 0.002, while the coefficient for pessimistic bias is 0.003. A larger optimistic bias does not lead to a statistically significant increase in the desired level of furlough reduction ($\chi^2 = 0.22$, non-significant). Nevertheless, a greater pessimistic bias does increase the desired level of furlough reduction in a statistically significant way ($\chi^2 = 5.85$, 5% significant).

A comparison of the correlation between the subjective probability of infection and the desired level of furlough reduction shows that in both the U.K. and Japan, the subjective probability of infection affects the desired furlough reduction only for those with a pessimistic bias. However, those with an optimistic bias do not affect the desired reduction in outings.

Regarding the influence of other variables, it is observed that the state of mental health is linked to behavioral change in reducing outings in both the U.K. and Japan. In both cases, the worse the state of mental health is, the more it is linked to the goal and practice of curtailing outings. In addition, the experience of infection has a common influence in both countries in the direction of trying to reduce the number of outings. Women are more willing to cut down on the number of days out than men, which is also common in both countries. In addition, factors with different significance were observed in the U.K. and Japan. In the U.K., the older a person is, the higher their intention to reduce going out is. In Japan, however, the desire to reduce going out is significantly lower among the more educated and the more employed. In the Tokyo area, there was a strong tendency for the respondents to cut down on leaving the house.

Actual reduction

Table 5 shows that in the U.K., the coefficient for optimistic bias is -0.001, whereas the coefficient for pessimistic bias is 0.002. A larger optimistic bias does not lead to a statistically significant decrease in the actual level of furlough reduction ($\chi^2 = 0.00$, non-significant). Nonetheless, a larger pessimistic bias statistically and significantly increases the desired level of furlough reduction ($\chi^2 = 6.55$, 5% significant).

In Japan, however, the coefficient for optimistic bias is -0.003, whereas the coefficient for pessimistic bias is 0.001. A larger optimistic bias does not lead to a statistically significant increase in the actual level of outing reduction ($\chi^2 = 0.37$, non-significant). Furthermore a larger pessimistic bias does not lead to a statistically significant increase in the actual level of furlough reduction (χ^2=0.54, non-significant).

Comparing the correlation between the subjective probability of infection and the actual level of furlough reduction in Japan and the U.K., no significance was found for the actual level of furlough reduction in Japan, even among those with a pessimistic bias. In other words, a discrepancy between intention and action was observed among those with a pessimistic bias in Japan, who had the intention to change their behavior but failed to do so. This can be interpreted as the fact that these people were fully aware of the importance of curtailing their outings, but were reluctant to take real actions under the state of emergency declaration because there were no penalties for going out freely and citizens were left free to make their own choices. In this respect, the lockdown in the U.K. was considered to have led people to take actual action to reduce curfews because there were penalties for going out. As for the other factors, the same trend was observed as in the case of the desire to reduce outings.

5.3.2 Desired and actual reduction of the number of contracts

In this subsection, we analyzed the subjective probability of infection and reduction in the number of contacts. The results of the analysis are summarized in Table 4. The upper part of Table 4 shows how the subjective probability of infection affected the targeted reduction efforts with respect to the number of contacts determined at the time of lockdown. The lower part of Table 4 shows how the subjective probability of infection affected the actual reduction in the number of contacts.

Table 4: Reduction of the number of contracts

Desired reduction

Table 5 shows that in the U.K., the coefficient for the optimistic bias is -0.001, whereas the coefficient for the pessimistic bias is 0.003. A larger optimistic bias does not lead to a statistically significant decrease in the number of desired contacts (χ^2=0.02, non-significant). However, a larger pessimistic bias does increase the number of desired contacts in a statistically and significantly(χ^2=7.44, 1% significant).

In Japan, the coefficient for the optimistic bias is 0.001, whereas the coefficient for the pessimistic bias is 0.005. A larger optimistic bias does not lead to a statistically significant increase in the number of desired contacts ($\chi^2 = 0.05$, non-significant). Nonetheless, a larger pessimistic bias does increase the number of desired contacts in a statistically and significantly ($\chi^2 = 21.77$, 1% significance).

Comparing the correlation between the subjective probability of infection and the desired number of contacts in Japan and the U.K., those with an optimistic bias are not as committed to reducing the number of contacts as in the case of reduced outings in both cases. However, those with a pessimistic bias are more committed to reducing the number of contacts, as in the case of the reduction in outings.

The following points can be found regarding the factors that influence the desired reduction in the number of contacts (Table 4). The common factor is that people with poorer mental health and women are more willing to reduce the number of contacts, which is the same result as in the case of the desire to reduce the number of outings. Differently, age had a significant effect in the U.K., while education and employment had a significantly negative effect in Japan, and experience of infection had a positive effect. London as an area of economic activity was found to have no significant effect, whereas in Tokyo, the desire for contact reduction was significantly stronger.

Actual reduction

Table 5 shows that in the UK, the coefficient for optimistic bias is 0.000, whereas the coefficient for pessimistic bias is 0.003. A larger optimistic bias does not lead to a statistically significant decrease in the actual number of contacts ($\chi^2 = 0.02$, non-significant). Nonetheless, a larger pessimistic bias does increase the actual number of contacts in statistically and significantly ($\chi^2 = 7.02$, 1% significant).

In Japan, the coefficient for optimistic bias is -0.002, whereas the coefficient for pessimistic bias is 0.002. A larger optimistic bias does not lead to a statistically significant increase in the actual number of contacts ($\chi^2 = 0.22$, non-significant). Also, a larger pessimistic bias does not lead to a statistically significant increase in the actual number of contacts ($\chi^2 = 2.70$, non-significant).

Comparing the correlation between the subjective probability of infection and the desired number of contacts in Japan and the U.K., those with an optimistic bias were not able to achieve a reduction in the number of contacts in both Japan and the U.K., as was the case for the reduction in outings. However, those with a pessimistic bias were able to reduce the number of contacts in the U.K., but not in Japan, as in the case of the furlough reduction. We observed a discrepancy between intention and action among the Japanese pessimistic bias holders, who had the intention to change their behavior but failed to do so. For the other variables, the results are similar to the desired reduction in the number of contacts (Table 4).

6. Political implications and conclusions

The effects of subjective probability on countermeasure evaluation and behavioral change can be summarized as shown in Table 5. The subjective probability of infection affects the intention to change behavior only among those with a pessimistic bias in both Japan and the U.K., and the intention leads to actual behavior change only in the U.K. One possible reason for this is that in the U.K., the lockdown strictly restricted people from going out, so that their willingness to participate in going out was directly related to their actual behavior, whereas in Japan, the state of emergency was declared and people were left to cooperate on their own initiative, which may have caused a discrepancy between their willingness and their actual behavior.

Table 5: Summary of Subjective Probability and Infection Prevention Behaviors

Let us here introduce a previous international comparison of infection risk. De Zwart et al. (2009), using the SARS pandemic as a case study, showed that the perceived likelihood of becoming infected was higher in Asia than in Europe.. However, they also reported that the perceived likelihood of dying from SARS was higher in Europe than in Asia. Taking COVID-19 as a case study, Dryhurst et al. (2020) compared risk perceptions, including severity, internationally and noted that the risk of COVID-19 was rated higher in the United Kingdom in March-April 2020. Thus, there is not always a consensus among previous studies on risk perception including infection risk and severity. Further accumulation of evidence is needed.

