COVID-19, stigma, and habituation: Theory and evidence from mobility data

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COVID-19, stigma, and habituation: Theory and evidence from mobility data*

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Abstract

This paper introduces a habituation effect into the stigma model of self-restraint behavior under the pandemic. The theoretical result indicates that the state of emergency's self-restraint effects weaken with the number of times. In order to confirm whether the results of the theoretical analysis are consistent with the current situation, the empirical analysis examines the impact of emergency declarations on going-out behavior using a prefecture-level daily panel dataset that includes Google's going-out behavior data, the Japanese government's policy interventions based on emergency declarations, and covariates that affect going-out behavior such as precipitation and holidays. The results of the empirical analysis can be summarized in two points: First, for multiple emergency declarations from the beginning of the pandemic to 2021, the effect of refraining from going-out was confirmed under emergency declarations in a model that did not distinguish the number of emergency declarations. Second, in the model that considers the number of emergency declarations, the effect of voluntary restraint on going-out was found to decrease with the number of declarations. These empirical analyses are consistent with the results of theoretical analyses, which show that people become more habituated to a policy intervention as the number of the intervention increases.

Keywords: COVID-19, Infection disease, Stigma, Self-restraint behavior, Non-pharmaceutical policy intervention, Mobility data

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1 Introduction

The new coronavirus infection (COVID-19) has caused a global pandemic with about 217 million cases and 4.5 million deaths as of 31 August 2021 (World Health Organization, 2021). Countries around the world that have anticipated, or already suffered, catastrophic loss of life and economic damage from this pandemic have adopted a range of policies (Martin et al., 2020; Mandel and Veetil, 2020; Gharehgozli et al., 2020). These policies have had a wide range of objectives, from saving the lives of those already infected to stopping the outbreak itself. The former policy interventions include subsidizing healthcare systems and preventing severe disease through rapid vaccination against COVID-19. The latter policy interventions, on the other hand, have been designed to reduce opportunities for people to come into contact with COVID-19, as the majority of infections are airborne and droplet-transmitted (Bahl et al., 2020).

Policies aimed at reducing contact with these people have been implemented by restricting their behavior. Restrictions on people's behavior have been adopted in various ways, including restricting gathering, restricting commuting to workplaces, and restricting going-out itself. For example, concerning the policy of restricting gatherings, Germany has notified that on 30 December 2020, private gatherings will be restricted to one household or another (deutschland.de, 2020); in terms of restrictions on commuting to workplaces, the state of Michigan in the US has issued a regulation on 12 November 2020 that imposes a fine of $7,000 on employers who are able to work remotely if they do not have an appropriate policy in place or a response plan in place (State of Michigan, 2020); restrictions on going-out were introduced in the UK on 4 January 2021, when the fine imposed on those who break a stay-home order was increased to £200 (nidirect, 2020). There are also differences between countries and local authorities in terms of whether there are penalties, i.e., legally binding or not, for restricting people's behavior.

As the policy mentioned above, interventions restricting people's behavior illustrate, many countries prescribe penalties for these restrictions. On the other hand, some countries have adopted policies that rely on non-legally binding restrictions on behavior, i.e., voluntary action (i.e., self-restraint). For example, these non-legally binding policies have been implemented through requests to the public by state representatives or through the declaration of a state of emergency. One such country, Sweden, is believed to have adopted a policy based on the concept of herd immunity, whereby a proportion of the population becomes infected and acquires immunity, which is then transmitted, rather than suppressing the infection itself (Habib, 2020). On the other hand, Japan, which has also adopted similar policies, has kept the number of infections and deaths under control compared to 36 other developed countries in the OECD, based on the government's declaration of a state of emergency, which includes a call for individuals to refrain from going-out (Njeru et al., 2021). Among these countries that have taken legally binding measures, there is an assessment that Japan has performed better in terms of COVID-19 outcomes. In the Covid Resilience Ranking (Bloomberg, 2021) on 26 March 2021, which is a ranking of the countries most effectively responding to pandemics, Japan is ranked eighth globally, while Sweden is 31st.

The Japanese government, which has controlled the COVID-19 pandemic situation better than other industrialized countries, has restricted people's behavior by declaring a state of emergency, despite having adopted a policy of no penalties and relying solely on people's self-restraint called *Jishuku* in Japanese. The emergency declarations are designed to exercise authority and alert the public to the emergency, and consist of requests to refrain from going-out unnecessarily, to refrain from holding public events, to refrain from opening restaurants, entertainment venues, and large mass merchandisers, and to shorten the opening hours of these facilities (Cabinet Secretariat, Japan, 2021; Ministry of Health, Labour, and Welfare, Japan, 2020). Until now, the Government of Japan has issued these emergency declarations on a prefecture-by-prefecture basis, depending on the status of COVID-19 infection. Figure 1 shows the status of the emergency declarations in Tokyo and the COVID-19 infection status[1]. From the infection situation in Japan, we can confirm that the first wave regarding the COVID-19 epidemic started in April 2020, the second wave in August 2020, the third wave in December 2020, the fourth wave in April 2021, and the fifth wave in July 2021. On the other hand, from the emergency declarations issued for Tokyo, it can be confirmed that the first emergency declaration was issued from April to May 2020 during the first wave, the second from January 2021 to March 2021 during the third wave, the third from April 2021 to June 2021 during the fourth wave, and the fourth from July 2021 onward before the fifth wave. This figure highlights the fact that the government of Japan has declared a state of emergency in order to

[1] In Figures 1 and 2, the reason for focusing on Tokyo as the target area for the declaration of a state of emergency can be summarized in three points: First, the duration of the declaration of a state of emergency is different for each prefecture. The second reason is that Tokyo is the most populous prefecture in Japan. Third, because the number of emergency declarations issued in Tokyo and their total duration are the highest and longest among the prefectures in Japan.

improve the situation of COVID-19 infection. On the other hand, in order to understand how the public has responded to the non-legally binding policy interventions through going-out activities, Figure 2 shows the changes in the volume of going-out for the four categories "Retail and recreation", "Grocery and pharmacy", "Workplaces" and "Residential" retrieved from Google (2021) and the declaration of a state of emergency in Tokyo prefecture. The figure can be summarised by the fact that the first emergency declarations show a significant decrease in going-out (and increase in time spent at home), whereas the second emergency declarations do not seem to have the same effect as the first and show an increasing trend in mobility (and a decreasing trend in time spent at home). Furthermore, it can be confirmed that the amount of decrease in the amount of mobility (increase in the amount of time spent at home) under such emergency declarations tends to decrease with the number of times the emergency is declared.

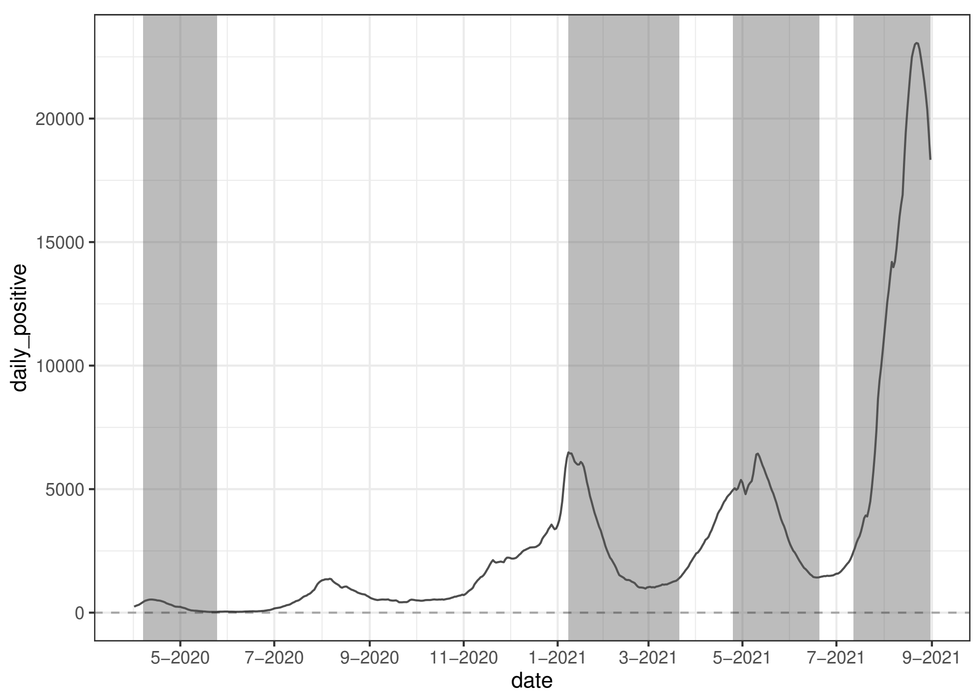

Figure 1: Trend of positive cases of COVID-19 and status of state of emergency of Japan
Notes: The solid line indicates 7-day moving average of daily COVID-19 positive cases in Japan. The shaded areas indicate the status of the declaration of a state of emergency in Tokyo prefecture, Japan, i.e., the date on which a state of emergency has been declared in Tokyo. The sample covers the period 1 April 2020 to 31 August 2021.
Source: TOYO KEIZAI ONLINE (2020), Katafuchi (2020) and authors' calculation.

