COVID-19 with Stigma: New Evidence from Mobility Data and "Go to Travel" Campaign

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Abstract

This study analyzes the stigma model under the context of COVID-19 by using evidence of the Japanese prefectures and the theoretical model proposed by Katafuchi et al. (2020). The authors propose that people refrain from going out under the declaration of emergency because of a psychological cost, which is composed of two elements: infection risk and a social stigma. In their paper, the stigma works as a force to encourage people to stay at home with the implied purpose of protecting community health. Nevertheless, the new evidence we present, using data of the *Go to travel* campaign, suggests that the stigma proposed by the authors works when there is a public policy that encourages people to stay at home (emergency state); however, it fails when the public policy encourage human mobility (*Go to travel*). In other words, the stigma is not independent of the public policy. For this purpose, we use a panel data model with information on prefectural mobility, emergency statement dummy, *Go to travel* campaign dummy, and COVID-19 daily positive rates of infections.

Keywords COVID-19 · Stigma · Self-restraint behavior · Go to Travel

JEL classification D6 · D7 · Z18

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1 Introduction

On December 12th of 2019, from there the number 19 that accompanies the name of COVID, China notified the World Health Organization (WHO) that Wuhan, a city with a population of approximately 11 million people, had identified a cluster of viral pneumonia cases, all apparently related to the Hunan Seafood Wholesale Market in the same city. By January 7th of 2020, Chinese scientists ruled out SARS as the cause of the disease, causing cough, fever, and respiratory distress symptoms. They temporally called it SARS-COV-2. Subsequently, cases of infection began to appear in Thailand and Japan. (Mendoza Valero & Carranza Jimenez, 2020; Rossman, 2020)

In response to the first deaths and infections, the Chinese government decided to quarantine Wuhan and other 13 cities by the end of January. Simultaneously, new cases arose in Europe, and the first deaths outside mainland China were confirmed in the Philippines, Japan, France, Hong Kong, and Taiwan. The disease had not yet reached Latin America until February 26th, when Brazil confirmed its first case. Two days later, the WHO raised the risk alert from "high" to "very high" because more than 50 nations were already confirmed positive cases. Finally, in light of the rapid increase in infections, the WHO considered declaring COVID-19 a pandemic on March 11th. Over the next few days, Europe's cases skyrocketed, while in America, the contagion rates accelerated. (Alwazir, 2020)

As a response to the increments of infections and deaths caused by COVID-19, countries began implementing restrictive measures to control them. Travel restrictions were established within infected zones between regions provinces within the same country (e.g., China). In other cases, schools and universities were closed, public events were prohibited, borders were closed, temporary lockdowns, curfews, and mandatory quarantines were set. By the first half of October, more than 38 million people were infected. Authors, such as Chinazzi et al. (2020), Yoo & Managi (2020), and Kraemer et al. (2020) sustain that those policies established by different governments to control the COVID-19 expansion through mobility restrictions succeeded and prevented that contagion rates to increase rapidly.

International Monetary Fund - IMF (2020) and Mendolia et al. (2020) make a recompilation of all policies established by governments to control the infection rates and recover their economies. Among the list, we can find that countries like Germany established many lockdowns after its first infection case on January 27th, 2020. Schools, restaurants, bars, sports areas were closed; also, the government decreed a maximum of five persons from two households may gather. Ecuador established a curfew as a countermeasure to control the infection rates that surpassed 250 000 confirmed cases by February 1st, 2020. The curfew applied from 14:00 to 05:00 on the following day, public transportation was limited, private vehicles were prohibited, and a schedule for allowing mobility among citizens was established. Similarly, Peru settled up curfews after its first confirmed case on March 6th, 2020. Schools and public events were restricted, public transportation canceled, private transportation prohibited or allowed under a strict schedule. Additionally, people were restricted from getting out of their homes; one person per family was allowed to go to local markets or drugstores to buy food or medicine. Kenya encouraged teleworking, night curfews, public transportation restrictions, public spaces such as schools and sports domes closed after its first infection case on March 14th, 2020. (Gutiérrez et al., 2020; Johns Hopkins University, 2020)

TABLE 1 Timeline of the COVID-19 evolution.

2019-Dec-12th	China notifies WHO that in Wuhan a cluster of viral pneumonia was identified.
2020-Jan-07th	China identifies SARS as cause of the infection.
Jan-13th	First recorded case outside China is confirmed in Thailand.
Jan-16th	Kanagawa confirms the first case of COVID-19 in Japan.
Jan-24th	Tokyo confirms the first case in the Japanese capital. Government arrange repatriation for all citizens in Hubei province.
Jan-31st	By this day, Nara, Hokkaido, Osaka, Mie, Kyoto, and Chiba confirmed their first infection cases.
Feb-01st	A passenger of the Diamond Princess cruise tested positive of COVID-19.
Feb-29th	Wakayama, Okinawa, Aichi, Fukuoka, Ishikawa, Kumamoto, Tochigi, Nagano, Tokushima, Gifu, Miyagi, Kochi, and Niigata confirmed their first cases during the month.
Mar-10th	Japanese government classifies COVID-19 as pandemic in Japan.
Mar-11th	WHO classifies COVID19 as global pandemic.
Mar-24th	International Olympic Committee postpones 2020 Olympic Games.
Apr-07th	After the spread of COVID-19 along the country. Primer Minister Shinzo Abe **proclaimed the state of emergency for Tokyo, Kanagawa, Saitama, Chiba, Osaka, Hyogo, and Fukuoka.**
Apr-16th	**Government expanded the emergency state to all prefectures.**
May-14th	The emergency state is suspended in 39 prefectures except for four prefectures in Kanto area, three prefectures in Kinki area, and Hokkaido.
May-21th	The state of emergency is suspended in Kinki area.
May-25th	The state of emergency is lifted on the remaining prefectures.
Jul-22th	**The government started the *Go to travel* campaign to promote tourism inside Japan.** Tokyo is excluded from the campaign.
Sep-18th	Tokyo starts to be included in the *Go to travel* campaign.
Oct-29th	The total number of positive cases surpassed over 100 000 in the entire country.