Therefore, in this paper, we analyzed the subjective probability of COVID-19 infection using Bayes' theorem and showed that the risk of infection is perceived as higher in Japan than in the U.K. Furthermore, we analyzed the correlation between the subjective probability of infection and policy evaluation and preventive behavior in the U.K. and Japan. The results of this study also showed that the correlation between subjective probability of infection and behavior change in infection prevention differed between those with a pessimistic bias and those with an optimistic bias.

The main conclusions of this paper can be summarized as follows. First, in lockdowns and emergency declarations, those with an optimistic bias are more likely to emphasize economic activity. This tendency is more pronounced in the U.K. than in Japan.

Second, in the U.K., those with a pessimistic bias rated the necessity and effectiveness of lockdown lower than those with an optimistic bias. However, in the first wave, those with a pessimistic bias rated the necessity and effectiveness of lockdowns higher than those with an optimistic bias in Japan, because the damage caused by infection was less severe than in other countries.

Third, perceived infection risk, such as pessimistic bias and optimistic bias, were related to behavioral changes such as reducing the frequency of going out and the number of contacts. In both the U.K. and Japan, those with a pessimistic bias were more willing to reduce the frequency of going out and the number of contacts. Nonetheless, those with an optimistic bias were not clearly willing to go out and reduce the number of contacts in both Japan and the U.K.

Fourth, a discrepancy between intention and action was observed among Japanese with a pessimistic bias, who had the intention to reduce and followed through with it. In previous studies, it has been pointed out that the higher the risk perception, the greater the preventive actions taken (Floyd et al. 2000). Such risk perception is defined by risk responses, such as risk communication (Fishoff 1995, Brewer et al. 2004). Therefore, Dryhurst et al. (2020) argued that it is important to promote accurate risk perception among citizens through risk communication.

Interestingly, the bias perspective focused on in this study raises the possibility of effectively using differences in risk perception attitudes, such as optimistic and pessimistic biases, to achieve the social goal of infection prevention. In general, infectious disease control adopts a paternalism in which governments and experts determine the behavioral limits of citizens. However, according to the results of the analysis in this study, people with an optimistic bias are reluctant to change their behavior in infection prevention, while those with a pessimistic bias are proactive in changing their behavior in infection prevention. From the perspective of preventing the spread of infection, the optimistic bias is considered to have a negative external effect on society, whereas the pessimistic bias is considered to have a positive external effect on society.

On this point, Camerer et al. (2003) proposed asymmetric paternalism[6]. According to their 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. From the perspective of preventing the spread of COVID-19, the optimistic bias has a negative social externality and should be corrected preferentially through risk communication. However, the pessimistic bias has a socially positive externality; thus, it should not be corrected.

This study revealed that a large number of people in the United Kingdom were observed to have an optimistic bias. The lockdown implemented in the U.K. may have been effective in preventing the spread of infection by forcing behavior change even among those with an optimistic bias. Nonetheless, a large number of people with a pessimistic bias were observed in Japan. The non-legally binding declaration of a state of emergency implemented in Japan may have been effective in preventing the spread of infection through voluntary behavioral change among the Japanese, given the pessimistic bias often observed among them.

Thus, this study shows that the degree of enforceability of regulations to prevent the spread of infection may depend on the risk attitude of the public. In conclusion, in a society with a strong optimistic bias, the use of coercive force to some extent is unavoidable from a public interest perspective. However, in societies with a strong pessimistic bias, policies that respect voluntary behavior change without necessarily using coercive force may be effective.

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

References

[1] Barari, S., S. Caria, , A. Davola, , P. Falco, , T. Fetzer, , S. Fiorin, L. Hensel, A. Ivchenko, J. Jachimowicz, G. King (2020) "Evaluating Covid-19 Public Health Messaging in Italy: Self-reported Compliance and Growing Mental Health Concerns," *MedRxiv*, 2020.

[2] Brewer, N.T., N.C. Weinstein, C.L. Cuite, J.E. Herrington, (2004) "Risk perceptions and their relation to risk behavior". *Annals of Behavioral Medicine*, 27(2), 125-30.

[3] Bundorf, M.K., J. DeMatteis, G. Miller, M. J. Polyakova, L. Streeter, J. Wivagg (2021) "Risk Perceptions and Protective Behaviors: Evidence from Covid-19 Pandemic," *NBER Working Paper* 28741.

[4] Butler, J.S. and P. Chatterjee (1997) "Test of the Specification of Univariate and Bivariate Ordered Probit," *Review of Economics and Statistics*, 79(2), 343-347

[5] Camerer, C., S. Issacharoff, G. Loewenstein, T. O'Donoghue and M. Rabin (2003) "Regulation for Conservatives: Behavioral Economics and the Case for 'Asymmetric Paternalism,'" *University of Pennsylvania Law Review*, 151 (3), 1211-1254.

[6] Dai, H., S. Saccardo, M.A. Han, L. Roh, N. Raja, S. Vangala, H. Modi, S. Pandya, D.M. Croymans (2021) "Behavioral Nudges Increase COVID-19 Vaccinations: Two Randomized Controlled Trials," medRxiv, 14.

[7] De Zwart O., I.K. Veldhuijzen, G. Elam, A.R. Aro, T. Abraham, G.D. Bishop, H.A.C.M Voeten, , J.H. Richardus, J. Brug, (2009) "Perceived threat, risk perception, and efficacy beliefs related to SARS and other (emerging) infectious diseases: results of an international survey", *International Journal of Behavioral Medicine*, 16(1), 30-40.

[8] Dryhurst, S., C.R. Schneider, J. Kerr, , A.L.J. Freeman, G. Recchia, A.M. Van der Bles, D. Spiegelhalter, S. Van der Linden, (2020) "Risk perceptions of COVID-19 around the world", *Journal of Risk Research*, 23:7-8, 994-1006

[9] Eddy, D.M. (1982) "Probabilistic reasoning in clinical medicine: problems and opportunities." In D. Kahneman, P. Slovic, & A. Tversky (Eds.), *Judgment under uncertainty: Heuristics and biases*. Cambridge, UK: Cambridge University Press.

[10] Everett, J., , C. Colombatto, V. Chituc, W. J. Brady, and M. Crockett. (2020) "The Effectiveness of Moral Messages on Public Health Behavioral Intentions During the COVID-19 Pandemic." *PsyArXiv*. March 20.

[11] Falco, P. and S. Zaccagni (2020) "Promoting social distancing in a pandemic: Beyond the good intentions", *OSF Preprints*, 8 May 2020. Web.

[12] Fischoff, B. (1995) "Risk Perception and communication unplugged: Twenty years of process", *Risk Analysis*, 15, 137-145.

[13] Floyd, D. L., S. Prentice-dunn, R.W. Rogers (2000) "A Meta-Analysis of Research on

Protection Motivation Theory", *Journal of Applied Social Psychology*, 30(2), pp. 407-429.

[14] Gigerenzer, G. and U. Hoffrage (1995) "How to Improve Bayesian Reasoning Without Instruction: Frequency Formats," *Psychological Review*, l02 (4), 684-704.

[15] Grether, D. M. (1980) "Bayes Rule as a Descriptive Model: The Representativeness Heuristic," *Quarterly Journal of Economics*, 95 (3), 537-557.