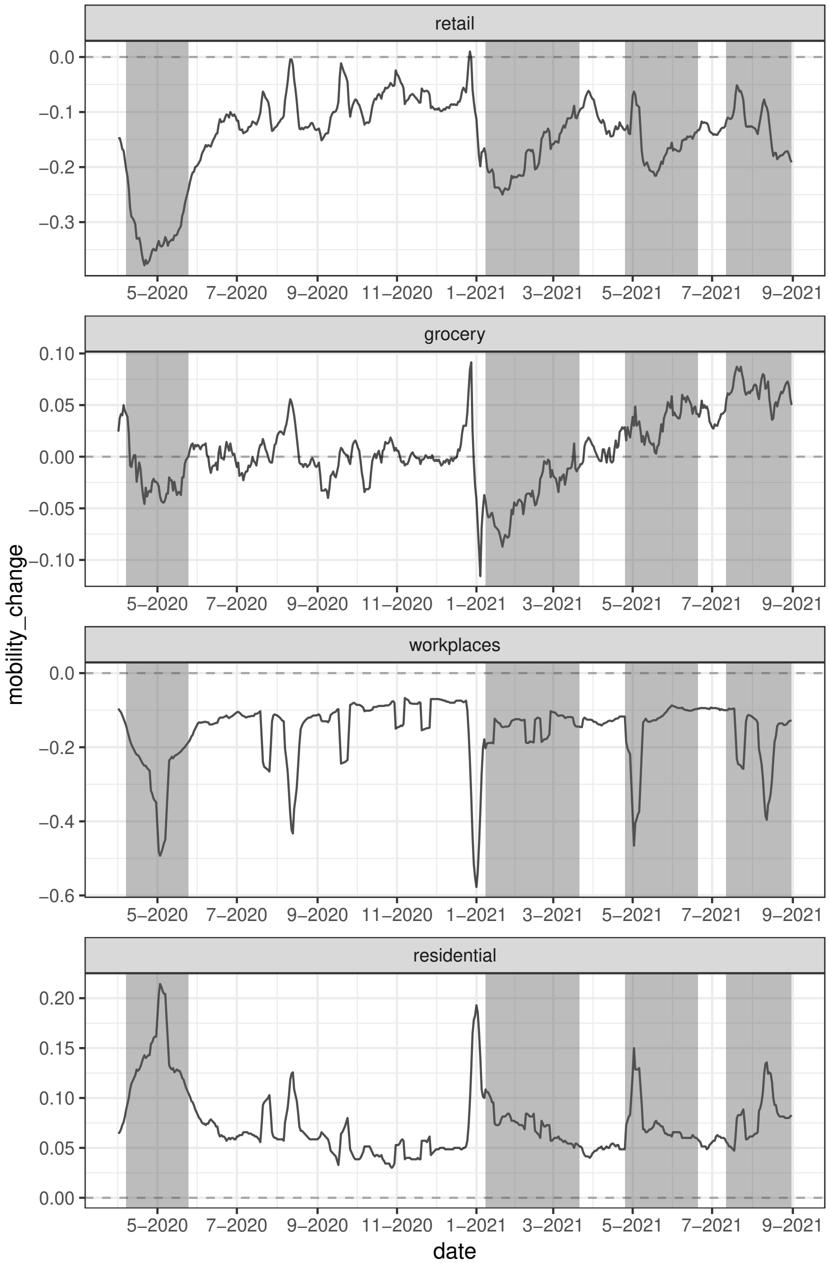

Figure 2: Mobility trend and status of the state of emergency of Japan

Notes: The solid lines represent the 7-day moving average of the change in the amount of movement across Japan for each category. The shaded areas indicate the status of the declaration of a state of emergency in Tokyo prefecture, Japan, i.e., the date on which a state of emergency has been declared in Tokyo. The category names at the top of each panel correspond to “Retail and recreation”, “Grocery and pharmacy”, “Workplaces”, and “Residential” from the top and indicate the amount of mobility change for each. The sample covers the period 1 April 2020 to 31 August 2021.

Source: Google (2021), Katafuchi (2020) and authors’ calculation.

The first emergency declaration issued by the Government of Japan in 2020, shown in the above-mentioned Figures 1 and 2, is seen as having been successful in reducing the contact opportunities represented by people's going-out behavior (Katafuchi et al., 2021). However, the second, third, and fourth emergency declarations, issued in 2021, have not yet been tested for effectiveness and criticized. For example, the The Mainichi (2021) shows that the number of people taking the train in Tokyo under the second emergency declaration, i.e., the volume of going-out activity using the train, is only slightly lower than in the seven months following the lifting of the first emergency declaration issued in 2020. Jiji Press (2021) also assesses the situation on 22 January 2021, two weeks after the second emergency declaration was issued, as being much higher than the number of cases reported during the first emergency declaration issued in 2020. In a questionnaire survey on how the public assessed this second declaration of a state of emergency, the smallest number of people assessed that their sense of urgency regarding the transmission of COVID-19 had "increased" (21.8%) compared to the first declaration of a state of emergency, with the rest saying it had "remained the same" (54.8%) and "decreased" (23.4%) (At Press, 2021). This situation reflects that people are tired of refraining from the effects of the prolonged state of emergency under the second declaration of emergency (The Yomiuri Shimbun, 2021). Furthermore, Reuters (2021) argues that the exhaustion of the Japanese people with regard to the COVID-19 situation, as a result of the experience of three emergency declarations, is manifested in a situation in which the effectiveness of unenforceable interventions is weakening.

Given this situation in Japan, the questions that this paper seeks to answer are as follows; first, what happens to people's going-out behavior when they experience multiple declarations of a state of emergency, i.e., multiple policy interventions that impose non-legally binding restrictions on behavior. Second, in light of the first question, whether the second, third, and fourth declaration of a state of emergency reduced people's going-out behavior. In the following, we review the studies related to these questions.

Various studies have been conducted on Japan's self-restraint behavior (Hanibuchi et al., 2021; Katafuchi, 2021; Katsuki et al., 2021). Furthermore, there is a growing body of research on social stigma and social pressures related to COVID-19 (Abdelhafiz and Alorabi, 2020; Badrfam and Zandifar, 2020; Bagcchi, 2020; Jecker and Takahashi, 2021; Takahashi and Tanaka, 2021; Wright, 2021). For example, Jecker and Takahashi (2021) discuss stigma against healthcare workers in

Japan, Takahashi and Tanaka (2021) investigate a hostility toward breaching restrictions under the COVID-19 pandemic, and Wright (2021) explores the Japanese government's response to COVID-19, places the concept of self-restraint in a historical context, and discusses what self-restraint means, expectations for solidarity actions among imagined compatriots, and stigma and social coercion. However, there are no studies on self-restraint behavior considering habituation based on the number of emergency declarations.

Based on the background, the research question and the review of previous papers on policy interventions on COVID-19 described above, the contribution of this paper is described as following: First, this paper describes how people's behavior changes when multiple non-legally binding policies aimed at restricting behavior are implemented. Specifically, this is achieved by presenting an economic theory model in which the number of announcements without penalty changes the effect of the announcements on going-out behavior. Second, this paper describes how the second and further announcements have affected people's behavior with respect to Japan's non-legally binding policy, namely the declaration of a state of emergency. Specifically, we construct prefectural and daily panel data on going-out behavior and emergency declarations and covariates that are expected to affect going-out behavior, and use the data to empirically show the impact of the second, third and fourth emergency declaration through estimations of econometric models.

The rest of the paper is organized as follows. First, in Section 2, we use a theoretical model to analyze the impact of announcements on going-out behavior, taking into account the fact that announcements are made multiple times. Second, in Section 3, we construct a daily and prefectural panel dataset consisting of secondary data on emergency declarations, going-out behavior, and covariates, and conduct an empirical analysis using this dataset. Finally, we conclude in Section 4.

2 Theoretical Analysis

We present a theoretical model of stigma following going-out behavior. The basic setting of the model follows Katafuchi et al. (2021) and Kurita and Managi (2020) while we extend it so that the effect varies with the number of emergency declarations (announcements), as described below.

Consider an economy where the population is normalized to 1. Individuals make decisions regarding two types of behavior: going-out or staying home. The payoff when choosing going-out is as follows:

$$u_{\text{out}} - \phi[\gamma c + \iota\sigma e^{-h(n)} s(x)]^{\delta}, \tag{1}$$

the payoff when choosing staying home is as follows:

$$u_{\text{home}}. \tag{2}$$

Here, u_{out} and u_{home} are utility from going-out and that from staying home. The second term in (1) is the total psychological cost and the cost contains two factors: ϕ is the sensitivity of psychological costs, $F(\cdot)$ is the distribution function, $F'(\cdot) = f(\cdot)$, the infection risk (γc), social stigma ($\sigma s(x)$). γ is the infection probability, δ is the cost to scale parameter, c is the cost, σ is the relative impact of stigma, s is the stigma cost and $s'(\cdot) < 0$. $\iota \in \{0, 1\}$ is the policy indicator variable, and $n = 1, 2, ...$ is the number of times that the state of emergency is implemented. $e^{-h(n)}$ represents the effect of stigma costs decreasing with the number of times that the state of emergency is implemented, and $h(\cdot)$ is an increasing function with n. This is inspired by *habituation* effect (Dodge, 1923) and it is not taken into account by Katafuchi et al. (2021) and Kurita and Managi (2020).

