COVID-19, stigma, and habituation: Evidence from mobility data

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RESEARCH

COVID-19, stigma, and habituation: Evidence from mobility data

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Abstract

Background: The Japanese government has restricted people's going-out behavior by declaring the non-punitive state of emergency for several times under COVID-19. This study aims to analyze how multiple policy interventions that impose non-legally binding restrictions on behavior affect people's going-out.

Theory: This study models the stigma model of self-restraint behavior under the pandemic with habituation effects. The theoretical result indicates that the state of emergency's self-restraint effects weaken with the number of times.

Methods: 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.

Results: 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.

Conclusion: 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 interventions increases.

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

Background

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 [1]. 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 [2–4]. 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 [5].

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 [6]; 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 [7]; 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 [8]. 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 [9]. 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 [10]. 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 [11] 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 [12, 13]. 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,

[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 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 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 [14] and the declaration of a state of emergency in Tokyo prefecture. The figure can be summarized 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.

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 [15]. However, the second, third, and fourth emergency declarations, issued in 2021, have not yet been tested for effectiveness and criticized [16–20].

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.

There is a wide range of literature on the analysis of mobility in relation to COVID-19 outside Japan [21–24]. However, with regard to the analysis of COVID-19 related mobility outside Japan, almost all studies have analyzed mobility in terms of legally binding policy interventions represented by punitive lockdowns.

On the other hand, various studies have been conducted on Japan's self-restraint behavior [25–28]. Furthermore, there is a growing body of research on social stigma and social pressures related to COVID-19 [29–34]. However, there are no studies on self-restraint behavior considering habituation based on the number of emergency declarations.

Katafuchi et al. (2021) [15] and Kurita and Managi (2022) [28] are two existing studies on the analysis of stigma-focused Japanese non-legally binding policy interventions on going-out behavioral self-restraint, which is the scope of this study.

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.

Katafuchi et al. (2021) [15] discusses this relationship from both theoretical and empirical analysis as in this study. However, the theoretical analysis in the paper does not incorporate the effect of voluntary restraint depending on the number of emergency declarations, and the empirical analysis estimates the voluntary restraint effect of the policy intervention using a sample that includes only the first emergency declaration. Kurita and Managi (2022) [28] extend Katafuchi et al. (2021) [15] to analyze the dynamic model endogenizing an infection risk in a framework of evolutionary game. They conduct a welfare analysis and show that the state of emergency increases social welfare. This study investigates the multiple emergency declarations not considered in the above studies.

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 demonstrates habituation effects on self-restraint behavior under multiple non-legally binding policies. 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 Theory, 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 Methods, we construct a daily and prefectural panel dataset consisting of secondary data on emergency declarations, going-out behavior, and covariates. In Results, we then conduct an empirical analysis using this dataset. Finally, we conclude in Conclusion.

Theory

We present a theoretical model of stigma following going-out behavior. The basic setting of the model follows Katafuchi et al. (2021) [15] and Kurita and Managi (2022) [28] 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 [35] and it is not taken into account by Katafuchi et al. (2021) [15] and Kurita and Managi (2022) [28].

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

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

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 equations 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 the same way as [15]. □

Proposition 1 shows same results as Katafuchi et al. (2021) [15]. 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. 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.*

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 . In the next section, we empirically test Proposition 3 using mobility data.

Methods

Econometric Method

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 [36].

The model in the econometric analysis is as follows:

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

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.

Data

The dependent variable used in this study is the Google COVID-19 Community Mobility Reports [14] 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: [2] retail and recreation, grocery and pharmacy, parks, transit stations,

[2] "Retail and recreation" refers to visits to entertainment venues, including restaurants, shopping centers, museums, 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 [14].

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 [3] , 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:

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

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 [37]. 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.

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

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

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 [38] 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 [4] ($\texttt{positive\_per1000}_{it}$). 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 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 [5] , 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

[4]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 [10].