[16] Hamano, M., M. Katayama, and S. Kubota (2020) "COVID-19 Misperception and Macroeconomy", *WINPEC Working Paper Series* No. E 2016, November 2020

[17] Heffner, J. M.L. Vives and O. FeldmanHall (2021), "Emotional responses to prosocial messages increase willingness to self-isolate during the COVID-19 pandemic", *Personality and Individual Differences*, 170.

[18] Hensher, D. A., J. M. Rose, and W. H. Green, (2015) *Applied Choice Analysis*, Cambridge University Press.

[19] Hertwig, R. and U. Hoffrage (2002) "Technology needs psychology: How natural frequencies foster insight in medical and legal experts," Frequency processing and cognition, Chapter 18, 285-302.

[20] Hoffrage, U., R. Hertwig, and G. Gigerenzer (2000) "Hindsight Bias: A By-Product of Knowledge Updating?" *Journal of experimental psychology*, 26 (3), 566-581.

[21] Jordan, J., E. Yoeli, and D. Rand (2021) "Don't Get It or Don't Spread It? Comparing Self-interested versus Prosocially Framed Covid-19 Prevention Messaging," *Scientific Reports*, 20222 .

[22] Kahneman, D. and A. Tversky (1981) "The Framing of Decisions and the Rationality of Choice," Science, 211, pp.453-458.

[23] Krpan, D., F. Makki, N. Saleh, S.I. Brink, and H. V. Klauznicer (2021) "When Behavioral Science Can Make a Difference in Times of COVID-19," *Behavioural Public Policy* 5.2: 153–179.

[24] Lowenstein, G. and E. Haisley (2008) "The Economist as Therapist: Methodological Issues Raised by Light Paternalism," in A. Caplin and A. Schotter eds., *The Foundations of Positive and Normative Economics*. Oxford University Press, 210–246.

[25] Lunn, P. C. Belton, C. Lavin, F. McGowan, S. Timmons, D. Robertson (2020) "Using behavioural science to help fight the coronavirus", *ESRI working paper* no. 656 March 2020

[26] Luttrell, A., and R.E. Petty (2021) "Evaluations of self-focused versus other-focused arguments for social distancing: An extension of moral matching effects," *Social Psychological and Personality Science*, 12(6).

[27] Meehl, P. E. and A. Rosen (1955) "Antecedent Probability and the Efficiency of Psychometrics Signs, Patterns, or Cutting Scores," *Psychological Bulletin*, 52 (3), 194-216.

[28] Moriwaki, D., S. Harada, J. Schneider and T. Hoshino (2020) "Nudging Preventive Behaviors in COVID-19 Crisis: A Large Scale RCT using Smartphone Advertising", *Keio-IES DP2020-021*,

Institute for Economic Studies, Keio University, 8 November, 2020

[29] Qian K. and T. Yahara (2020) “Mentality and behavior in COVID-19 emergency status in Japan: Influence of personality, morality and ideology”, *PLoS ONE*, 15(7): e0235883.

[30] Sasaki, S., H. Kurokawa, and F. Ohtake (2021) “Effective but Fragile? Responses to Repeated Nudge-based Messages for Preventing the Spread of COVID-19 Infection,” *Japanese Economic Review*, 72, 371-408.

[31] Sasaki, S., T. Saito, and F. Ohtake (2022) “Nudges for COVID-19 Voluntary Vaccination: How to Explain Peer Information?” *Social Science and Medicine*, 292, January 2022, 114561.

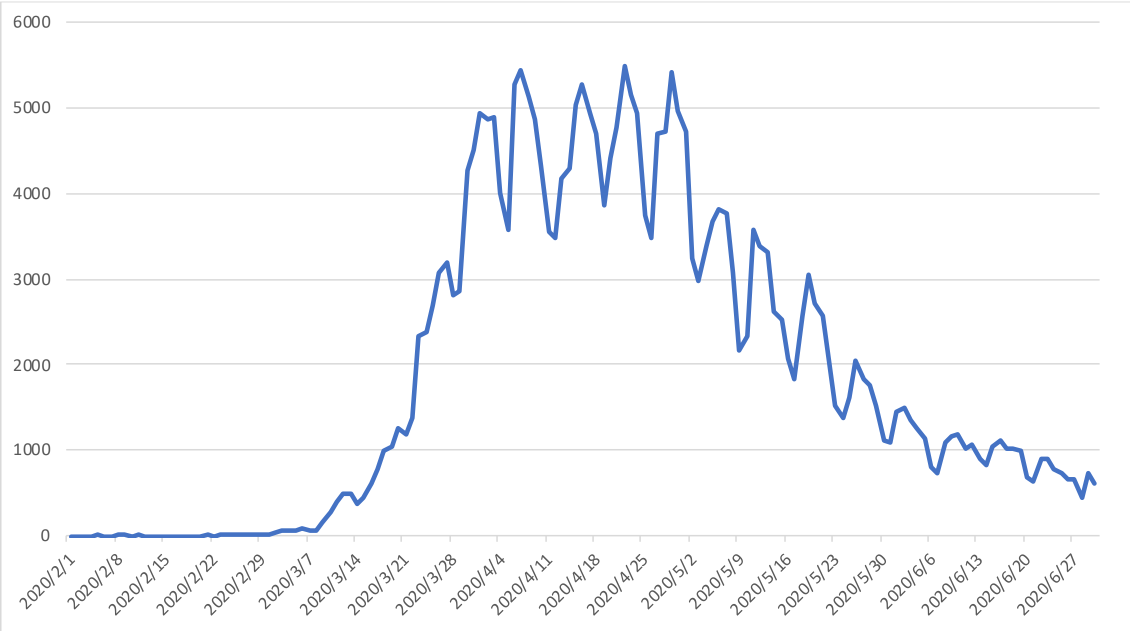
[32] Sunstein, C. R. and R. H. Thaler (2003) "Libertarian Paternalism Is Not an Oxymoron," *University of Chicago Law Review*, 70, 1159-1202.

[33] Utych, S.M., and L. Fowler (2020) “Age-based Messaging Strategies for Communication about Covid-19,” *Journal of Behavioral Public Administration*, 3(1), 1-14.