We define the critical level of the sensitivity to psychological costs as follows:

$$u_{\text{out}} - \hat{\phi}[\gamma c + \iota\sigma e^{-h(n)} s(x)]^{\delta} = u_{\text{home}}. \tag{3}$$

From Equation (3), players with sensitivities $\phi \leq \hat{\phi}$ choose going-out meanwhile players with sensitivities $\phi > \hat{\phi}$. We get the following:

$$\hat{\phi} = \frac{u_{\text{out}} - u_{\text{home}}}{[\gamma c + \iota\sigma e^{-h(n)} s]^{\delta}}. \tag{4}$$

The population share of players who go out is given by

$$x = \Pr(\phi \leq \hat{\phi}) = F(\hat{\phi}). \tag{5}$$

We assume that the stigma cost is an decreasing function with the population share, x, formally, $s = g(x)$, $g'(\cdot) < 0$, $s \in [0, +\infty)$, and $s(0) > 0$.

The fixed point of the following Equation corresponds to the equilibrium in this model:

$$\begin{cases} \hat{\phi} & = \frac{u_{\text{out}} - u_{\text{home}}}{[\gamma c + \iota \sigma e^{-h(n)} s]^{\delta}}, \\ x & = F\left(\hat{\phi}\right), \\ s & = s(x). \end{cases} \tag{6}$$

Summarizing Equation (6), we define the function $\chi(x)$ as follows:

$$\chi(x) = F\left(\frac{u_{\text{out}} - u_{\text{home}}}{[\gamma c + \iota \sigma e^{-h(n)} s(x)]^{\delta}}\right), \tag{7}$$

Therefore, the fixed point in $x = \chi(x)$, x^*, is the equilibrium population share of players who go out. To distinguish the population share of players who go out between under and without a state of emergency, we denote the former as x_1 and the latter as x_0.

Proposition 1 *Without the state of emergency, there exist an unique interior equilibrium as follows:*

$$x_0^* = F\left(\frac{u_{\text{out}} - u_{\text{home}}}{(\gamma c)^{\delta}}\right). \tag{8}$$

Under the state of emergency, there can be multiple equilibria, $x_1^* \in \{x_{1,1}^*, ..., x_{1,k}^*\}$, $x_{1,1}^* < x_{1,2}^* < ... < x_{1,k}^*$, k is positive integer greater than or equal to one.

Proof. Proof is tha same way as Katafuchi et al. (2021). ■

Proposition 1 shows same results as Katafuchi et al. (2021). Since we focus the effect of the number of times that the state of emergency is implemented on the self-restraint behavior, we do not discuss the multiplicity of equilibria[2]. We define the self-restraint effect, R, as follows:

$$R := x_0^* - x_1^*. \tag{9}$$

It means that the state of emergency has the self-restraint effect if $R > 0$.

Proposition 2 *The state of emergency has a self-restraint effect on going-out behavior.*

[2]Katafuchi et al. (2021) discuss multiple equilibria in the model of self-restraint behavior with stigma.

Proof. The maximum value of $\chi(x)|_{\iota=1}$ is $\chi(1)|_{\iota=1}$ because $\chi(x)|_{\iota=1}$ is an increasing function with x. Comparing $\chi(1)|_{\iota=1}$ with x_0^*, we obtain as follows:

$$\chi(1) - x_0^* = F\left(\frac{u_{\text{out}} - u_{\text{home}}}{[\gamma c + \sigma e^{-h(n)} s(1)]^\delta}\right) - F\left(\frac{u_{\text{out}} - u_{\text{home}}}{(\gamma c)^\delta}\right) < 0, \tag{10}$$

because

$$[\gamma c + \iota \sigma e^{-h(n)} s(1)]^\delta > (\gamma c)^\delta. \tag{11}$$

The equilibrium level of x_1 is less than $\chi(1)$. Therefore,

$$R > 0. \tag{12}$$

■

The effect of the number of times that the state of emergency on the self-restraint behavior is summarized in the following proposition:

Proposition 3

$$\frac{\partial R}{\partial n} < 0. \tag{13}$$

Proof.

$$\frac{\partial R}{\partial n} = -\frac{\partial x_1^*}{\partial n}. \tag{14}$$

Here,

$$\frac{\partial x_1^*}{\partial n} = \frac{\frac{\partial \chi(x_1^*)}{\partial n}}{1 - \frac{\partial \chi(x_1^*)}{\partial x}}. \tag{15}$$

The denominator in Equation (15) is positive by the following stability condition:

$$\frac{\partial \chi(x_1^*)}{\partial x} < 1.$$

Thus, the sign of Equation (15) is positive because

$$\frac{\partial \chi(x_1^*)}{\partial n} = f\left(\frac{u_{\text{out}} - u_{\text{home}}}{[\gamma c + \sigma e^{-h(n)} s(x_1^*)]^{\delta}}\right)(-\delta)\left(\frac{u_{\text{out}} - u_{\text{home}}}{[\gamma c + \sigma e^{-h(n)} s(x_1^*)]^{\delta+1}}\right)[-h'(n)\sigma e^{-h(n)} s(x_1^*)] > 0.$$

Therefore, the sign of Equation (14) is negative. ∎

The implication of Proposition 3 is that the self-restraint effect of the state of emergency weakens with the number of times that the state of emergency is implemented. The result of Proposition 3 is consistent with an observation in section 1. In the next section, we empirically test Proposition 3 using mobility data.

3 Econometric Analysis

3.1 Design and data

In order to identify how the first, second, third, and fourth emergency declarations issued by the Japanese government have affected people's going-out behavior, this paper conducts an econometric analysis using secondary data. Specifically, we construct a panel data set including going-out behavior and some covariates that affect it, and try to estimate the effect of emergency declaration by using the one-way error component model introduced by Baltagi (1984).

The model in the econometric analysis is as follows:

$$\begin{aligned} y_{it} &= \mathbf{x}_{it}'\boldsymbol{\beta} + \varepsilon_{it}, \qquad (16)\\ \varepsilon_{it} &= \alpha_i + \nu_{it}, \end{aligned}$$

where y is dependent variable of human flow, i is the index for the ith prefecture for $i = 1, \ldots, n$, t is the date for $t = 1, \ldots, T$, $\mathbf{x}$ is an explanatory variable vector containing covariates, $\boldsymbol{\beta}$ is an unknown parameter vector, ε is the disturbance term, α is prefecture-level heterogeneity, and ν is stochastic variability.

The dependent variable used in this study is the Google COVID-19 Community Mobility Reports, which is published by Google (2021) as data showing the amount of change in people's mobility. The dataset consists of the change in mobility against a reference value for six categories[3]:

[3] "Retail and recreation" refers to visits to entertainment venues, including restaurants, shopping centers, museums,

retail and recreation, grocery and pharmacy, parks, transit stations, workplaces, and residential. Furthermore, the dataset consists of both comprehensive data for Japan and data on changes in mobility at the sub-regional level, which is made up of 47 prefectures.

This data is based on anonymized location data obtained from users of services using Google Account, including applications such as Google Maps, and from users of devices using the Android operating system who have turned on the "Location History" setting. This data defines the number of visits as the volume of activity, except Residential[4], and has the daily change in volume of activity relative to the median volume of activity for each day of the week between 3 January 2020 and 6 February 2020, before the spread of COVID-19.

In addition, in order to eliminate the trend by day of the week regarding the amount of mobility brought about by behavioral changes under COVID-19, such as the prevalence of work-from-home, as described in the introduction, we use a 7-day moving average for the mobility of the dependent variable. From the perspective of missing values, the mobility categories used in this analysis are the "Retail and recreation", "Grocery and pharmacy", "Workplaces", and "Residential" categories in the Google COVID-19 Community Mobility Reports corresponding to the four dependent variables `retail`, `grocery`, `workplaces`, and `residential`, respectively. Furthermore, in order to confirm the robustness of this analysis, we also conduct an analysis using data obtained by Apple's map application in addition to this data as a sensitivity analysis.

This paper define the explanatory vector as:

$$\mathbf{x}_{it} := \left[\mathbf{d}'_{it}, \mathbf{w}'_{it}\right]',$$

where $\mathbf{d}$ is vector of target variables, and $\mathbf{w}$ is covariate vector. The target explanatory variables in this paper are the emergency declarations issued by the Japanese government in 2020 and 2021. The date data on the emergency declarations are obtained from Katafuchi (2020). More specifically, we use a binary dummy variable as the target explanatory variable, which takes the value 1 when prefecture i is under a state of emergency declaration at date t, and 0 otherwise.

and other shopping and experiential facilities; "Grocery and pharmacy" refers to visits to grocery shops, drugstores and other facilities where people can purchase daily essentials; "Parks" refers to visits to parks, including national parks and gardens; "Transit stations" refers to visits to public transport hubs; "Workplaces" refers to visits to workplaces; and "Residential" refers to targeted time spent at home. For more detail of mobility data, see Google (2021).

[4] For Residential, the time spent is counted as the amount of mobility, not the number of visits.