[5]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`.

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.

Results

In this section, 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.

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. Moreover, Table 2 shows the period over which emergency declarations related to COVID-19 have been issued in 2021. As these tables 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 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 [14] 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.

This study analyzes the effects of the declaration of a state of emergency on going-out behavior using a panel data analysis rather than descriptive statistic analysis for the following reasons; first, it is difficult to establish precise treatment and control group for data in 2020. Second, it is also difficult to compare the effect of the declaration of a state of emergency in 2020 with the effect in 2021. Third, 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.

Table 4 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. The result, which is consistent with the empirical analysis conducted in Katafuchi et al. (2021) [15], 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.

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 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`.

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`).

The primary 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 5 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 with distinguished or undistinguished emergency, the results of sensitivity analysis are presented below; first, the results without the addition of the covariate vector are presented in Tables 6 and 7. Second, we present the estimation results of the unchosen estimator, i.e., a random effect estimator, in Tables 8 and 9 with respect to the Hausman test statistic. Third, the results for the different mobility datasets, COVID-19 Mobility Trends Reports [39] are shown in Tables 10 and 11. All of the sensitivity analysis generally supports the results presented in Tables 4 and 5.

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.

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) [15] 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 [6]. 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.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

[6] 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 [40].

Availability of data and materials
This study uses the publicly available datasets to analyze how policy interventions aimed at reducing the spread of COVID-19 with respect to Japanese prefectures have affected going-out behavior. Data on going-out behavior for the four categories used as outcomes in this statistical analysis can be downloaded from the Google Community Mobility Report (https://www.google.com/covid19/mobility/). Data on the implementation of prefectural emergency declarations in Japan, the focus of this study, are available at the github repository "covid-19_emergency_statement_japan" (https://github.com/yuya-katafuchi/covid-19_emergency_statement_japan). In addition, this study has put in place prefecture- and time-dependent observable confounding factors in the statistical analysis: (1) precipitation at the prefectural level is available for download from the Japan Meteorological Agency (https://www.data.jma.go.jp/gmd/risk/obsdl/index.php), (2) the number of COVID-19 cases at the prefectural level is available for download from the TOYO KEIZAI ONLINE (https://github.com/kaz-ogiwara/covid19), and (3) dates of the official holidays designated by Japanese government can be downloaded at Cabinet Office of Government of Japan (https://www8.cao.go.jp/chosei/shukujitsu/gaiyou.html). The alternative data of going-out behavior in our sensitivity analyses is available at Apple Mobility Trend Reports (https://covid19.apple.com/mobility).

Competing interests
The authors declare that they have no competing interests.

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Authors' contributions
KK and YK conducted the analysis, prepared the primary manuscript, and participated in the revised manuscript. The authors read and approved the final manuscript.

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Abbreviations
Not applicable.

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Figures

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: [38], [37] 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: [14], [37] and authors' calculation.

Tables

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: [37].

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: [37].

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: [14], [38] and authors' calculation.

Table 4 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 sample size is $N = nT = 47 \times 518 = 24,346$. 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 5 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 sample size is $N = nT = 47 \times 518 = 24,346$. 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 6 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 sample size is $N = nT = 47 \times 518 = 24,346$. 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 7 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 sample size is $N = nT = 47 \times 518 = 24,346$. 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: 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 sample size is $N = nT = 47 \times 518 = 24,346$. 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 4 and 5.

Table 9 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 sample size is $N = nT = 47 \times 518 = 24,346$. 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 4 and 5.

Table 10 Result of panel data analysis for the association between emergency statement and mobility for the prefectures in Japan: sensitivity analysis using Apple's Data [39]

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 sample size is $N = nT = 47 \times 518 = 24,346$. 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 11 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's Data [39]

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 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.