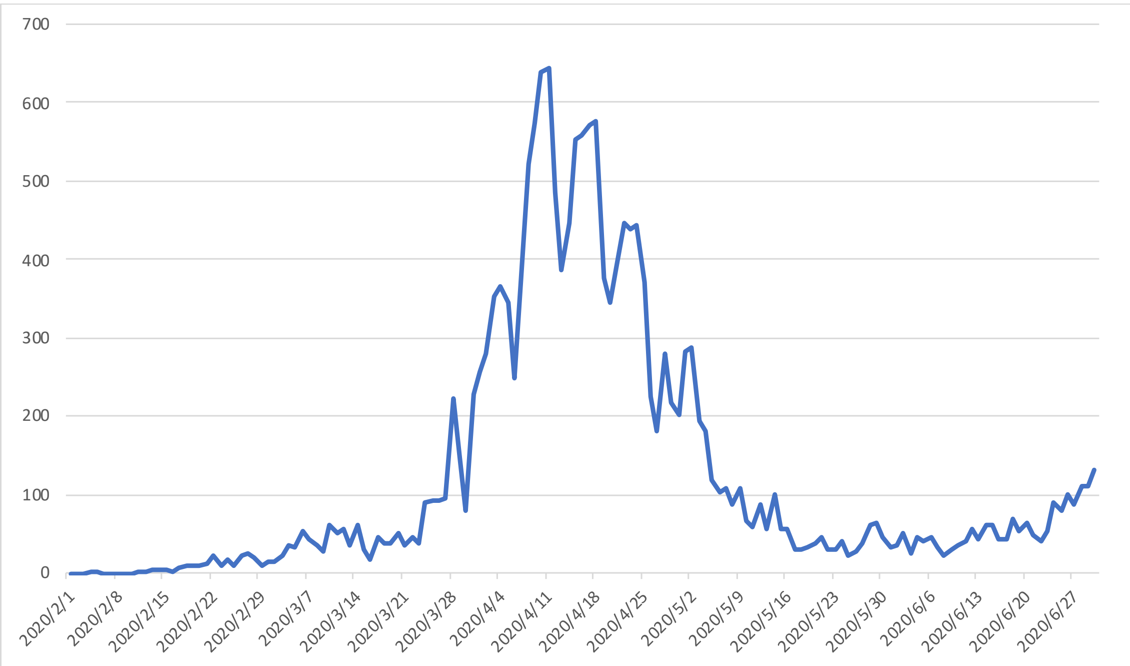
[34] Wong, L.P., H. Alias, P.F. Wong, H.Y. Lee, and S. Abu Bakar (2020) “The Use of The Health Belief Model to Assess Predictors of Intent to Receive The COVID-19 Vaccine and Willingness to Pay,” *Human Vaccines & Immunotherapeutics*,16(9), 2204–2214.

Figure 1: Number of COVID-19 cases in the U.K. and Japan

(a) The U.K. (before and after the initial lockdown)



(b) Japan (before and after the declaration of emergency)

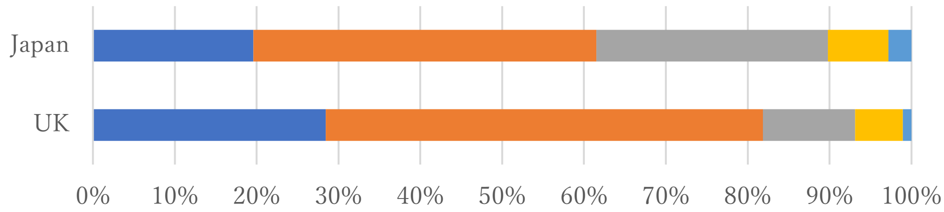


Note: (a) includes the data in England only.

Source: The U.K. government（https://coronavirus.data.gov.uk/#category=nations&map=case）

Japan government（https://www.mhlw.go.jp/stf/covid-19/open-data.html）

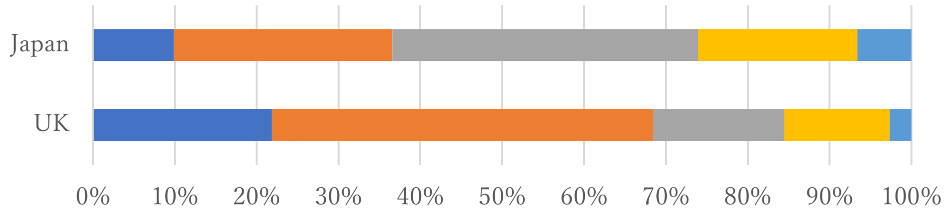
Figure 2: Physical condition during the lockdown/emergency declaration



	UK	Japan
Very good	28.5%	19.6%
Generally good	53.4%	41.9%
Can't say either way	11.3%	28.3%
Generally bad	5.8%	7.4%
Very bad	1.1%	2.8%

Very good   Generally good   Can't say either way   Generally bad   Very bad

Figure 3: Mental state during the lockdown/emergency declaration

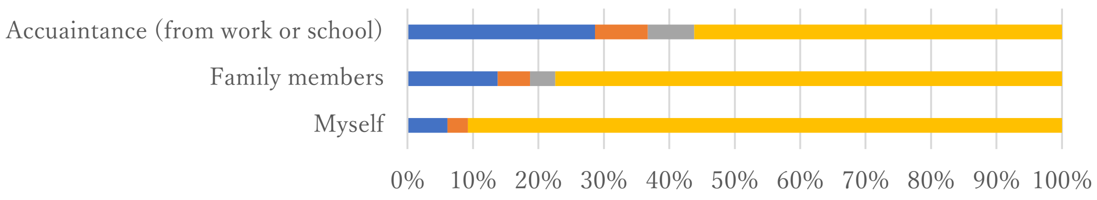


	UK	Japan
Very good	21.9%	9.9%
Generally good	46.6%	26.7%
Can't say either way	16.0%	37.3%
Generally bad	12.9%	19.5%
Very bad	2.6%	6.6%

Very good Generally good Can't say either way Generally bad Very bad

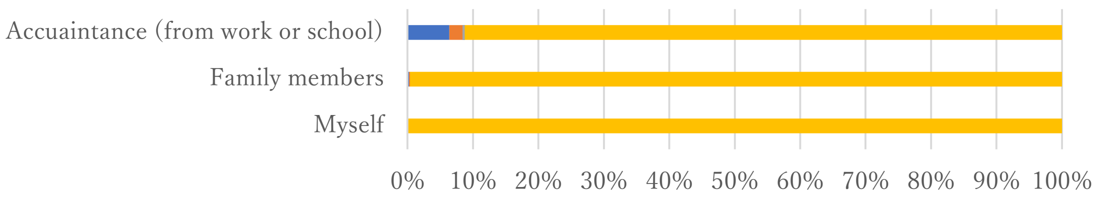
Figure 4: COVID-19 infection status of the respondents

UK



	Myself	Family members	Accuaintance (from work or school)
Infection	6.2%	14.2%	30.5%
Hospitalisation	3.2%	5.1%	8.5%
Death	0.0%	4.0%	7.6%
Non-infection	92.0%	79.7%	59.7%

Japan



	Myself	Family members	Accuaintance (from work or school)
Infection	0.0%	0.2%	5.7%
Hospitalisation	0.0%	0.1%	1.8%
Death	0.0%	0.0%	0.3%
Non-infection	91.1%	84.9%	81.5%