Source: Information was collected from: (1) Japan Times: Japan Times (2020); and, (2) Japan Broadcasting Corporation - NHK (2020)

Japan, in contrast to the strict restrictions established by other countries, the government did not impose private rights restrictions; on the contrary, the policy instituted was based on encouraging people's self-restriction. Besides, schools and universities were shortly close to preparing online classes and protocols to continue classes under the contagion situation; companies were encouraged to move from in-person work to telework; restaurants were asked to close earlier. The first emergency state was established for 7 out of 47 prefectures on April 7th, 2020, to respond to their high contagion rates. Those prefectures were Tokyo, Kanagawa, Saitama, Chiba, Osaka, Hyogo, and Fukuoka. The emergency was expanded to all prefectures on April

16th as a response to the contagion situation. After almost a month, the emergency declaration was suspended for 39 prefectures (May 14th) and finally for the whole country on May 25th. This situation created a particular scenario because, contrary to most countries worldwide, Japan proclaimed a state of emergency differentiated by areas based on local contagion situations. In this regard, Table 1 presents a timeline of the COVID-19 evolution and the government response.

Yabe et al. (2020) studied human mobility response in Tokyo as a response to the non-compulsory policies settled by the government. By using location data of smartphones collected by Yahoo Japan corporation in Tokyo (Japan) and a transmissibility of an infection disease model, they find that by April 15th, one week after the emergency statement was established, the human mobility decreased by around 50%, which implies 70% less social contacts in Tokyo. In other words, they find evidence of a strong relationship between non-compulsory measures and human mobility. Similarly, and with a broader period, Katafuchi et al. (2020) present a stigma model using data from April 8th to June 22th, 2020 from the Google COVID-19 Community Mobility Reports; they find evidence that emergency state declaration effectively reduced human mobility. In their model, they assume that people, under the emergency declaration, refrain from going out due to psychological costs arising from the risk of infection and the stigma of going out, which implicitly increase the risk of infect other people. Therefore, the model suggests that people do not go out because they may infect others, and there is social pressure to protect society even though the emergency state is non-legally binding.

The evidence presented by Katafuchi et al. (2020) may lead us to assume that people refrain from going out due to the psychological costs, infection risk, and social stigma, regardless of the emergency statement, which is non-legally binding. Consequently, after the emergency state lift, if the infection rates keep rising, we might expect people to refrain from going out since the infection risk and social stigma are independent of the emergency state. In this sense, this research analyzes the performance of the stigma model proposed by Katafuchi et al. (2020) after the emergency state and contrasting it when the government establishes a specific policy that encourages human mobility, which is the *Go to travel* campaign, launched by the Japanese government on July 22nd, 2020. This campaign cuts the cost of accommodation and travel packages by 50%, 35% discount of the total cost and 15% in coupons that can be used in different stores and restaurants during the trip [1]. The main objective of this campaign was to promote internal tourism. Officially, the campaign was launched on July 22nd for all prefectures except Tokyo due to the relatively high number of contagions; later, on September 18th, Tokyo was included in the campaign. (see Table 1 for more details.)

Figure 1 shows the daily positive cases' evolution from the first case until November 25th. The figure marks the dates when the emergency state started and ended; additionally, it shows when the *Go to travel* campaign started. We observe that the contagion rates grew rapidly before the emergency state and slowed down during it; these slow increments were maintained after the post-emergency stage. Nevertheless,

[1] Information about the campaign was obtained from Ministry of Land & Tourism (2021)

after the *Go to travel* campaign was launched, the number of daily positive cases rose sharply until the last date analyzed.