The purpose of the empirical analysis in this study is to clarify the extent to which the change in mobility differs under the declaration of a state of emergency. As the first econometric model-based analysis in this study, the binary dummy variable $\texttt{emergency}_{it}$, which does not distinguish the number of emergency declarations, is used as the explanatory variable of interest in order to ascertain the pure correlation that exists between emergency declarations and the volume of mobility. As a second analysis using the econometric model, we use the binary dummy variables $\texttt{emergency\_1st}_{it}$, $\texttt{emergency\_2nd}_{it}$, $\texttt{emergency\_3rd}_{it}$, and $\texttt{emergency\_4th}_{it}$ as target explanatory variables in order to determine the extent to which people's going-out behavior was affected by the policy intervention of declaring a state of emergency, depending on the number of times it was declared.

For the covariates vector, this paper includes weather information and prior information on the infection status of COVID-19 as factors that vary from prefecture to prefecture and from day to day and holiday information as factors that vary from day to day, which are likely to affect going-out behavior. We describe the detail of these covariates below.

First, daily precipitation data $\texttt{precipitation}_{it}$ obtained from the Japan Meteorological Agency is used as weather information. The data observed at the prefectural capital of each prefecture is used as the weather information data for that prefecture. The reason why precipitation data is used here is that precipitation is a factor that can be predicted in advance by weather forecasting, and thus may affect the decision-making process for going-out. In addition, in order to deal with precipitation anomalies caused by disasters such as torrential rains and typhoons, precipitation data are logarithmically converted from values adjusted by the average of all prefectures during the sample period.

Second, as prior information on COVID-19 infection status, we use the data obtained from TOYO KEIZAI ONLINE (2020) on the number of daily COVID-19 positive cases by prefecture one day before the seven-day moving average to remove the day-of-week trend[5] ($\texttt{positive\_per1000}_{it}$). Furthermore, since the size of the population is reflected in the actual size of the number of positive cases, we use the number of positive cases per 1,000 people using the 2020 population projection

[5]In Japan, there is a trend in the number of positive cases by day of the week, with a significant decrease in the number of positive cases the day after weekend and a national holiday. It has been suggested that this trend may be a manifestation of the strategy of health authorities and hospitals with COVID-19 testing resources to deliberately reduce the number of tests on weekends and national holidays in order to prevent pressure on medical conditions such as the number of hospital beds (Njeru et al., 2021).

data from the Ministry of Internal Affairs and Communications in order to control for the effect of population on the number of positive cases and to make the covariate more representative of the reality of the pandemic situation. We consider that this variable allows us to control the impact of the number of COVID-19 positives by prefecture, which is reported daily in the news, on people's decisions to go out or stay home on the following day.

Third, as a factor that does not vary by prefecture but varies with time, this study uses a binary dummy variable for national holidays that takes the value of 1 if it is a national holiday and 0 otherwise, which may affect people's going-out behavior ($\texttt{national\_holiday}_t$). In addition, we use as $\texttt{unofficial\_holiday}_t$ a dummy variable that takes a value of 1 for days that are not designated as "national holidays" by Japanese law, but on which people tend to take holidays[6], and 0 otherwise. We expect these variables, $\texttt{national\_holiday}_t$ and $\texttt{unofficial\_holiday}_t$ to control for the considerable variation in people's going-out behavior during national holidays observed in the changes in mobility as seen in the introduction.

These dependent variables, explanatory variables of interest, and covariate data will be combined to construct a prefecture-specific daily panel data set. Regarding data availability, the sample period is from 1 April, 2020 to 31 August, 2021. The number of prefectures in the sample is $n = 47$, the number of days in the sample is $T = 518$, and the sample size therefore is $N = nT = 47 \times 518 = 24,346$. Using the sample, we estimate the model (16) using the fixed effects and random effects estimators to estimate heterogeneity by prefecture, respectively. After estimating the model using both estimators, we interpret the coefficients estimated by the fixed effects estimator if the Hausman test statistic exceeds the 95% statistical significance level, and by the random effects estimator otherwise.

3.2 Result

In this subsection, we use the secondary data described above to analyze how these declarations affected people's going-out behavior in the prefectures in Japan that experienced the first and second emergency declarations. First, we provide an overview of how emergency declarations, the explanatory variable of most interest to us, have been issued.

[6]In this paper, we define new year holidays and Obon holidays as `unofficial_holiday` for which this variable takes the value 1. Specifically, we define the new year holidays as January 2 and 3 in 2021 and the Obon holidays as 13 August to 16 in 2020 and 2021 as `unofficial_holiday`.

Table 1 shows the period over which emergency declarations related to COVID-19 have been issued in the early stage of the pandemic in 2020. Firstly, the table shows that in 2020 the emergency declarations were issued in two phases: the first phase (7 April 2020) and the second phase (16 April 2020), which eventually covered the whole of the Japanese prefectures. The starting date for the declaration of a state of emergency depends on the infection situation and medical system in each prefecture (Cabinet Secretariat, Japan, 2021; Ministry of Health, Labour, and Welfare, Japan, 2020). This table confirms the fact that the first stage of the emergency declarations took place mainly in the metropolitan areas. Secondly, it can be seen that the dates for the lifting of these emergency declarations vary in small increments: stage 1 (14 May 2020), stage 2 (21 May 2020), and stage 3 (25 May 2020). These release dates also depend on the extent to which the situation has been alleviated by the declaration of a state of emergency (Cabinet Secretariat, Japan, 2021).

Next, Table 2 shows the period over which emergency declarations related to COVID-19 have been issued in 2021. First, the table shows that, unlike the 2020 emergency declarations, the 2021 emergency declarations were not issued for all of Japan's prefectures for all of its times. The table also shows that among the prefectures where emergency declarations were issued at the beginning of 2021, the start dates were divided into Phase 1 (8 January 2021) and Phase 2 (14 January 2021). This difference is due to the fact that, as with the declaration of a state of emergency in 2020, it depends on the infection situation in each prefecture. Secondly, as in 2020, the table shows that the date of the lifting of the state of emergency at the beginning of 2021 depends on the COVID-19 status and the medical system of each prefecture, with the first stage (7 February 2021), the second stage (28 February 2021) and the third stage (21 March 2021). The table also shows that the prefectures with the highest number of emergency declarations among all prefectures are Tokyo, Osaka, and Fukuoka.

As Tables 1 and 2 show, the declaration of a state of emergency in 2020 was issued to all prefectures, but with a difference between the start date and the lift date, while the declaration of a state of emergency in 2021 was issued to a limited number of prefectures, with a difference between the start date and the lift date. Using this heterogeneity of emergency declarations at the prefecture and date level, this study analyzes the effect of emergency declarations on going-out behavior.

Before proceeding to the analysis using the panel data model, we first use descriptive statistical analysis to see how going-out behavior and COVID-19 infection status in Japan have changed over

Table 1: Range of emergency statement in relation to COVID-19 declared in 2020 for prefectures of Japan

prefecture_en	emergency_start	emergency_end	times
Chiba	2020-04-07	2020-05-25	1
Fukuoka	2020-04-07	2020-05-14	1
Hyogo	2020-04-07	2020-05-21	1
Kanagawa	2020-04-07	2020-05-25	1
Osaka	2020-04-07	2020-05-21	1
Saitama	2020-04-07	2020-05-25	1
Tokyo	2020-04-07	2020-05-25	1
Aichi	2020-04-16	2020-05-14	1
Akita	2020-04-16	2020-05-14	1
Aomori	2020-04-16	2020-05-14	1
Ehime	2020-04-16	2020-05-14	1
Fukui	2020-04-16	2020-05-14	1
Fukushima	2020-04-16	2020-05-14	1
Gifu	2020-04-16	2020-05-14	1
Gunma	2020-04-16	2020-05-14	1
Hiroshima	2020-04-16	2020-05-14	1
Hokkaido	2020-04-16	2020-05-25	1
Ibaraki	2020-04-16	2020-05-14	1
Ishikawa	2020-04-16	2020-05-14	1
Iwate	2020-04-16	2020-05-14	1
Kagawa	2020-04-16	2020-05-14	1
Kagoshima	2020-04-16	2020-05-14	1
Kochi	2020-04-16	2020-05-14	1
Kumamoto	2020-04-16	2020-05-14	1
Kyoto	2020-04-16	2020-05-21	1
Mie	2020-04-16	2020-05-14	1
Miyagi	2020-04-16	2020-05-14	1
Miyazaki	2020-04-16	2020-05-14	1
Nagano	2020-04-16	2020-05-14	1
Nagasaki	2020-04-16	2020-05-14	1
Nara	2020-04-16	2020-05-14	1
Niigata	2020-04-16	2020-05-14	1
Oita	2020-04-16	2020-05-14	1
Okayama	2020-04-16	2020-05-14	1
Okinawa	2020-04-16	2020-05-14	1
Saga	2020-04-16	2020-05-14	1
Shiga	2020-04-16	2020-05-14	1
Shimane	2020-04-16	2020-05-14	1
Shizuoka	2020-04-16	2020-05-14	1
Tochigi	2020-04-16	2020-05-14	1
Tokushima	2020-04-16	2020-05-14	1
Tottori	2020-04-16	2020-05-14	1
Toyama	2020-04-16	2020-05-14	1
Wakayama	2020-04-16	2020-05-14	1
Yamagata	2020-04-16	2020-05-14	1
Yamaguchi	2020-04-16	2020-05-14	1
Yamanashi	2020-04-16	2020-05-14	1

Notes: emergency_start indicates the date on which a state of emergency was declared for the prefecture indicated in the row, and emergency_end indicates the date on which the state of emergency was lifted.