Figure 5: Balance between the economy and COVID-19 control in the U.K. and Japan

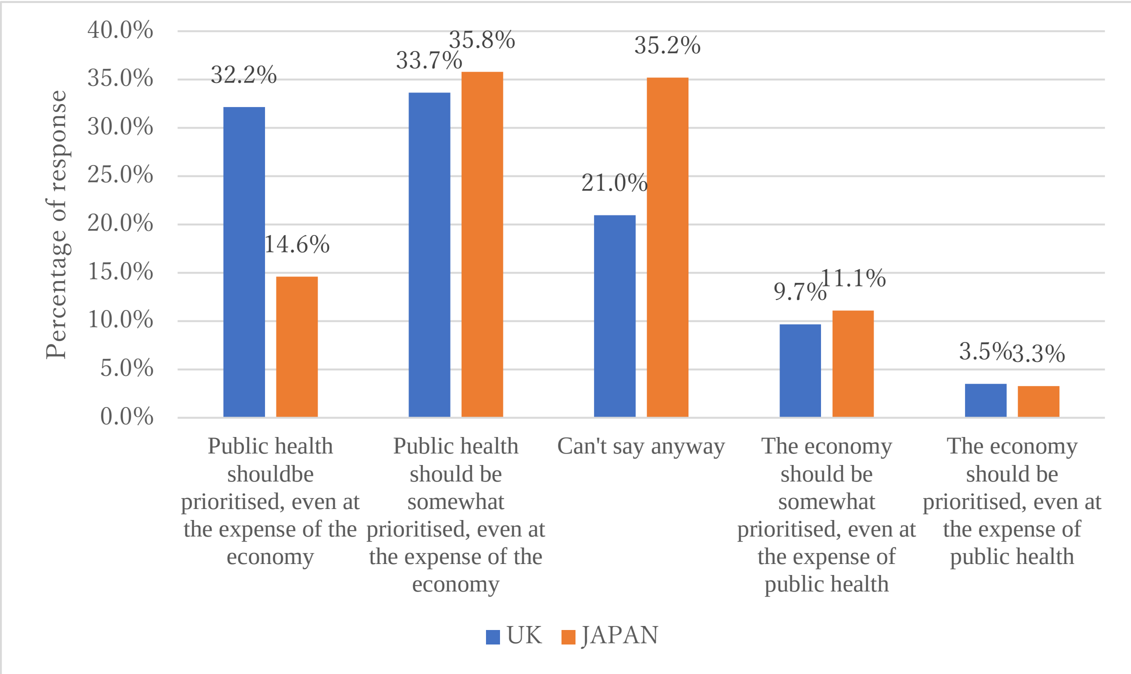
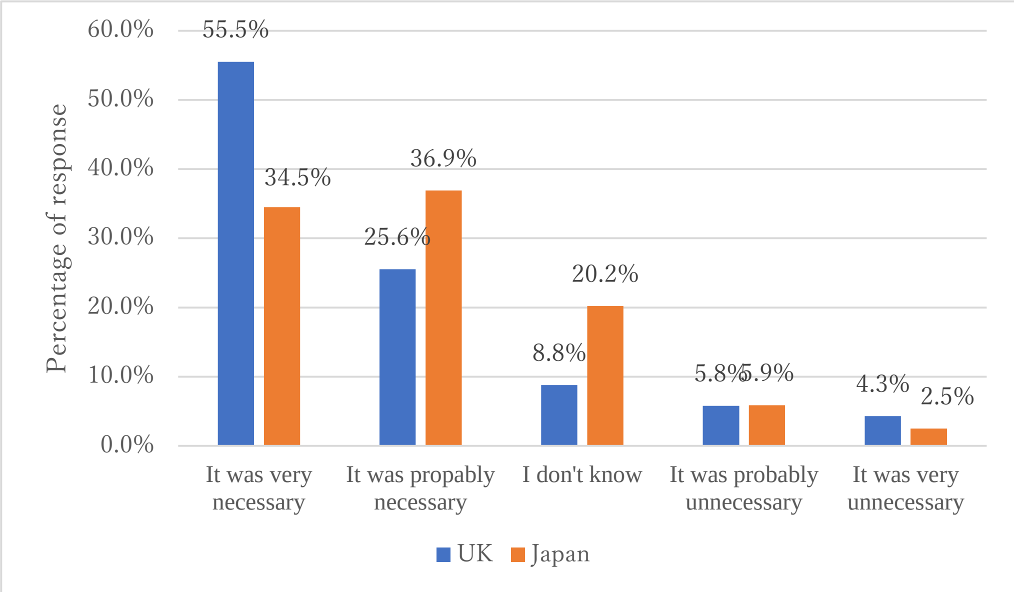


Figure 6: Evaluation of Lockdown (U.K.) and Declaration of Emergency (Japan)

Necessity



Effectiveness

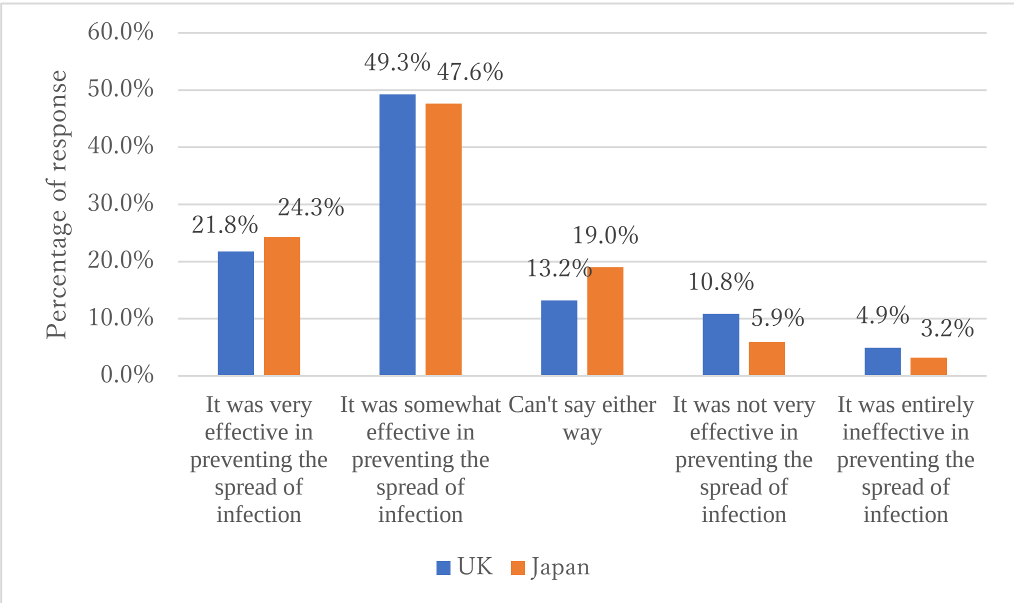
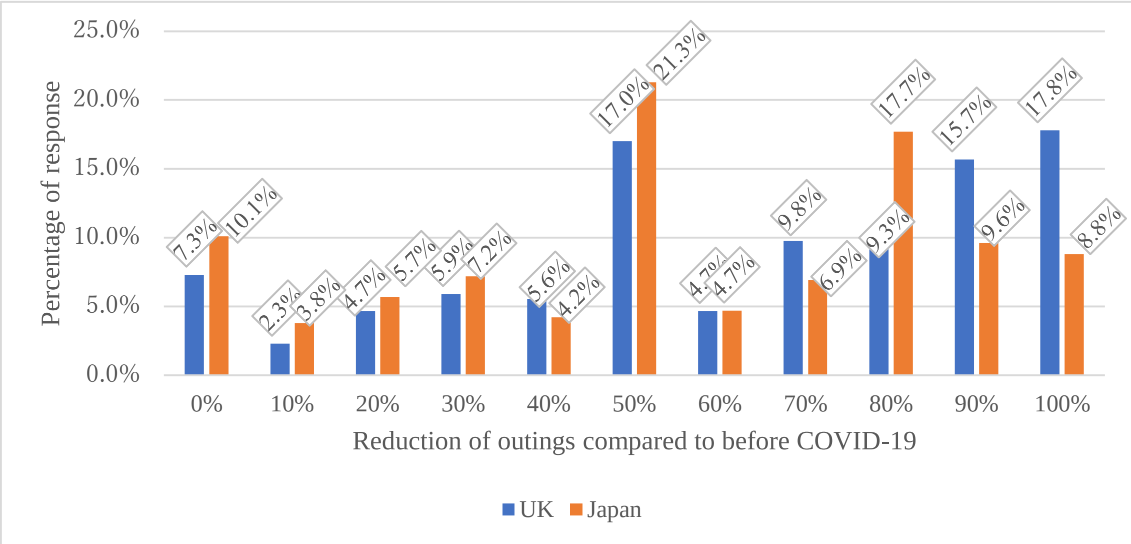