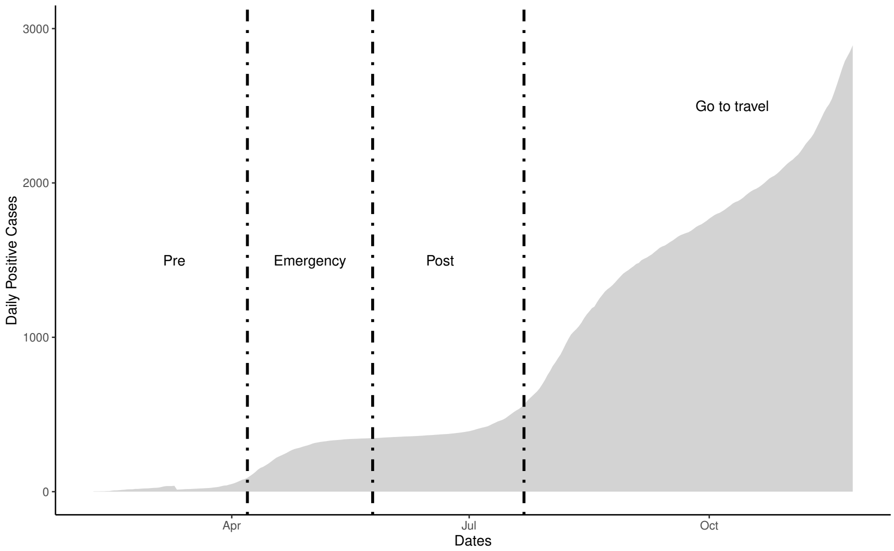

Fig. 1: Evolution of Daily Positive Cases and the Policy Stages established by the Japanese government.

The situation observed in Figure 1 creates the perfect environment to contrast the stigma model proposed by Katafuchi et al. (2020). By following the stigma model and examining the increasing number of contagion rates, which implies higher infection risk, we might expect lower human mobility, i.e. people refrain from going out in response to higher infection risk and the social stigma created by the social health situation, regardless the presence of *Go to travel* campaign. If we validate the findings of Katafuchi et al. (2020), we prove that the social stigma is independent of any government policy. Nevertheless, suppose we reject the authors' findings. In that case, we will prove that the stigma model works appropriately only when the governmental policies restrict, even in non-legally binding policies, human mobility, and it fails when the government establishes policies that encourage human mobility. In this sense, this research hypothesizes that the stigma model is not independent of public policies and fails to assume that the stigma is a social punishment *per se* independent from governmental policies and based on the social health environment. On the contrary, we propose a refined interpretation of the stigma of Katafuchi et al. (2020), instead of being a social pressure to avoid causing social health worse, it works as a social force that drives people to obey the policies established by the government regardless of their mobility binding legacy.

In the literature, Anzai & Nishiura (2021) studied the relationship between infection cases and the *Go to travel* campaign. The authors find evidence that the campaign increased the number of infections implicitly because the number of people with travel history increased. However, as far as we are awarded, no research analyzes the impact of the *Go to travel* campaign by using a theoretical and econometrical model and its impact on human mobility.

The remainder of this research is organized on the following way: in Section 2, Methodology, we present the theoretical model based in Katafuchi et al. (2020) (Subsection 2.1), the econometrical model, which is a modified version of that presented by the authors (Subsection 2.2). In Section 3, Results, we present the empirical evidence (Subsection 3.1) and the econometric evidence (Subsection 3.2). Finally, in Section 4, Conclusions, we present the final conclusions.

2 Methodology

2.1 The theoretical model

By following Katafuchi et al. (2020), lets consider an economy where the population is normalized to the unity and each person may choose whether to go out or not. His payoff is defined as follow:

$$\begin{cases} \mathrm{u}_{out} - \phi[\gamma c + \iota\sigma s]^{\delta} & \text{if going out,} \\ \mathrm{u}_{home} & \text{if staying at home,} \end{cases} \tag{1}$$

where u_{out} is the utility from going out and u_{home} is the utility of staying at home. Additionally, it is assumed that $u_{out} > u_{home}$, i.e. people enjoy more when they go out than when they stay at home.

Regarding the option of getting out, $u_{out} - \phi[\gamma c + \iota\sigma s]^{\delta}$ represents the psychological cost, which contains the risk of contagion (γc) and the stigma ($\iota\sigma s$). These two components are complementary. ϕ, on the other hand, is the sensitivity to the psychological cost and limited to $\phi \in [0, \bar{\phi}]$; $\gamma \in [0, 1]$ is the probability of getting infected if the person goes out; c is the cost of infection; s is the stigma cost; $\sigma \in (0, +\infty)$ indicates the relative size of the stigma to the infection in the psychological cost; $\delta \in (0, +\infty)$ is the parameter of cost to scale. Finally, ι is equal to 1 for the case of emergency statement declaration, 0 otherwise.

Taking the indifference point in equation (1), we obtain that:

$$\hat{\phi} = \frac{u_{out} - u_{home}}{[\gamma c + \iota\sigma s]^{\delta}}, \tag{2}$$

this parameter determines the proportion of individuals who go out, x, in other words, when the sensitivity cost is not high enough, people prefer to go out rather than stay at home. x is defined as:

$$x = Pr(\phi \leq \hat{\phi}) = F(\hat{\phi}). \tag{3}$$

Therefore, from equation (1) to (3), we obtain:

$$\begin{cases} \hat{\phi} = \frac{u_{out} - u_{home}}{[\gamma c + \iota\sigma s]^{\delta}}, \\ x = F(\frac{u_{out} - u_{home}}{[\gamma c + \iota\sigma s]^{\delta}}), \\ s = s(x), \end{cases} \tag{4}$$

we assume that $u_{out} - u_{home} > 0$, which means that people prefer to go out than stay at home; $\partial s(x)\ \partial x < 0$, which means that the stigma cost decreases with the proportion of individuals who go out[2]; finally, when there is no state of emergency, i.e. $\iota = 0$, people prefer to go out than stay at home, i.e. $u_{out} - u_{home} > \gamma c$.