Source: Katafuchi (2020).

Table 2: Range of emergency statement in relation to COVID-19 declared in 2021 for prefectures of Japan

prefecture_en	emergency_start	emergency_end	times
Chiba	2021-01-08	2021-03-21	2
Kanagawa	2021-01-08	2021-03-21	2
Saitama	2021-01-08	2021-03-21	2
Tokyo	2021-01-08	2021-03-21	2
Aichi	2021-01-14	2021-02-28	2
Fukuoka	2021-01-14	2021-02-28	2
Gifu	2021-01-14	2021-02-28	2
Hyogo	2021-01-14	2021-02-28	2
Kyoto	2021-01-14	2021-02-28	2
Osaka	2021-01-14	2021-02-28	2
Tochigi	2021-01-14	2021-02-07	2
Hyogo	2021-04-25	2021-06-20	3
Kyoto	2021-04-25	2021-06-20	3
Osaka	2021-04-25	2021-06-20	3
Tokyo	2021-04-25	2021-06-20	3
Aichi	2021-05-12	2021-06-20	2
Fukuoka	2021-05-12	2021-06-20	3
Hiroshima	2021-05-16	2021-06-20	2
Hokkaido	2021-05-16	2021-06-20	2
Okayama	2021-05-16	2021-06-20	2
Okinawa	2021-05-23		2
Tokyo	2021-07-12		4
Chiba	2021-08-02		3
Kanagawa	2021-08-02		3
Osaka	2021-08-02		4
Saitama	2021-08-02		3
Fukuoka	2021-08-20		4
Gunma	2021-08-20		2
Hyogo	2021-08-20		3
Ibaraki	2021-08-20		2
Kyoto	2021-08-20		3
Shizuoka	2021-08-20		2
Tochigi	2021-08-20		3
Aichi	2021-08-27		3
Gifu	2021-08-27		3
Hiroshima	2021-08-27		2
Hokkaido	2021-08-27		3
Mie	2021-08-27		2
Miyagi	2021-08-27		2
Okayama	2021-08-27		2
Shiga	2021-08-27		2

Notes: emergency_start indicates the date on which a state of emergency was declared for the prefecture indicated in the row, and emergency_end indicates the date on which the state of emergency was lifted. The missing value in emergency_end indicates that a state of emergency was in effect at the end of the sample period (August 31, 2021).

Source: Katafuchi (2020).

the sample period. Table 3 shows the monthly means of how the four explanatory variables of our panel data model, i.e., going-out, and one of the covariates, i.e., infection status, have changed across Japan. The table shows, first, that for the whole of Japan in the sample period, except grocery, mobility was lower than in the reference period (Google, 2021) before the COVID-19 pandemic. Residential is positive in all periods, but since this is time spent at home, it can be interpreted as an increase in time spent at home, i.e., a decrease in going-out behavior, in all of Japan during the sample period compared to the reference period. Second, we can confirm that going-out behavior during the declaration of the state of emergency in 2020 (April and May 2020) and the initial declaration of the state of emergency in 2021 (January and February 2021) was reduced compared to before and after. Similar to the findings above, it is possible to identify a similar trend in `residential`. On the other hand, for the third and fourth emergency declarations after April 2021, it can be confirmed that it is difficult to interpret changes in the amount of mobility from this monthly average for all prefectures.

Table 3: Mean of mobility data and infection status by month for whole Japan

year	month	`retail`	`grocery`	`workplaces`	`residential`	`positive_per1000`
2020	4	-0.293	-0.004	-0.216	0.120	0.0029
2020	5	-0.294	-0.020	-0.268	0.138	0.0010
2020	6	-0.139	0.002	-0.127	0.069	0.0004
2020	7	-0.114	-0.003	-0.145	0.070	0.0027
2020	8	-0.097	0.014	-0.196	0.075	0.0087
2020	9	-0.094	-0.010	-0.139	0.055	0.0044
2020	10	-0.079	-0.002	-0.092	0.041	0.0040
2020	11	-0.069	-0.002	-0.107	0.048	0.0098
2020	12	-0.075	0.011	-0.134	0.067	0.0193
2021	1	-0.211	-0.065	-0.201	0.098	0.0390
2021	2	-0.177	-0.031	-0.152	0.073	0.0167
2021	3	-0.109	-0.008	-0.124	0.052	0.0091
2021	4	-0.124	0.010	-0.145	0.056	0.0251
2021	5	-0.167	0.027	-0.181	0.083	0.0416
2021	6	-0.144	0.046	-0.096	0.059	0.0174
2021	7	-0.111	0.058	-0.135	0.063	0.0195
2021	8	-0.147	0.062	-0.201	0.092	0.1214

Notes: Each row shows the monthly level average for the whole Japan in the month indicated by the year-month pair.

Source: Google (2021), TOYO KEIZAI ONLINE (2020) and authors' calculation.

In order to check the descriptive statistics more precisely, Table 4 shows how the going-out behavior changed during the period of the initial emergency declaration in 2021 by means of averages calculated for the areas where the initial emergency declaration was issued in January, February, and March 2021 (where `emergency` is 1), and the areas where it was not issued (where `emergency` is 0). These averages are population-weighted averages for each of the initial emergency declarations in 2021. The results show that in each of the periods, going-out behavior is lower (`residential`, time spent at home is higher) in areas where the state of emergency has been declared compared to areas where it has not been declared.

Table 4: Grouped mean of mobility and infection status by emergency declaration status for January, Feburuary, and March 2021

year	month	`emergency`	`retail`	`grocery`	`workplaces`	`residential`	`positive_per1000`
2021	1	0	-0.0046	-0.0018	-0.0044	0.0022	0.0005
2021	1	1	-0.0212	-0.0063	-0.0210	0.0102	0.0052
2021	2	0	-0.0037	-0.0009	-0.0030	0.0015	0.0002
2021	2	1	-0.0182	-0.0027	-0.0166	0.0083	0.0016
2021	3	0	-0.0017	-0.0001	-0.0024	0.0009	0.0002
2021	3	1	-0.0124	-0.0010	-0.0137	0.0061	0.0012

Notes: Each row shows the average value at the monthly level, indicated by the year, month, `emergency` pair, where `emergency` is 1 if prefectures have been under a state of emergency in corresponding year-month pair, and 0 if it has not. The monthly averages here are weighted averages using population for the prefectures that make up the subset indicated by the flags `emergency`.

Source: Google (2021), TOYO KEIZAI ONLINE (2020) and authors' calculation.

Thus, the descriptive statistical analysis shows that going-out behavior decreased in the sample period compared to the pre-pandemic period. It can also be confirmed that during the period of the emergency declaration issued at the beginning of 2021, there was a decrease in going-out behavior in the areas where the declaration was issued. However, for the reason that the declaration of the state of emergency in 2020 was issued to all prefectures, although there is a difference between the start and termination dates, it is not possible to conduct an analysis for 2020 like the one conducted by Table 4 because it is difficult to establish a precise treatment and control group as in the beginning 2021. Furthermore, it is also difficult to compare the effect of the declaration of a state of emergency on going-out behavior in 2020 with the effect in 2021. In addition, from the emergency declarations other than the initial one in 2021, it is not possible to correspond the setting of the treatment and control groups because the number of declarations is often different even if they were issued during the same period in each prefecture. Therefore, this study analyzes the effects of the declaration of a state of emergency on going-out behavior using a panel data analysis in the following.

Table 5 shows the correlation between the declaration of a state of emergency and going-out behavior under the control of daily variables that influence going-out behavior. Here, the target explanatory variable for the emergency declaration is the explanatory variable expressed by a binary variable that does not distinguish between the number of times on the day the emergency was declared. For all four dependent variables, the Hausman test statistics all show statistical significance of 99.9% or higher, so the results using the fixed effects estimator are shown. The results of the estimation of the coefficients show a statistically significant negative correlation between the declaration of emergency and going-out behavior with a p-value of less than 0.1% when all the dependent variables except `residential` are used. On the other hand, when `residential` is used as the dependent variable, there is a statistically significant positive correlation of the same magnitude between emergency declaration and time at home. This result suggests the possibility that the declaration of a state of emergency had a negative causal effect on the going-out behavior (and that the declaration of a state of emergency had a positive causal effect on the staying-home behavior) in terms of the comparative value of the going-out behavior with the pre-pandemic one. This result is consistent with the empirical analysis conducted in Katafuchi et al. (2021).