Figures

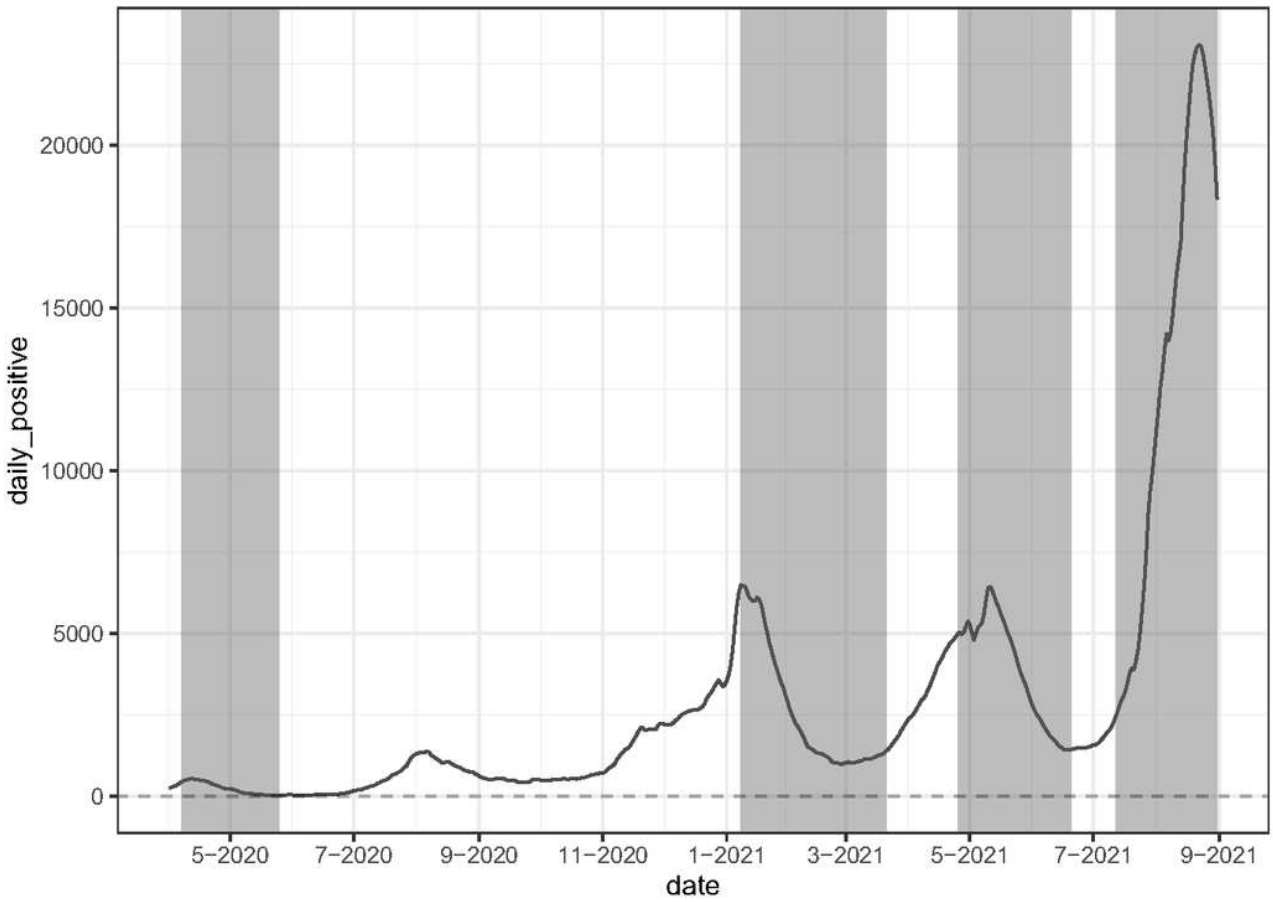

Figure 1

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: [38], [37] and authors' calculation.