From these equations, Katafuchi et al. (2020) present three main propositions:

1. There is a unique equilibrium when there is no state of emergency is established. Conversely, the declaration of the state of emergency generates multiple equilibria.
2. In equilibrium, the proportion of people who go out under the emergency state is less than those under normal conditions.
3. Under the state of emergency, people restrain themselves from going out, even if all people even if the contagion probability is close to zero.

Additionally, the authors present a set of comparative static results, which can be summarized on the following statements:

- An increment on the u_{out} provokes an increment on the population who goes out under the emergency state and after.
- An increment on the u_{home} provokes a reduction in the population who goes out under the state of emergency and after.
- An increment on the probability of being infected after going out reduces the population who goes out under the state of emergency and after.
- An increment in the infection cost reduces the population who goes out under the state of emergency and after.
- An increment of the stigma reduces the population who goes out under the state of emergency.
- An increment on (δ), cost to scale, reduces the population who goes out under the state of emergency and after.

2.2 The empirical model

2.2.1 Econometric Methodology

By following the one-way error component model proposed by Baltagi (1984):

$$\begin{aligned} y_{it} &= \mathbf{x}`_{it}\beta + e_{it}, \\ e_{it} &= \alpha_i + v_{it}, \end{aligned} \tag{5}$$

where y is the dependent variable that captures the flow of going out activities, $i = 1, 2, ..., n$ is the index for the $i - th$ prefecture, $t = 1, 2, ..., T$ is the date, $\mathbf{x}$ is the set of explanatory variables, β is the vector of parameters, and e is the error terms. More specifically, the error terms can be decomposed into stochastic variability v and prefectural heterogeneity α.

On the other hand, the set of explanatory variables it is decomposed as:

$$\mathbf{x}_{it} := [d`_{it}, z`_{it}]` \tag{6}$$

[2] We can understand the stigma as social stress to stay at home because the rest of people in the society are also staying at home

where d_{it} is the set of dummy variables, one for the state of emergency declaration, and one for the *go to travel* campaign. z_{it} is the set of control variables.

Equation (5) can be estimated by using one-way Fixed Effects model or one-way Random Effects model. The main difference between them is that the FE model assumes perfect heterogeneity among prefectures, i.e. there are no two prefectures with similar characteristics; on the other hand, the RE model assumes that the heterogeneity is distributed among prefectures, i.e. there is a chance for finding two prefectures with similar characteristics. To choose between these two models, we use the Hausman test.

2.2.2 Data

This investigation contrast the evidence introduced by Katafuchi et al. (2020), which assumes that people do not go out due to the stigma provoked by the society under the context of a state of emergency. Nonetheless, in this study, we hypothesize that people do not go not because of the stigma itself or social punishment; rather, people refrain from going out due to the compromise with rules (emergency state declaration). To contrast this hypothesis, we use the people's flow under the context of the *go to travel* campaign. Therefore, if the stigma proposition works appropriately, the evidence must show that people refrain from going out even during the *go to travel* campaign because there still a high contagion risk among Japanese prefectures.

For our endogenous variable, y_{it}, which captures the going out behavior, we use the Google COVID-19 Community Mobility Reports[3]. The data is anonymized and aggregated by prefecture. Google reports that, in Japan, around 80% of people used Google Maps application at least once, and 90% any map application at least once[4]. The data available is divided into six categories: "Retail & Recreation", "Grocery & Pharmacy", " Parks", "Transit stations", "Workplaces", and "Residential". In this study, similarly to Katafuchi et al. (2020), we use four out of six categories:

- "Retail & Recreation" (`retail`), refers to the entertainment or leisure purpose going out behavior such as purchases in restaurant, cafes, shopping centers, museums, libraries, among others.
- "Grocery & Pharmacy" (`grocery`), refers to the daily necessities purchasing purpose going out behavior such as grocery stores, food wholesalers, fruits and vegetables markets, drugstores, pharmacies, among others.
- "Parks" (`parks`), refers to going out to any park such as prefectural parks, national parks, dog parks, beaches, gardens, among others.
- "Workplaces" (`workplace`), refers to the going out for working purpose.

This data is presented as a percentage change from the baseline value of the week's corresponding day measures between January 3rd to February 6th, 2020. In all the cases, we take their smoothed series with a time width of seven days.