Table 5: Result of panel data analysis for the association between emergency statement and mobility for the prefectures in Japan

dependent	explanatory	estimate	s.e.	p	hausman	hausman_p	estimator
`retail`	`emergency`	-0.1500	0.0047	<0.0001	132.8206	<0.0001	fixed_effect
`grocery`	`emergency`	-0.0302	0.0035	<0.0001	95.5653	<0.0001	fixed_effect
`workplaces`	`emergency`	-0.0779	0.0050	<0.0001	197.4278	<0.0001	fixed_effect
`residential`	`emergency`	0.0497	0.0023	<0.0001	185.0906	<0.0001	fixed_effect

Notes: The estimation of the panel data in this table is based on a vector of explanatory variables including a vector of covariates composed of COVID-19 infection status (`positive_per1000`), weather conditions (`precipitation`) by prefecture by day, and holiday status (`national_holiday` and `unofficial_holiday`). The sample size is 47 prefectures between 1 April 2020 and 31 August 2021, i.e., $N = nT = 47 \times 518 = 24,346$. The estimation results for each row show the coefficients estimated using the fixed effects estimator if the Hausman test statistic indicated by the "hausman" column is statistically significant at 95% or more, and the random effects estimator otherwise. s.e. stands for cluster robust standard errors.

Next, the results for the target explanatory variable, the declaration of emergency, distinguishing between the first (2020), second, third, and fourth (2021) declarations, i.e., `emergency_1st`, `emergency_2nd`, `emergency_3rd`, and `emergency_4th`, are shown in Table 6. In this estimation, as in Table 5, the covariate vector is composed of day-specific variables that affect going-out behavior. First, for the estimator, a fixed-effects estimator is adopted for all dependent variables according to the results of the Hausman test statistic as well as 5. The statistical significance of the estimated coefficients for the four target explanatory variables discussed above all show p-values below 5%, except for `emergency_4th` when `retail` is used as the dependent variable, `emergency_4th` for `grocery`, `emergency_2nd` and `emergency_3rd` for `workplace`, and `emergency_4th` for `residential`.

Table 6: Result of panel data analysis for the association between emergency statement and mobility for the prefectures in Japan, using divided emergency statement for 2020 and 2021

dependent	explanatory	estimate	s.e.	p	hausman	hausman_p	estimator
`retail`	`emergency_1st`	-0.2045	0.0065	<0.0001	91.1657	<0.0001	fixed_effect
	`emergency_2nd`	-0.0757	0.0055	<0.0001			
	`emergency_3rd`	-0.0572	0.0116	<0.0001			
	`emergency_4th`	-0.0024	0.0154	0.8773			
`grocery`	`emergency_1st`	-0.0358	0.0029	<0.0001	492.5250	<0.0001	fixed_effect
	`emergency_2nd`	-0.0372	0.0061	<0.0001			
	`emergency_3rd`	0.0135	0.0063	0.0320			
	`emergency_4th`	-0.0075	0.0117	0.5194			
`workplaces`	`emergency_1st`	-0.1332	0.0049	<0.0001	467.4400	<0.0001	fixed_effect
	`emergency_2nd`	0.0028	0.0033	0.3937			
	`emergency_3rd`	0.0067	0.0100	0.5058			
	`emergency_4th`	0.0435	0.0144	0.0024			
`residential`	`emergency_1st`	0.0773	0.0023	<0.0001	718.3960	<0.0001	fixed_effect
	`emergency_2nd`	0.0092	0.0010	<0.0001			
	`emergency_3rd`	0.0078	0.0041	0.0586			
	`emergency_4th`	-0.0140	0.0066	0.0340			

Notes: The estimation of the panel data in this table is based on a vector of explanatory variables including a vector of covariates composed of COVID-19 infection status (`positive_per1000`), weather conditions (`precipitation`) by prefecture by day, and holiday status (`national_holiday` and `unofficial_holiday`). by day. The sample size is 47 prefectures between 1 April 2020 and 31 August 2021, i.e., $N = nT = 47 \times 518 = 24,346$. The estimation results for each row show the coefficients estimated using the fixed effects estimator if the Hausman test statistic indicated by the "hausman" column is statistically significant at 95% or more, and the random effects estimator otherwise. s.e. stands for cluster robust standard errors.

In the model with the dependent variables of `retail`, `grocery`, and `workplaces`, the signs of the coefficients are negative for all explanatory variables that showed statistical significance with p-values below 0.1%, but positive for all explanatory variables that showed statistical significance with p-values below 5% and greater or equal than 0.1%. On the other hand, in the model using `residential` as the dependent variable, the coefficient of `emergency_1st` and `emergency_2nd`, which showed statistical significance with p-value less than 0.0001, is positive, but for coefficients of explanatory variables with p-value less than 0.05 and greater or equal than 0.0001, the coefficient of `emergency_4th` is negative. As for the magnitude of the coefficients, it can be confirmed that the coefficients become smaller as the number of emergency declarations increases in the model with the dependent variable of `retail`, which showed statistical significance $p < 0.1\%$ for the coefficients of the explanatory variables for the first through third emergency declarations. Furthermore, in the models using `workplace` and `residential`, the coefficients with $0.1\% \leq p < 5\%$ increase with the number of emergency declarations (and decrease for `residential`).

These results obtained by Table 6 can be summarized by two points. First, the results suggest that the first, second, and third declarations of emergency may have a negative causal effect on going-out behavior when `retail` is the target of going-out behavior. Furthermore, the negative causal effects are smaller for the second than for the first and for the third than for the second. Second, when `workplaces` is the target of going-out behavior, the results suggest that the first emergency declaration may have a negative causal effect and the fourth emergency declaration may have a positive causal effect on commuting behavior. Third, in the case of `residential`, i.e., time at home, the results suggest that the first and second emergency declarations may have had a positive causal effect, and the fourth may have had a negative causal effect on stay-home behavior.

The interpretation of the results is as follows: First, the estimation results of the model with `retail` as the dependent variable suggest that people refrained from going-out for retail and entertainment purposes during the first three emergency declarations. However, the degree of restraint may have decreased with each additional declaration. Second, the estimated coefficients for emergency declarations in the model with `grocery` as the dependent variable, i.e., the estimated coefficients for emergency declarations for going-out to purchase daily necessities such as food and medicine, indicate the possibility that the decrease in the effect of refraining from going-out with an increase in the number of declarations, as seen in the results for `retail`, is unlikely to be reflected. Third, for `workplaces`, although people did not work in the workplace under the first declaration of emergency compared to before the pandemic, they may have worked in the workplace more in 2021, i.e., under the second and subsequent declarations of emergency, than before the pandemic. Fourth, the coefficient on emergency declarations in the model with `residential` as the dependent variable indicates that although the time spent at home increased under the first emergency declaration compared to the pre-pandemic period, the increase in time spent at home decreased in the second declaration, and by the fourth declaration, the time spent at home may have decreased compared to the pre-pandemic period.

Even if a person has sufficient subjective risk of COVID-19 infection and stigma against going-out, the purpose of going to a place represented by the `grocery` category may result in the need to go out to purchase items needed for survival. For going-out behavior for the purpose of going to a place represented by the `workplaces` category, people may also be required to commute by order of their company or their boss. Therefore, going-out for these purposes differs from `retail` and can be interpreted as going-out behavior that cannot be refrained from in some cases. In addition, since `residential` is a variable that indicates the time spent at home, it is subject to complex fluctuations depending on the types of going-out that can be restrained, such as `retail`, and the types of going-out that cannot be restrained, such as `workplaces` and `grocery`. Therefore, an increase in `residential` does not necessarily mean that people are refraining from going-out, and a decrease in `residential` does not necessarily mean that people are not refraining from going-out.

Taking into account these characteristics of categories of mobility, the results presented by Table 6 can be interpreted as follows: for completely restraint-able going-out (`retail`), the effect of restraint decreased as the number of emergency declarations increased, but this relationship could not be confirmed for non-restraint-able going-out (`grocery` and `workplaces`). Therefore, the empirical analysis of this study supports the results presented by the theoretical model, which shows that the declaration of a state of emergency causes people to refrain from going-out, and that the effect of this refraining weakens with each successive declaration for those going-out that can be refrained from, where people have more freedom of decision-making.

In order to check the robustness of this relationship, the results of sensitivity analysis are presented below; first, the results without the addition of the covariate vector are presented in Tables 7 and 8. Table 7 shows the results with explanatory variables that do not distinguish the numebr of emergency declarations, while Table 8 shows the results with explanatory variables that do distinguish between them. These results are generally consistent with those of Tables 5 and 6 in that emergency declarations have a restraint effect on going-out, and that the restraint effect on `retail`, the going-out behavior with the highest degree of decision-making freedom, decreases as the number of emergency declarations increases.

Second, we present the estimation results of the unchosen estimator, i.e., a random effect estimator, in Tables 5 and 6 with respect to the Hausman test statistic. Table 9 shows the estimation results with the estimator not selected by the Hausman test statistic using explanatory variables

Table 7: Result of panel data analysis for the association between emergency statement and mobility for the prefectures in Japan: sensitivity analysis without covariates

dependent	explanatory	estimate	s.e.	p	hausman	hausman_p	estimator
`retail`	`emergency`	-0.1452	0.0051	<0.0001	54.5103	<0.0001	fixed_effect
`grocery`	`emergency`	-0.0223	0.0033	<0.0001	5.4977	0.0190	fixed_effect
`workplaces`	`emergency`	-0.0836	0.0060	<0.0001	150.7838	<0.0001	fixed_effect
`residential`	`emergency`	0.0510	0.0026	<0.0001	353.5378	<0.0001	fixed_effect

Notes: The estimation of the panel data in this table is based on a vector of explanatory variables not including a vector of covariates. The sample size is 47 prefectures between 1 April 2020 and 31 August 2021, i.e., $N = nT = 47 \times 518 = 24,346$. The estimation results for each row show the coefficients estimated using the fixed effects estimator if the Hausman test statistic indicated by the "hausman" column is statistically significant at 95% or more, and the random effects estimator otherwise. s.e. stands for cluster robust standard errors.