Figure 7: Desired and actual reduction in outings

Desired



Actual

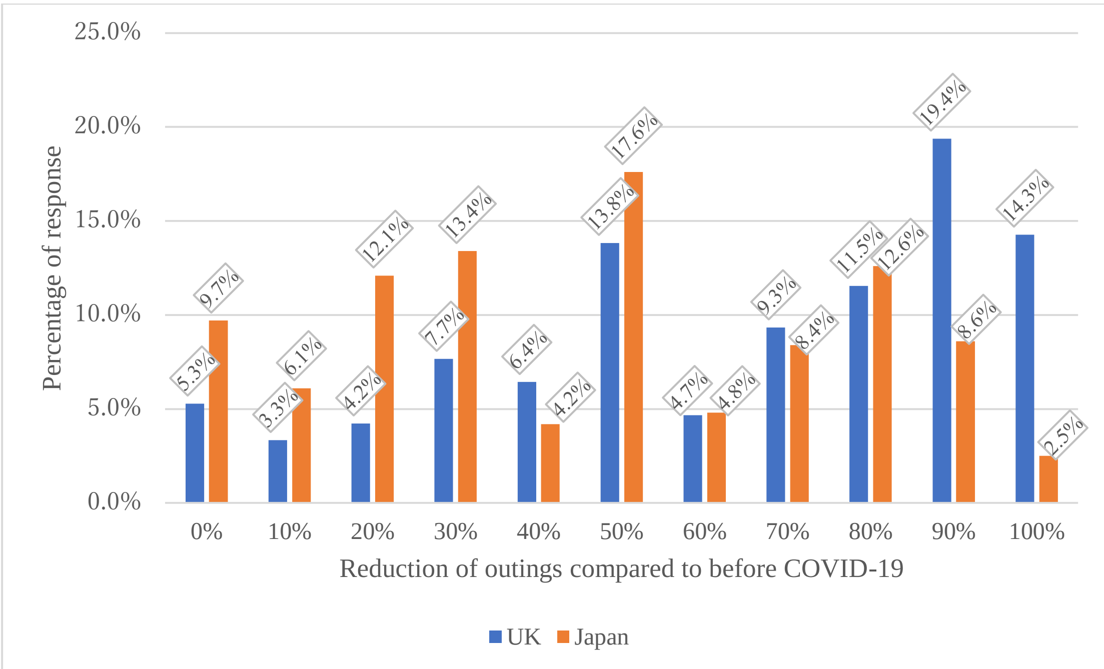
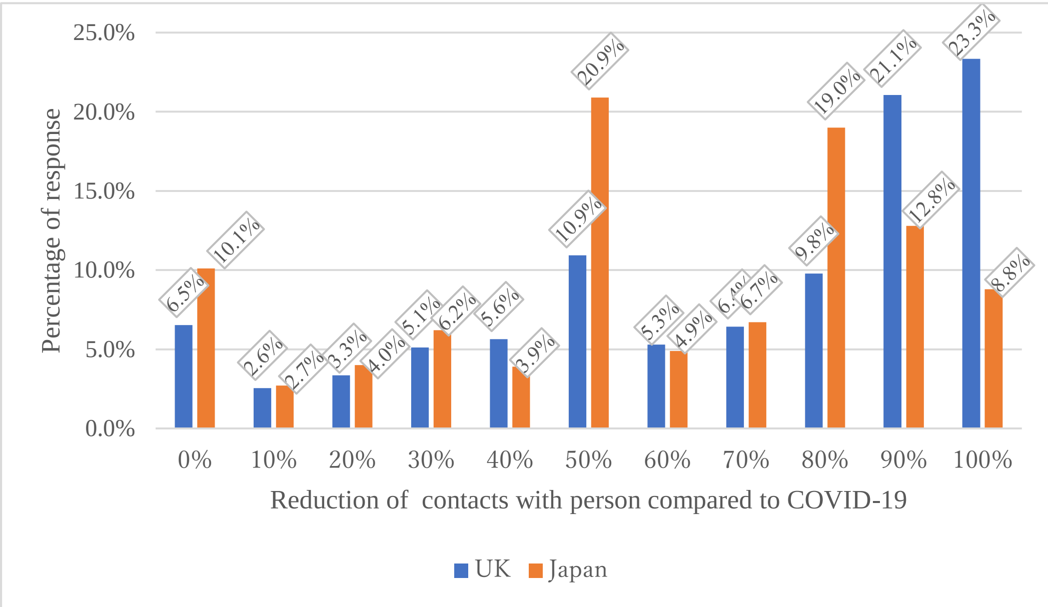