On the second group of variables, we have the set of explanatory and control variables. The explanatory variables or variables of interest, d_{it}, which includes the

[3] Google Community Mobility Reports (2020)

[4] More detail about the survey in `https://www.value-press.com/pressrelease/215276`, only in Japanese, accessed on December 15th, 2020.

dummy variables for the emergency state and *go to travel* campaign. Since these are the main variables for our interest, we use different variables than Katafuchi et al. (2020), but with the same purpose of analysis. Therefore, the variables we use for this purpose are:

– Emergency statement dummy (`emergency`), defined as 1 on the dates under the emergency statement and 0 otherwise. It is important to notice that in Japan, the state of emergency was not declared uniformly across the country; on the contrary, some prefectures (Saitama, Chiba, Tokyo, Kanagawa, Osaka, and Hyogo) were declared in emergency earlier than the rest of the country. For more detail of the specific dates and duration of the emergency statement for each prefecture, see Table 2.[5]
– Go to travel campaign dummy (`go to travel`), defined as 1 on the dates where the campaign was active and 0 otherwise. In the case of the *go to travel* campaign, the dummy takes the value of 1 from July 22nd, 2020, until the last date of our data (November 25th, 2020). In the specific case of Tokyo, it was initially excluded from the campaign until September 18th. Therefore, the dummy takes the value of 1 since September 18th for the prefecture of Tokyo.

Table 2: Start date, end date, and length of the emergency statement among Japanese prefectures.

id	Prefecture Name	Emergency Start	Emergency End	Total date
1	Hokkaido	4/16/20	5/25/20	39
2	Aomori	4/16/20	5/14/20	28
3	Iwate	4/16/20	5/14/20	28
4	Miyagi	4/16/20	5/14/20	28
5	Akita	4/16/20	5/14/20	28
6	Yamagata	4/16/20	5/14/20	28
7	Fukushima	4/16/20	5/14/20	28
8	Ibaraki	4/16/20	5/14/20	28
9	Tochigi	4/16/20	5/14/20	28
10	Gunma	4/16/20	5/14/20	28
11	Saitama	4/7/20	5/25/20	48
12	Chiba	4/7/20	5/25/20	48
13	Tokyo	4/7/20	5/25/20	48
14	Kanagawa	4/7/20	5/25/20	48
15	Niigata	4/16/20	5/14/20	28
16	Toyama	4/16/20	5/14/20	28
17	Ishikawa	4/16/20	5/14/20	28
18	Fukui	4/16/20	5/14/20	28
19	Yamanashi	4/16/20	5/14/20	28

Continued on next page...

[5] For more details of the dates of emergency statement, check: Katafuchi (2020). “covid-19 emergency statement japan”. URL: `https://github.com/yuya-katafuchi/covid-19_emergency_statement_japan`.

Table 2 – continued from previous page

id	Prefecture Name	Emergency Start	Emergency End	Total date
20	Nagano	4/16/20	5/14/20	28
21	Gifu	4/16/20	5/14/20	28
22	Shizuoka	4/16/20	5/14/20	28
23	Aichi	4/16/20	5/14/20	28
24	Mie	4/16/20	5/14/20	28
25	Shiga	4/16/20	5/14/20	28
26	Kyoto	4/16/20	5/21/20	35
27	Osaka	4/7/20	5/21/20	44
28	Hyogo	4/7/20	5/21/20	44
29	Nara	4/16/20	5/14/20	28
30	Wakayama	4/16/20	5/14/20	28
31	Tottori	4/16/20	5/14/20	28
32	Shimane	4/16/20	5/14/20	28
33	Okayama	4/16/20	5/14/20	28
34	Hiroshima	4/16/20	5/14/20	28
35	Yamaguchi	4/16/20	5/14/20	28
36	Tokushima	4/16/20	5/14/20	28
37	Kagawa	4/16/20	5/14/20	28
38	Ehime	4/16/20	5/14/20	28
39	Kochi	4/16/20	5/14/20	28
40	Fukuoka	4/7/20	5/14/20	37
41	Saga	4/16/20	5/14/20	28
42	Nagasaki	4/16/20	5/14/20	28
43	Kumamoto	4/16/20	5/14/20	28
44	Oita	4/16/20	5/14/20	28
45	Miyazaki	4/16/20	5/14/20	28
46	Kagoshima	4/16/20	5/14/20	28
47	Okinawa	4/16/20	5/14/20	28

Within the second group of variables, the set of control variables, z_{it}, includes the following information:

- Temperature (`temperature`), which captures the daily average temperature by prefecture, this variable may affect the going out behavior of the population. The data was collected from the Japan Meteorology Agency[6].
- Precipitation (`precipitation`), which captures the average rain quantity per prefecture, similarly to temperature, this variable may affect the going out behavior of the population. The data was collected from the Japan Meteorology[7].
- Daily infection cases (`covid-19`), this variable controls the contagion risk environment in each prefecture . Higher daily infection rates may affect the going out

[6] Japan Meteorological Agency (2020)
[7] Japan Meteorological Agency (2020)

behavior of the population. The data was collected from the Minister of Health, Labor, and Welfare[8].

In Katafuchi et al. (2020) we observe that the authors are using daily sunshine hours per day rather than the temperature in order to control the heterogeneity and volatility that temperature data may generate; additionally, they use one day lag of the infection rates per day under the assumption that people consider rates rather than absolute numbers in their going out decisions. On the contrary, we consider that temperature and absolute numbers of infection cases are better indicators; to solve the main problems claimed by Katafuchi et al. (2020) we smooth the data of our covariates. The smooth version of the series reduces their volatility, and also, in the case of daily positive infections, it shows the trend of infections, which is the numbers that people observe and consider into their going out decisions.