Table 8: Result of panel data analysis for the association between emergency statement and mobility for the prefectures in Japan, using distinguished emergency statement for 2020 and 2021: sensitivity analysis without covariates

dependent	explanatory	estimate	s.e.	p	hausman	hausman_p	estimator
`retail`	`emergency_1st`	-0.1961	0.0068	<0.0001	74.2635	<0.0001	fixed_effect
	`emergency_2nd`	-0.0861	0.0051	<0.0001			
	`emergency_3rd`	-0.0748	0.0084	<0.0001			
	`emergency_4th`	-0.0521	0.0069	<0.0001			
`grocery`	`emergency_1st`	-0.0376	0.0029	<0.0001	22.4570	0.0002	fixed_effect
	`emergency_2nd`	-0.0266	0.0080	<0.0001			
	`emergency_3rd`	0.0339	0.0053	<0.0001			
	`emergency_4th`	0.0514	0.0021	<0.0001			
`workplaces`	`emergency_1st`	-0.1409	0.0046	<0.0001	278.5815	<0.0001	fixed_effect
	`emergency_2nd`	-0.0042	0.0040	0.2947			
	`emergency_3rd`	-0.0181	0.0112	0.1068			
	`emergency_4th`	-0.0301	0.0133	0.0233			
`residential`	`emergency_1st`	0.0779	0.0023	<0.0001	1337.0266	<0.0001	fixed_effect
	`emergency_2nd`	0.0141	0.0019	<0.0001			
	`emergency_3rd`	0.0201	0.0031	<0.0001			
	`emergency_4th`	0.0217	0.0022	<0.0001			

Notes: The estimation of the panel data in this table is based on a vector of explanatory variables not including a vector of covariates. The sample size is 47 prefectures between 1 April 2020 and 31 August 2021, i.e., $N = nT = 47 \times 518 = 24,346$. The estimation results for each row show the coefficients estimated using the fixed effects estimator if the Hausman test statistic indicated by the "hausman" column is statistically significant at 95% or more, and the random effects estimator otherwise. s.e. stands for cluster robust standard errors.

that do not distinguish between emergency declarations. In contrast, Table 10 shows the estimation results with explanatory variables that distinguish the number of emergency declarations. The estimation results are consistent with those estimated by Tables 5 and 10, concerning the sign of the explanatory variables and the magnitude of the estimated coefficients for the first (2020), second, third, and fourth (2021) emergency declarations.

Table 9: Result of panel data analysis for the association between emergency statement and mobility for the prefectures in Japan: sensitivity analysis using the estimator not chosen by Hausman test statistics

dependent	explanatory	estimate	s.e.	p	hausman	hausman_p	estimator
`retail`	`emergency`	-0.1502	0.0047	<0.0001	132.8206	<0.0001	random_effect
`grocery`	`emergency`	-0.0302	0.0035	<0.0001	95.5653	<0.0001	random_effect
`workplaces`	`emergency`	-0.0787	0.0050	<0.0001	197.4278	<0.0001	random_effect
`residential`	`emergency`	0.0498	0.0023	<0.0001	185.0906	<0.0001	random_effect

Notes: The estimation of the panel data in this table is based on a vector of explanatory variables including a vector of covariates composed of COVID-19 infection status (`positive_per1000`), weather conditions (`precipitation`) by prefecture by day, and holiday status (`national_holiday` and `unofficial_holiday`). The sample size is 47 prefectures between 1 April 2020 and 31 August 2021, i.e., $N = nT = 47 \times 518 = 24,346$. The estimation results for each row show the coefficients estimated using the random effects estimator if the Hausman test statistic indicated by the "hausman" column is statistically significant at 95% or more, and the fixed effects estimator otherwise, contrary to Tables 5 and 6.

Third, Tables 11 and 12 show the analysis conducted using only the 2021 sample. The reasons for this analysis are threefold: First, the content of the request to declare a state of emergency is different in 2020 and 2021[7]. Second, the means of declaring a state of emergency are different between 2020 and 2021[8]. Third, it is possible that people's perceptions and decisions about emergency declarations have changed between 2020 and 2021[9]. In the analysis that does not distinguish the number of emergency declarations using the 2021 sample, i.e., Table 11, all of the results suggest the possibility that emergency declarations have a voluntary restraint effect of going-out, as in Table 5, except for the model that employs `workplaces` as the dependent variable. In the results of the

[7] Under the first emergency declaration issued in 2020, the Japanese government requested the closure of elementary, junior high, and nursery schools, while no such request was made under the second, third, and fourth emergency declarations in 2021. In addition, under the 2021 emergency declaration, the government requested that restaurants shorten their hours of operation to 8 p.m., while no such request was made in the 2020 emergency declaration (NHK, 2021).

[8] The first emergency declaration issued in 2020 targeted all prefectures, while the 2021 emergency declaration narrowed down the target prefectures, depending on medical conditions (NHK, 2021).

[9] The period between the first declaration of a state of emergency in 2020 and the second declaration of a state of emergency in early 2021 was about seven months, which was longer than the period between other consecutive declarations of a state of emergency.

Table 10: Result of panel data analysis for the association between emergency statement and mobility for the prefectures in Japan, using distinguished emergency statement for 2020 and 2021: sensitivity analysis using the estimator not chosen by Hausman test statistics

dependent	explanatory	estimate	s.e.	p	hausman	hausman_p	estimator
`retail`	`emergency_1st`	-0.2046	0.0065	<0.0001	91.1657	<0.0001	random_effect
	`emergency_2nd`	-0.0760	0.0055	<0.0001			
	`emergency_3rd`	-0.0577	0.0116	<0.0001			
	`emergency_4th`	-0.0031	0.0153	0.8412			
`grocery`	`emergency_1st`	-0.0359	0.0029	<0.0001	492.5250	<0.0001	random_effect
	`emergency_2nd`	-0.0373	0.0061	<0.0001			
	`emergency_3rd`	0.0135	0.0063	0.0318			
	`emergency_4th`	-0.0075	0.0118	0.5212			
`workplaces`	`emergency_1st`	-0.1337	0.0050	<0.0001	467.4400	<0.0001	random_effect
	`emergency_2nd`	0.0013	0.0036	0.7224			
	`emergency_3rd`	0.0048	0.0102	0.6377			
	`emergency_4th`	0.0414	0.0147	0.0047			
`residential`	`emergency_1st`	0.0774	0.0023	<0.0001	718.3960	<0.0001	random_effect
	`emergency_2nd`	0.0094	0.0010	<0.0001			
	`emergency_3rd`	0.0081	0.0041	0.0510			
	`emergency_4th`	-0.0137	0.0066	0.0363			

Notes: The estimation of the panel data in this table is based on a vector of explanatory variables including a vector of covariates composed of COVID-19 infection status (`positive_per1000`), weather conditions (`precipitation`) by prefecture by day, and holiday status (`national_holiday` and `unofficial_holiday`). by day. The sample size is 47 prefectures between 1 April 2020 and 31 August 2021, i.e., $N = nT = 47 \times 518 = 24,346$. The estimation results for each row show the coefficients estimated using the random effects estimator if the Hausman test statistic indicated by the "hausman" column is statistically significant at 95% or more, and the fixed effects estimator otherwise, contrary to Tables 5 and 6.

analysis that distinguishes the number of emergency declarations using the 2021 sample (Table 12), focusing on the dependent variables (`retail`, `residential`) whose coefficients for two or more emergency declarations are statistically significant at 95% or higher, we can confirm that the effect of voluntary restraint from going-out decreases as the number of emergency declarations increases. These results support the results estimated by Table 5 and 6.

Table 11: Result of panel data analysis for the association between emergency statement and mobility for the prefectures in Japan: sensitivity analysis using the sample in 2021

dependent	explanatory	estimate	s.e.	p	hausman	hausman_p	estimator
`retail`	`emergency`	-0.0708	0.0042	<0.0001	48.1004	<0.0001	fixed_effect
`grocery`	`emergency`	-0.0276	0.0078	0.0004	1.6776	0.8917	random_effect
`workplaces`	`emergency`	0.0049	0.0046	0.2867	112.8472	<0.0001	fixed_effect
`residential`	`emergency`	0.0106	0.0015	<0.0001	92.7958	<0.0001	fixed_effect

Notes: The estimation of the panel data in this table is based on a vector of explanatory variables including a vector of covariates composed of COVID-19 infection status (`positive_per1000`), weather conditions (`precipitation`) by prefecture by day, and holiday status (`national_holiday` and `unofficial_holiday`). The sample size is 47 prefectures between 1 January 2021 and 31 August 2021, i.e., $N = nT = 47 \times 243 = 11,421$. The estimation results for each row show the coefficients estimated using the fixed effects estimator if the Hausman test statistic indicated by the "hausman" column is statistically significant at 95% or more, and the random effects estimator otherwise. s.e. stands for cluster robust standard errors.