Figure 8: Desired and actual reduction in the number of contacts with persons

Desired



Actual

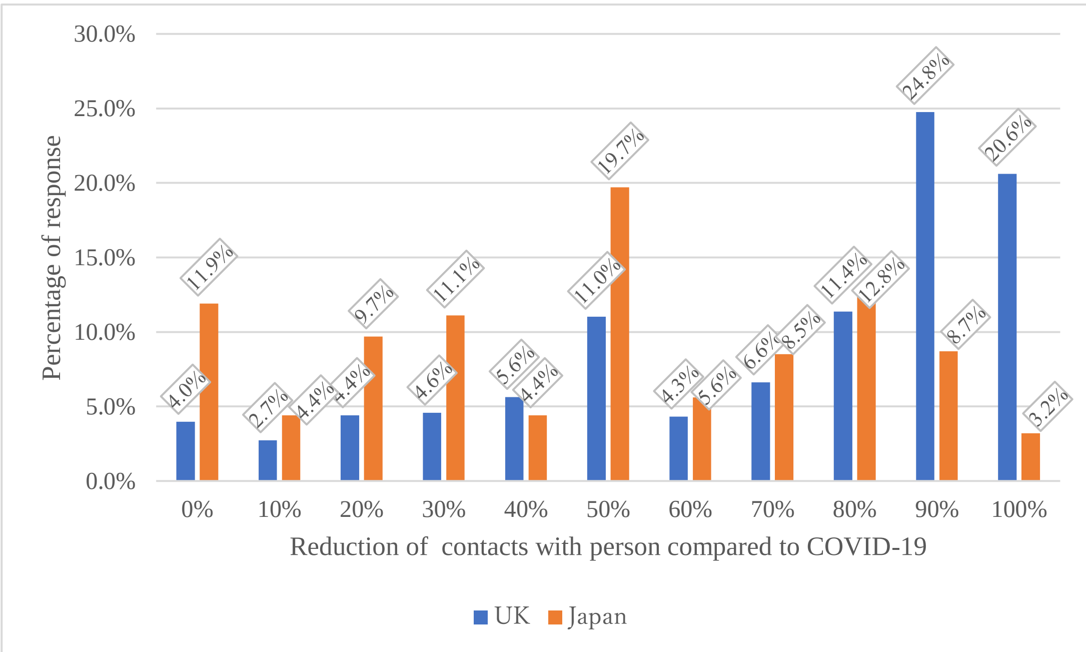


Figure 9: Subjective probability response distributions for the U.K. and Japan

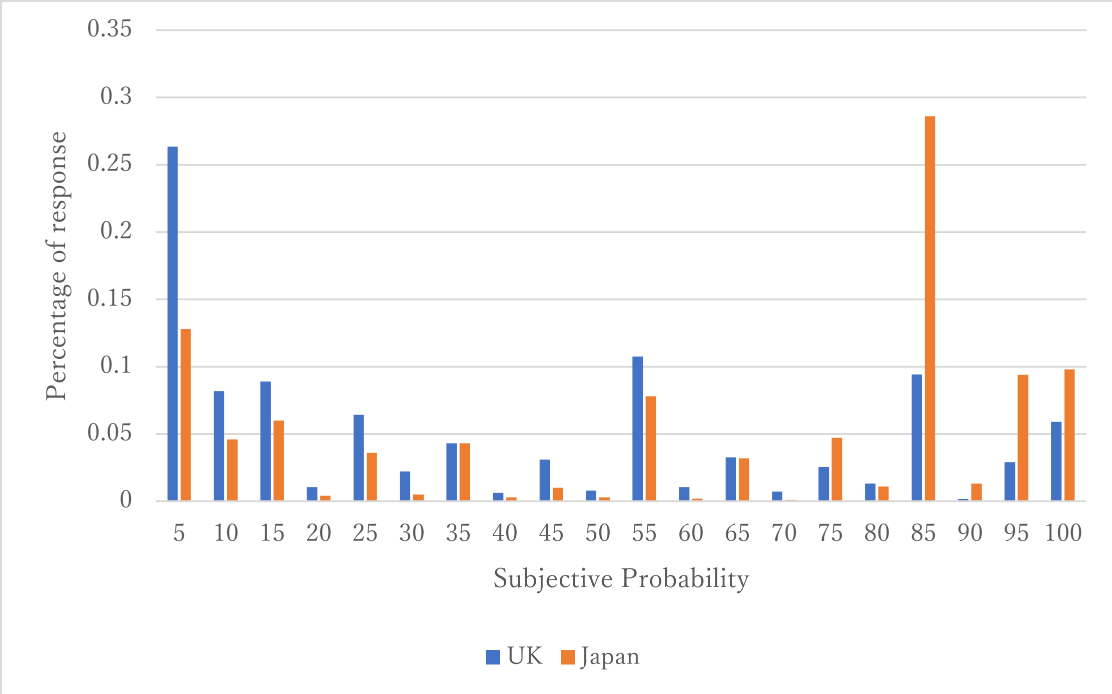


Table 1: Infection control vs economy

	UK		Japan	
Variables	Coefficient	Standard error	Coefficient	Standard error
Const.	1.222***	0.224	0.999***	0.247
Subjective Probability	0.017***	0.004	0.008*	0.005
Cross term	-0.013***	0.003	-0.005	0.004
London/Tokyo	-0.140	0.095	-0.077	0.091
Physical health	0.002	0.044	0.047	0.043
Mental health	-0.007	0.037	-0.012	0.040
Gender (Female=1)	-0.023	0.065	0.123*	0.071
Age	0.008***	0.003	0.011***	0.003
Marital Status	0.068	0.074	-0.023	0.080
Family member	0.004	0.030	0.054*	0.030
Child	-0.117	0.112	n.a.	
Education	0.004	0.018	-0.014	0.024
Employment	-0.107	0.077	-0.159**	0.078
Infection experience	0.256***	0.066	-0.080	0.143
Threshold 1	0.721***	0.043	0.806***	0.046
Threshold 2	1.453***	0.038	1.892***	0.041
Threshold 3	2.350***	0.043	2.976***	0.051
Log-likelihood (LL)	-1561.407		-1350.091	
Restricted LL	-1592.409		-1372.777	
Pseudo R-sq	0.019		0.017	
AIC	3156.8		2732.2	
N	1135		1000	

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 2: Evaluation of lockdown/state of emergency

	Variable	UK Coefficient	UK Standard error	Japan Coefficient	Japan Standard error
Necessity of Lockdown/State of Emergency	Const.	0.783***	0.241	1.720***	0.256
	Subjective Probability	-0.007*	0.004	0.002	0.005
	Cross term	-0.001	0.004	0.000	0.005
	London/Tokyo	0.042	0.103	0.008	0.099
	Physical health	0.018	0.050	-0.062	0.044
	Mental health	0.012	0.039	0.019	0.040
	Gender (Female=1)	-0.014	0.070	0.056	0.075
	Age	-0.012***	0.003	0.004	0.003
	Marital Status	-0.108	0.082	0.052	0.083
	Family member	-0.026	0.033	0.045	0.032
	Child	0.068	0.126	n.a.	
	Education	-0.007	0.019	-0.046*	0.025
	Employment	0.128	0.084	-0.154*	0.080
	Infection experience	-0.192**	0.076	0.338**	0.154
	Threshold 1	0.771***	0.042	0.587***	0.078
	Threshold 2	1.202***	0.054	1.425***	0.092
	Threshold 3	1.687***	0.075	2.402***	0.097
Effectiveness of Lockdown/State of Emergency	Const.	1.160***	0.225	1.601***	0.254
	Subjective Probability	-0.007**	0.004	0.001	0.005
	Cross term	0.003	0.003	0.001	0.004
	London/Tokyo	0.149	0.094	-0.046	0.099
	Physical health	0.031	0.046	-0.129***	0.041
	Mental health	0.074*	0.038	-0.027	0.039
	Gender (Female=1)	-0.070	0.066	0.160**	0.077

	Age	-0.005*	0.003	0.005*	0.003
	Marital Status	0.010	0.076	0.121	0.086
	Family member	-0.081**	0.032	0.065**	0.029
	Child	0.098	0.108	n.a.	
	Education	0.005	0.018	-0.065***	0.025
	Employment	0.040	0.081	-0.139*	0.082
	Infection experience	-0.062	0.069	0.346**	0.151
	Threshold 1	1.347***	0.049	0.503***	0.067
	Threshold 2	1.801***	0.056	1.290***	0.085
	Threshold 3	2.473***	0.078	2.633***	0.094
Disturbance Correlation (ρ)		0.660***	0.020	0.571***	0.023
Log-likelihood (LL)		-2612.705		-2415.900	
Restricted LL		-2809.158		-2553.783	
Pseudo R-sq		0.070		0.054	
AIC		5295.4		4897.8	
N		1135		1000	