Finally, considering all our variables' available information, our panel data is composed of $n = 47$, 47 prefectures, and $T = 258, 284$, 258 days for balanced and 284 days for the case of unbalanced panel data. The days' collections start on January 1st, 2020, to November 25th, 2020. However, there is no complete information for all variables for all prefectures; therefore, the initial day may vary for our unbalanced panel data. For the balanced panel data, the initial day is March 12th, 2020. Therefore, the total number of data is $N = n \times T = 12204$

3 Results

3.1 Empirical Evidence

First of all, we analyze people's going out behavior across prefectures during the stages along 2020. Since the start of infection cases in the country, Japan had four stages until the end of November. First, the pre-emergency stage, which is defined before the date of the emergency declaration in each prefecture, for example, in the case of Tokyo is defined for the dates before April 7th, while for Tottori are the dates before April 16th (more details refers to Table 2). Second, the emergency stage, defined by the dates when the emergency state was declared, varies across prefectures, as it can be checked in Table 2. Third, the post-emergency stage, defined as the dates after the emergency declaration across prefectures but before the starting date of the *Go to travel* campaign. Finally, fourth, the Go to travel stage, define as the dates after the end of the emergency state and when the *Go to travel* campaign started for each prefecture.

Figure 2 displays the distribution of the going out behavior across prefectures during the different stages that the country had in 2020. On the left column, we observe the boxplot graphic for their distribution, while on the right column, we observe the histogram across prefectures in each of the stages. On the left column figures, the horizontal axis represents the stages, which can be defined as: pre-emergency stage (`Before`), under the emergency stage (`Emergency`), post-emergency stage (`After`), and Go to travel stage (`Go to Travel`); on the other hand, the vertical axis

[8] Japan Meteorological Agency (2020)

represents the going out behavior obtained from the Google COVID-19 Community Mobility Reports. Each of the rows on the left column represents one of the four going out behavior we are examining, which are: “Retail & Recreation”, “Grocery & Pharmacy”, “Parks”, and “Workplaces”. On the right column figures, the axis is reversed to have an easier look at the distributions. The vertical axis represents the stages Japan had during the year, while the horizontal axis represents the going out behavior. Similarly to the left column, each of the rows represents each of the going out behaviors we previously defined.

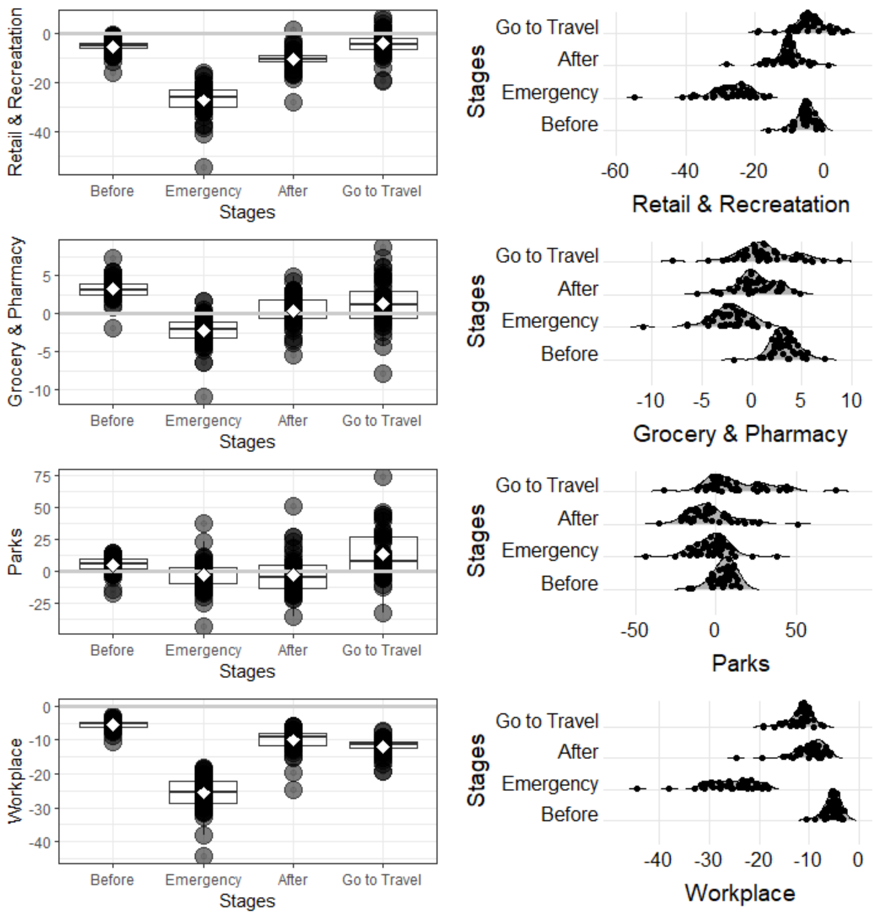

Fig. 2: Average Going out behavior across prefectures in the different stages during 2020. Left columns represents the boxplots for each going out behavior, and the right column represents the histogram for each going out behavior.