Fourth, the results for the different mobility datasets, Apple (2021) COVID-19 Mobility Trends Reports are shown in Tables 13 and 14. As in the previous discussion above, Table 13 shows the case with explanatory variables that do not distinguish the number of emergency declarations, while Table 14 shows the case with explanatory variables that do distinguish the number of the declarations. Apple's (2021) data are similar to Google's (2021) in that they are mobility data obtained from location data acquired by a map application of smartphones, but they differ in two ways: Apple (2021) is categorized by means of mobility (`driving` and `walking`) rather than by the purpose of mobility (Google, 2021), and the change in mobility of Apple (2021) is expressed as a comparison of the change in mobility for a given day (January 13 2020) rather than a comparison with the median value for each day of the week (Google, 2021)[10]. The results shown by these Tables can be summarized in two ways: First, the model that does not distinguish the number of emergency declarations shows a decrease in mobility under the declarations. Second, in the models that distinguish the number of emergency declarations, if we focus on the coefficients that show p-values

[10]In order to get closer to Google's (2021) definition of the change in mobility used for analyses in Tables 5-10, this paper adds the dummy variables (`sunday`, `monday`, `tuesday`, `thursday`, `friday`, and `saturday`) for each day of the week as new covariates to the vector of explanatory variables in sensitivity analysis using Apple (2021).

Table 12: Result of panel data analysis for the association between emergency statement and mobility for the prefectures in Japan, using distinguished emergency statement for 2021: sensitivity analysis using the sample in 2021

dependent	explanatory	estimate	s.e.	p	hausman	hausman_p	estimator
	`emergency_2nd`	-0.0754	0.0054	<0.0001			
`retail`	`emergency_3rd`	-0.0622	0.0096	<0.0001	64.0374	<0.0001	fixed_effect
	`emergency_4th`	-0.0223	0.0100	0.0251			
	`emergency_2nd`	-0.0418	0.0087	<0.0001			
`grocery`	`emergency_3rd`	0.0088	0.0071	0.2195	27.9151	0.0002	fixed_effect
	`emergency_4th`	-0.0083	0.0106	0.4324			
	`emergency_2nd`	0.0031	0.0040	0.4389			
`workplaces`	`emergency_3rd`	0.0071	0.0095	0.4585	113.1250	<0.0001	fixed_effect
	`emergency_4th`	0.0423	0.0148	0.0043			
	`emergency_2nd`	0.0116	0.0010	<0.0001			
`residential`	`emergency_3rd`	0.0096	0.0042	0.0221	89.5418	<0.0001	fixed_effect
	`emergency_4th`	-0.0127	0.0065	0.0503			

Notes: The estimation of the panel data in this table is based on a vector of explanatory variables including a vector of covariates composed of COVID-19 infection status (`positive_per1000`), weather conditions (`precipitation`) by prefecture by day, and holiday status (`national_holiday` and `unofficial_holiday`). by day. The sample size is 47 prefectures between 1 January 2021 and 31 August 2021, i.e., $N = nT = 47 \times 243 = 11,421$. The estimation results for each row show the coefficients estimated using the fixed effects estimator if the Hausman test statistic indicated by the "hausman" column is statistically significant at 95% or more, and the random effects estimator otherwise. s.e. stands for cluster robust standard errors.

of 5% or less, the amount of mobility decreases under the issuance of the emergency declarations, and the magnitude of the decrease becomes smaller as the number of emergency declarations increases except for the fourth emergency declaration with walking as the dependent variable. Third, the results suggest that the fourth declaration of emergency may not affect refraining from going-out using the means of driving. Thus, the analysis using the different datasets, Apple's 2021 data generally supports the results presented in Tables 5 and 6.

In this section, we conducted an empirical analysis of the effect of emergency declarations on voluntary restraint from going-out, taking into account the number of declarations. The results are consistent with the theoretical analysis conducted in Section 2, in that the declaration of a state of emergency has the effect of refraining from going-out, and that the effect of refraining from going-out decreases as the number of declarations of a state of emergency increases in the category of going-out that can be completely refrained from. The results of the empirical analysis were also shown to be robust by sensitivity analyses.

Table 13: Result of panel data analysis for the association between emergency statement and mobility for the prefectures in Japan: sensitivity analysis using Apple (2021)

dependent	explanatory	estimate	s.e.	p	hausman	hausman_p	estimator
`driving`	`emergency`	-0.3898	0.0315	<0.0001	2.7416	0.9937	random_effect
`walking`	`emergency`	-0.3770	0.0281	<0.0001	200.4244	<0.0001	fixed_effect

Notes: The estimation of the panel data in this table is based on a vector of explanatory variables including a vector of covariates composed of COVID-19 infection status (`positive_per1000`), weather conditions (`precipitation`) by prefecture by day, holiday status (`national_holiday` and `unofficial_holiday`). by day, and day of week dummy (`sunday`, `monday`, `tuesday`, `thursday`, `friday`, and `saturday`) by day. The sample size is 47 prefectures between 1 April 2020 and 31 August 2021, i.e., $N = nT = 47 \times 518 = 24,346$. The estimation results for each row show the coefficients estimated using the fixed effects estimator if the Hausman test statistic indicated by the "hausman" column is statistically significant at 95% or more, and the random effects estimator otherwise. s.e. stands for cluster robust standard errors.

Table 14: Result of panel data analysis for the association between emergency statement and mobility for the prefectures in Japan, using distinguished emergency statement for 2020 and 2021: sensitivity analysis using Apple (2021)

dependent	explanatory	estimate	s.e.	p	hausman	hausman_p	estimator
`driving`	`emergency_1st`	-0.6031	0.0149	<0.0001	27.6678	0.0157	fixed_effect
	`emergency_2nd`	-0.1717	0.0161	<0.0001			
	`emergency_3rd`	-0.0578	0.0243	0.0172			
	`emergency_4th`	-0.0687	0.0451	0.1273			
`walking`	`emergency_1st`	-0.5243	0.0179	<0.0001	196.0327	<0.0001	fixed_effect
	`emergency_2nd`	-0.1638	0.0184	<0.0001			
	`emergency_3rd`	-0.1208	0.0281	<0.0001			
	`emergency_4th`	-0.1469	0.0419	0.0005			

Notes: The estimation of the panel data in this table is based on a vector of explanatory variables including a vector of covariates composed of COVID-19 infection status (`positive_per1000`), weather conditions (`precipitation`) by prefecture by day, holiday status (`national_holiday` and `unofficial_holiday`). by day, and day of week dummy variables (`sunday`, `monday`, `tuesday`, `thursday`, `friday`, and `saturday`) by day. The sample size is 47 prefectures between 1 April 2020 and 31 August 2021, i.e., $N = nT = 47 \times 518 = 24,346$. The estimation results for each row show the coefficients estimated using the fixed effects estimator if the Hausman test statistic indicated by the "hausman" column is statistically significant at 95% or more, and the random effects estimator otherwise. s.e. stands for cluster robust standard errors.

4 Conclusion

This study examined the effect of non-legally binding policy interventions on people's going-out behavior when the number of interventions is increased, from two aspects: theoretical analysis and empirical analysis. In the theoretical analysis, we constructed a model that extends Katafuchi et al. (2021) so that the effect of the policy intervention changes with the number of times the announcement is executed. Furthermore, in comparative statics using the model, we confirmed that the effect of the policy intervention on the suppression of going-out declines with each increase in the number of implementations. In the empirical analysis, we developed a daily panel dataset at the prefectural level, focusing on the declaration of a state of emergency, a non-legally binding policy intervention in Japan to change behavior to mitigate the disadvantages arising from COVID-19. Furthermore, using the data, we analyzed the relationship between the four emergency declarations and going-out behavior and found that the effect of going-out decreased as the number of emergency declarations increased in the analysis of going-out behavior related to the objective category with a high degree of freedom to refrain from going-out, which is consistent with the theoretical model.

In light of the findings of this study, namely that similar emergency declarations have a diminishing effect on behavior change with each successive declaration, we suggest that policymakers should make more fundamental changes to the requests and punitive nature of emergency declarations to make them more progressive and practical in their policy interventions.

The change in going-out behavior due to the declaration of emergency is heterogeneous across occupations and industries[11]. This may be due to whether remote work is possible or not. However, even if remote work is possible and the types of jobs are similar, the changes in going-out behavior may differ across firms. One hypothesis is that the stigma of not coming to work (i.e., the stigma of working remotely) may change depending on how often one's colleagues come to work. We will analyze this hypothesis by constructing a social norm model for each workplace for future work.

Given this heterogeneity in social norms, there may also be heterogeneity at the prefectural level in the amount of increase in going-out from pre-pandemic to post-pandemic. There may be similar heterogeneity in the effects of non-legally binding policy interventions on prefectures with such heterogeneous increases in going-out during a pandemic. Such an analysis may be feasible in

[11]For example, in a survey in Japan, about 50% of consultants are able to telework, but less than about 5% of drivers are able to telework (Kawaguchi and Motegi, 2021).

a quantile regression[12] framework.

[12] For theory, see Koenker and Bassett Jr (1978); Koenker and Hallock (2001); Katafuchi (2019), and for application of the theory regarding COVID-19, see Azimli (2020); Lu et al. (2020a,b)

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