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 3: Reduction of outings

		UK		Japan	
Variables		Coefficient	Standard error	Coefficient	Standard error
Desired reduction of outings	Const.	-0.096	0.217	0.625***	0.238
	Subjective Probability	0.003	0.004	-0.002	0.005
	Cross term	-0.001	0.003	0.004	0.004
	London/Tokyo	0.013	0.093	0.233**	0.094
	Physical health	0.012	0.040	0.000	0.040
	Mental health	0.076**	0.036	0.132***	0.039
	Gender (Female=1)	0.261***	0.065	0.275***	0.070
	Age	0.016***	0.003	-0.004	0.003
	Marital Status	0.121	0.074	0.062	0.081
	Family member	-0.020	0.031	0.050*	0.029
	Child	-0.057	0.122	n.a.	
	Education	0.009	0.017	-0.054**	0.023
	Employment	-0.034	0.074	-0.179**	0.075
	Infection experience	0.152**	0.065	0.333**	0.149
	Threshold 1	0.138***	0.030	0.217***	0.037
	Threshold 2	0.371***	0.040	0.477***	0.046
	Threshold 3	0.608***	0.046	0.729***	0.050
	Threshold 4	0.798***	0.050	0.855***	0.052
	Threshold 5	1.279***	0.053	1.434***	0.059
	Threshold 6	1.400***	0.054	1.564***	0.061
	Threshold 7	1.662***	0.059	1.756***	0.063
	Threshold 8	1.933***	0.063	2.319***	0.070
	Threshold 9	2.438***	0.070	2.735***	0.079

Actual reduction of outings	Const.	0.212	0.215	0.999***	0.235
	Subjective Probability	0.001	0.004	0.003	0.004
	Cross term	0.002	0.003	-0.002	0.004
	London/Tokyo	-0.034	0.092	0.180**	0.090
	Physical health	-0.011	0.041	-0.017	0.041
	Mental health	0.100***	0.036	0.132***	0.040
	Gender (Female=1)	0.227***	0.065	0.183***	0.070
	Age	0.017***	0.003	-0.003	0.003
	Marital Status	0.041	0.074	0.069	0.080
	Family member	-0.005	0.031	0.014	0.027
	Child	-0.061	0.125	n.a.	
	Education	-0.007	0.017	-0.044*	0.023
	Employment	-0.023	0.073	-0.319***	0.075
	Infection experience	0.149**	0.065	0.293*	0.151
	Threshold 1	0.253***	0.042	0.300***	0.040
	Threshold 2	0.480***	0.049	0.724***	0.050
	Threshold 3	0.789***	0.055	1.103***	0.054
	Threshold 4	1.001***	0.057	1.217***	0.056
	Threshold 5	1.393***	0.061	1.687***	0.060
	Threshold 6	1.521***	0.063	1.823***	0.062
	Threshold 7	1.778***	0.066	2.086***	0.066
	Threshold 8	2.100***	0.070	2.587***	0.074
	Threshold 9	2.760***	0.077	3.304***	0.104
Disturbance Correlation (ρ)		0.828***	0.008	0.777***	0.011
Log likelihood (LL)		-4451.316		-4042.152	
Restricted LL		-5005.398		-4447.091	
Pseudo R-sq		0.111		0.091	

AIC	8996.6	8174.3
N	1135	1000

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Reduction of the number of contracts

	Variables	UK Coefficient	UK Standard error	Japan Coefficient	Japan Standard error
Desired reduction of contracts	Const.	0.081	0.227	0.402*	0.237
	Subjective Probability	0.001	0.004	-0.001	0.005
	Cross term	0.002	0.004	0.006	0.004
	London/Tokyo	-0.069	0.104	0.305***	0.094
	Physical health	-0.034	0.039	-0.013	0.041
	Mental health	0.086**	0.034	0.108***	0.038
	Gender (Female=1)	0.325***	0.064	0.284***	0.070
	Age	0.018***	0.003	0.001	0.003
	Marital Status	0.069	0.074	0.128	0.082
	Family member	-0.022	0.030	0.043	0.029
	Child	-0.111	0.119	n.a.	
	Education	-0.005	0.017	-0.065***	0.023
	Employment	-0.117	0.076	-0.224***	0.073
	Infection experience	0.092	0.069	0.338**	0.165
	Threshold 1	0.148***	0.031	0.175***	0.036
	Threshold 2	0.317***	0.042	0.379***	0.049
	Threshold 3	0.537***	0.050	0.631***	0.057
	Threshold 4	0.744***	0.054	0.766***	0.059
	Threshold 5	1.087***	0.058	1.365***	0.065
	Threshold 6	1.239***	0.061	1.500***	0.066
	Threshold 7	1.421***	0.062	1.683***	0.067
	Threshold 8	1.697***	0.067	2.252***	0.073
	Threshold 9	2.320***	0.073	2.758***	0.083
Actual reduction of contracts	Const.	0.286	0.222	0.837***	0.235
	Subjective Probability	0.000	0.004	0.002	0.005
	Cross term	0.003	0.003	-0.001	0.004
	London/Tokyo	-0.075	0.105	0.265***	0.093
	Physical health	-0.049	0.043	-0.038	0.041

	Mental health	0.099***	0.036	0.130***	0.037
	Gender (Female=1)	0.331***	0.064	0.181***	0.070
	Age	0.021***	0.003	-0.002	0.003
	Marital Status	0.011	0.073	0.092	0.078
	Family member	-0.030	0.030	0.024	0.028
	Child	-0.128	0.116	n.a.	
	Education	-0.002	0.017	-0.072***	0.024
	Employment	-0.061	0.076	-0.330***	0.074
	Infection experience	0.198***	0.069	0.335**	0.163
	Threshold 1	0.272***	0.054	0.217***	0.035
	Threshold 2	0.557***	0.066	0.580***	0.048
	Threshold 3	0.778***	0.070	0.901***	0.053
	Threshold 4	1.003***	0.073	1.016***	0.055
	Threshold 5	1.376***	0.075	1.527***	0.061
	Threshold 6	1.512***	0.076	1.681***	0.063
	Threshold 7	1.711***	0.076	1.934***	0.067
	Threshold 8	2.025***	0.076	2.418***	0.076
	Threshold 9	2.732***	0.081	3.096***	0.101
Disturbance Correlation (ρ)		0.779***	0.011	0.788***	0.011
Log likelihood (LL)		-4324.682		-3964.249	
Restricted LL		-4751.323		-4381.375	
Pseudo R-sq		0.090		0.095	
AIC		8743.4		8018.5	
N		1135		1000	

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Summary of Subjective Probability and Infection Prevention Behaviors

	UK		Japan	
	Optimistic bias ($-\beta_{SP}$)	Pessimistic bias ($\beta_{SP}+\beta_{Pess}$)	Optimistic bias ($-\beta_{SP}$)	Pessimistic bias ($\beta_{SP}+\beta_{Pess}$)
Infection control vs economy	–0.017 *** (23.47)	0.005*** (20.93)	–0.008* (2.92)	0.003*** (9.56)
Necessity of Lockdown/State of Emergency	0.007* (3.34)	-0.006*** (29.32)	–0.002 (0.22)	0.003** (5.69)
Effectiveness of Lockdown/State of Emergency	0.007** (4.56)	-0.004*** (14.65)	–0.001 (0.11)	0.003*** (7.00)
Desired reduction of outings	–0.003 (0.68)	0.002*** (7.02)	0.002 (0.22)	0.003** (5.85)
Actual reduction of outings	–0.001 (0.00)	0.002** (6.55)	–0.003 (0.37)	0.001 (0.54)
Desired reduction of contracts	–0.001 (0.02)	0.003*** (7.44)	0.001 (0.05)	0.005*** (21.77)
Actual reduction of contracts	0.000 (0.02)	0.003*** (7.02)	–0.002 (0.22)	0.002 (2.70)

Note: The coefficients for optimistic and pessimistic biases are calculated for the difference from 44.5%, the correct response to Bayesian inference.

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The chi-square values for the Wald test are shown in parentheses.