On the left column figures, each of the bubbles represents each prefecture, the horizontal line inside the rectangle represents the mean, and the diamond symbol represents the median. When the mean and the median are the same, the distribution is symmetric on its sides. There is also a horizontal line representing the level of the going out behavior; values below this line indicate that people refrain from going out, while values above the line indicate that people go out more than the baseline. On the right column figures, the points represent each prefecture, while the lines are the histogram's limits.

Then, on the first row, we observe that for "Retail & Recreation", before the emergency declaration, on average, people reduced their flow toward restaurants, stores, and cafes; during the emergency stage, people refrained from going those places; however, we observe that after the emergency statement, people's flow to restaurants, cafes, libraries, among others, increased significantly. Moreover, the *Go to travel* campaign impulsed by the government impulsed people's flow to recreational places. On the right side, we observe the distribution of the average behavior across prefectures; in the emergency stage, Tokyo was the prefecture where people refrained from going out more than the rest of the prefectures. We also notice that all prefectures reduced their going out behavior with respect to the baseline.

On the second row, "Grocery & Pharmacy", Figure 2 shows that on average, people reduced their activities related to purchasing daily necessities goods during the state of emergency and increased after it. Contrary to the case of "Retail & Recreation", the level of flow behavior during the *Go to travel* campaign does not reach pre-emergency stage levels. On the third row, "Parks", the going out behavior does not change much before, during, or after the state of emergency, while in the *Go to travel* stage, we observe a slight increase. Finally, on the fourth row, "Workplace", the going out behavior reduces dramatically during the emergency stage and increases after that; however, it does not recover pre-emergency stage levels. Also, during the *Go to travel* stage, people's flow to working places did not change much. The right side figures show that the histograms seem to be symmetric with a strong concentration of the cases close to the mean.

3.2 Econometric Evidence

In this subsection, we estimate the econometric model. Based in equation (5), we define the explicit equation:

$$\begin{aligned} y_{it} = \beta_1 \ \texttt{emergency}_{it} + \beta_2 \ \texttt{go to travel}_{it} + \beta_3 \ \texttt{temperature}_{it} + \\ \beta_4 \ \texttt{precipitation}_{it} + \beta_5 \ \texttt{covid-19}_{it} + e_{it} \end{aligned} \tag{7}$$

$$e_{it} = \alpha_i + v_{it} \tag{8}$$

where y_{it} is the endogenous variables, which represents the going out behavior such as `retail`, `grocery`, `parks`, or `workplace`. The set of explanatory variables are divided in our variables of interest, `emergency` and `go to travel`, and our control variables, `temperature`, `precipitation`, and `covid-19`. i represents the prefectures and t represents the dates in our panel data. e_{it} represents the disturbance terms, which can be divided into the individual effects, α_i, for the case of FE models, its value are dummies for each prefecture to capture the heterogeneity of the model; on the other hand, in the case of RE models, $\alpha_{it} \sim N(0, \sigma_\alpha^2)$, i.e. the heterogeneity of the individual characteristics has a distribution. Finally, $v_{it} \sim N(0, \sigma_v^2)$ are the uncorrelated error terms.

Table 3 shows the results of the econometric estimation based in equation (7). We estimate a panel data model where each column represents each of the endogenous variables used in the estimation (`retail`, `grocery`, `park`, and `workplace`). On the bottom side of the table, we show the main characteristics of the model we estimate. $R2$ and $Adjusted - R2$, which represent the strength of the model to produce less residuals; therefore, values close to 1 means that our model produces small residuals. The row *Estimator* shows the type of model we are estimating, Random Effects (RE) or Fixed Effects (FE). The decision is based on the Hausman test, which compares the FE model versus the RE model. When the $p - value$ of the Hausman test is lower than 0.05, the FE model is preferred over the RE model. In the table, we present the $chi - square$ value, and the number of asterisks will determine the model we use. Finally, θ represents the size of the errors that come from the heterogeneity among prefectures.

On the results of Table 3, we observe that in all the cases, the RE models are preferred over the FE models based on the Hausman test, in which the $p - values$ do not fall below the threshold of 0.05. The RE models imply that many individuals have the chance to have similar characteristics among them; therefore, a constant is included in the estimation results to capture the baseline.

Regarding the estimated parameters, there is a variety of results for each endogenous variable. First of all, the variable `emergency`, which denotes the emergency statement state, has negative estimated parameters statistically significant at 1% in all the cases. These results are consistent with the stigma model results showed by Katafuchi et al. (2020). These results imply that under the emergency declaration, people refrain from going out to do many activities such as going to restaurants, cafes, supermarkets, parks, and working places. Second, the variable `go to travel`, which denotes the *Go to travel* stage, has no consistent results across the models. These parameters' results seem to be inconsistent with our hypothesis that the stigma model only works underflow restriction incentives regardless of the contagion risk context. Nevertheless, this inconsistency is reverted in Table 4.

Table 4 shows the estimation results when the control variables (`temperature`, `precipitation`, and `covid-19`) are included. Also, we notice that only when `grocery` is used as endogenous variable, the Hausman test suggest the usage of RE model rather than the FE model ($p - value > 0.05$). For the other cases, the FE model is preferred.