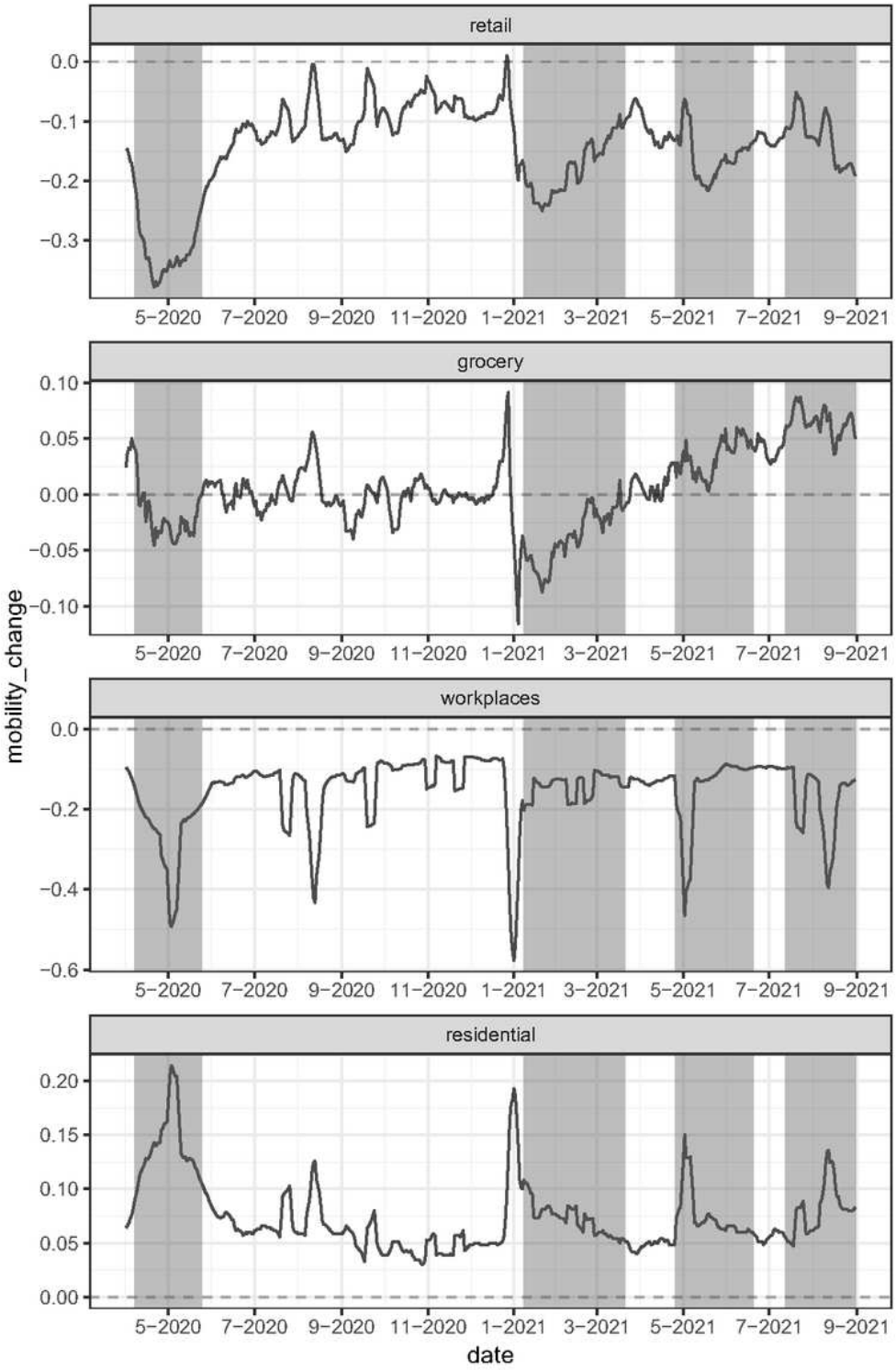

Figure 2

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: [14], [37] and authors' calculation.