The estimated parameters of the table show coefficients consistent with our hypothesis. We observe that the `emergency` variable has a negative sign, which is statistically significant at 1% across the models. These results determine that during the emergency state declaration, people refrain from going out. Specifically, we observe that the emergency state affected particularly strong to the flow behavior toward working places, restaurants, and cafes. On the contrary, the emergency state had a weak effect on the going out behavior to supermarkets or grocery stores. We obtain a similar effect to the flow toward parks. These results are in concordance with the nature of this going out behavior. During the emergency state declaration, people refrain

Table 3: Estimation Results for the mobility data without Control Variables

	Dependent Variables			
	`retail`	`grocery`	`park`	`workplace`
`emergency`	-19.338***	-3.929***	-3.351***	-17.560***
	(0.171)	(0.078)	(0.405)	(0.203)
`go to travel`	3.772***	-0.412***	11.321***	-3.342***
	(0.110)	(0.050)	(0.268)	(0.130)
`Constant`	-8.362***	1.702***	0.974	-8.269***
	(0.499)	(0.315)	(1.871)	(0.249)
Observations	13066	13066	13066	13066
R2	0.58445	0.16721	0.15492	0.36383
Adjusted R2	0.58439	0.16708	0.15478	0.36374
Hausman test	0.73092	0.66921	0.65131	4.60500
θ	0.8961	0.9254	0.9331	0.7434
Estimator	RE	RE	RE	RE
Covariates	NO	NO	NO	NO

Notes: Numbers in parentheses stand for clustered-robust standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. FE=fixed effect; RE=random effect.

from going to places where the main purpose is recreation or leisure; also, companies and working places established new policies to have part of their employees working online.

Secondly, with respect to the `go to travel`, we observe that in all the cases, the *Go to travel* campaign has a positive and statistically significant effect at 1% in all the cases except for the `workplace` as endogenous variable. In this sense, the policy impulsed by the government was successful. Nevertheless, it exposes evidence that the stigma theory proposed by Katafuchi et al. (2020) is incomplete. The results obtained infer that even under the context of high contagion risk because the number of positives cases increased steadily, the campaign increased the flow of people to public places (see Figure 1). Consequently, the stigma that people receive from the rest of the population to abstain from going out only holds when there is a restriction incentive, such as the emergency state, but it does not work when there is a positive incentive with the goal of incrementing the flow of people. The only case where the variable `go to travel` does not have any significant effect is in the `workplace` model; this result is robust and goes in concordance with Figure 2, which shows that *Go to travel* campaign did not modify the going out behavior to working places.

Regarding the impact of *Go to travel* campaign over human mobility, we identify two possible causes. First, there is a psychological impact of the policy on citizens; the government creates a safe feeling through this policy, and people will have more confidence to go out of their homes. Second, once some people take the campaign, they already create human movement in the places they go, which impulse others to go out of their homes with more confidence. Notwithstanding, the significance of these links between *Go to travel* campaign and human mobility is beyond the objective of this research and remains as a research agenda.

Table 4: Estimation Results for the mobility data with Control Variables

	Dependent Variables			
	`retail`	`grocery`	`park`	`workplace`
`emergency`	-18.021***	-3.776***	-5.538***	-17.036***
	(0.170)	(0.077)	(0.406)	(0.199)
`go to travel`	6.203***	0.207***	12.566***	-0.148
	(0.123)	(0.056)	(0.298)	(0.144)
`Constant`		2.863***		
		(0.314)		
Observations	11922	11922	11922	11922
R2	0.63659	0.19833	0.21740	0.43080
Adjusted R2	0.63503	0.19799	0.21387	0.42836
Hausman test	578.07***	8.4003	55.757***	90.466***
θ		0.9227		
Estimator	FE	RE	FE	FE
Covariates	YES	YES	YES	YES

Notes: Numbers in parentheses stand for clustered-robust standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. FE=fixed effect; RE=random effect.

4 Conclusions

This study contrast the theory and evidence presented by Katafuchi et al. (2020) regarding the Stigma model. From their hypothesis, it is possible to infer that people refrain from going out due to the existence of a social stigma or social pressure over the rest of the population with the objective of protecting the society from raising the pace of contagion by COVID-19. They presented evidence by using the Mobility Data from the Google COVID-19 Community Mobility Reports. They show that under the context of the state of emergency, people refrain from going out to different places such as restaurants, supermarkets, cafes, parks, and working places. Although, the evidence is presented under the context of a restrictive rule placed by the government that gives a negative incentive on the population to abstain from going out regardless of the enforcement of the state.

To contrast the stigma model, we incorporate data from the *Go to travel* campaign established by the government, which influences the population behavior to go out with the intention of impulse tourism inside Japan. At the same time, the rates of daily contagions with COVID-19 were increasing. This situation creates the chance to contrast the stigma model. If stigma works suitably, under a high risk of infection, people may refrain from going out due to the stigma received from the rest of society. However, the evidence we present shows the contrary. During the *Go to travel* campaign, people increased their going out behavior, even though the number of daily infections was increasing. These results show that stigma model works when there are negative incentives over the going out behavior but fails when there are positive incentives, such as the *Go to travel* campaign. In this sense, the stigma model presented by Katafuchi et al. (2020) captures the eagerness of people to obey the settled rules or the incentives create by the government rather than consider the social risk circumstances.

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