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# Japanese travel behavior trends and change under COVID-19 state-of-emergency declaration: Nationwide observation by mobile phone location data

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## Abstract

In the early stages of the COVID-19 pandemic, the Japan government could not impose strong restrictions such as lockdowns. Since there has been no such nation-wide behavioral analysis, we calculated indicators of nation-wide behavioral change using data based on mobile phone network. This study shows empirical facts and findings on behavioral changes under COVID-19 “state-of-emergency” declarations in Japan that are obtained by using mobile terminal network operational data. Results show that a significant reduction in trips and inter-prefectural travel was achieved without strong restrictions by the government. In addition, the population density index decreased by 20% and people avoided traveling to densely populated areas. This analysis shows that once people’s behavior is changed by the declaration of a state of emergency, it does not return to normal immediately after the lifting of the declaration; rather, it recovers slowly.

**Keywords:** Coronavirus, COVID-19, Travel behavior analysis, Behavioral change, Japan, Mobile Spatial Statistics

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## 1. Introduction

Following the identification of a novel coronavirus (SARS-CoV-2) in Wuhan, China, in December 2019 and its global spread, large epidemics of the disease (COVID-19) ensued around the world. In response to rising numbers of cases and deaths and to preserve health systems, many countries have been implementing measures to control their epidemics. These large-scale non-pharmaceutical interventions vary between countries. However, they include social distancing (such as bans against large gatherings), border closures, school closures, isolation measures for symptomatic individuals and their contacts, and large-scale lockdowns of populations with all but essential internal travel banned. For example, strict movement restrictions and other measures including case isolation and quarantine, were introduced in China beginning January 23, 2020 and achieved a downward trend in the number of new confirmed cases in February and zero new confirmed indigenous cases in Wuhan by March 19 (Kraemer et al., 2020). Flaxman et al. (2020) studied the impact of lockdowns in Europe and clarified that current interventions have been sufficient to drive the reproduction number  $R_t$  below 1 by using statistical modeling, thus achieving epidemic control. Until an effective vaccine against COVID-19 is developed, countries need to use non-pharmaceutical interventions to prevent the spread of infection.

Unlike many countries, Japan could not impose urban lockdowns because of the Constitution of Japan, which states that citizens should be allowed to move freely. In addition, there is no

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law that enforces the citizens to stay at home in Japan. For example, under Act on Special Countermeasures against New-Type Flu and Other Novel Infections, the government can request citizens to limit their outings or to restrict the use of facilities used by large numbers of people, but there are no penalties. Therefore, Japan could only encourage people to refrain from activities even after the state of emergency declared by the prime minister. Moreover, the non-pharmaceutical interventions in Japan are considerably more lenient than those in other countries. In this report on how people changed their behavior in Japan, we focus on the following measures:

- Increase or decrease in the number of trips in each prefecture,
- Increase or decrease in travel across prefectures, and
- Change in population density patterns

by using mobile terminal network operational data, which indicate estimated real-time population. Documenting the impact of these lenient non-pharmaceutical interventions on behavioral change is useful for understanding people's behavior under pandemics and international comparisons. However, as we are not epidemiology experts, we report the behavioral impact of these non-pharmaceutical interventions, but we cannot conclude whether or not such policies prevented the spread of infection.

The contributions of this study are as follows.

- We created some indicators that give an overview of nationwide behavioral changes from the spatial distribution of the grid-based aggregated population.
- We showed empirical evidence of nationwide behavioral changes during the first wave of the COVID-19 pandemic in Japan.
- We showed that the preliminary nationwide behavioral analysis of such data was useful for pandemic preparedness and associated urban and transportation policies. In addition, this approach allows us to monitor the current state of cities while protecting the privacy of each individual.

And the findings of this study are as follows.

- A significant reduction in trips and inter-prefectural travel was achieved despite the lack of strong restrictions by the government.
- Through the implementation of school closures and declaration of state of emergency, three metropolitan areas in Japan (Tokyo, Osaka, and Nagoya) reduced their numbers of trips by 45%, 27%, and 13%.
- On the other hand, in prefectures with lower population density and fewer infected people, the downward trend in the number of trips was smaller than in large cities.
- The number of inter-prefectural travel was halved around Japan compared with that under normal conditions.
- The population density index, which shows how people tend to congregate in densely populated areas, decreased to 20%.
- The population density index decreased even a few days before school closure or “state of emergency” declaration. This indicates the possibility of a spontaneous behavioral change.
- Such a behavioral change does not immediately reverse even after the “state of emergency” declaration is lifted; rather, it returns slowly.

## 2. Literature review

Some evidence of behavioral change under COVID-19 pandemic has been reported. Google (2020) showed time series of trends in some locations such as entertainment facilities, stores, and public transportation by using GPS data from Smartphones. Apple (2020) also reported on changing trends in the amount of people using cars, pedestrians, and public transportation in 63 countries and major cities around the world by using route guidance request data. Both data show only the rate of increase or decrease; absolute numbers are not available. Washington State Department of Transportation (WSDOT) (2020) reported that traffic on the Interstate Highway in King County, where the Seattle metropolitan area is located, was down 50% in April. In the United Kingdom, the government gradually increased the number of measures, leading to a lockdown. Hadjidemetriou et al. (2020) reported that the behavior decreased to about 80% after the lockdown situation by several mobility data. de Haas et al. (2020) reported that under the Dutch ‘intelligent lockdown’ policy, there was also a reduction in outing behavior of about 80%. Saladié et al. (2020) reported a 62.9% reduction in behavior and a related 74.3% reduction in traffic accidents in Tarragona province in Spain, where lockdown was implemented. Thus, under the lock down policy, people reportedly reduced most of their movement behaviors. On the other hand, Sweden, like Japan, has chosen a strategy relying mainly on recommendations rather than mandatory enforcements to limit human interaction. Even under such a strategy, Jenelius and Cebecauer (2020) reported a 40-60% decrease in the number of public transport users. Since a shift from public transport to cars has also been observed (Hadjidemetriou et al., 2020; de Haas et al., 2020), a simple comparison is not possible, but the result indicates that many people changed their behavior even under unenforced policies. Shamshiripour et al. (2020) used the SP-RP survey in the Chicago metropolitan area to analyze changes in people’s travel styles, and showed that long-distance commuting tends to change online. Teixeira and Lopes (2020) analyzed the relationship between subway and bike-sharing in New York, and found that the number of users of both systems decreased substantially. They found that the rate of decline was smaller for bike-sharing than for the subway, and that the average ride time was longer. Yilmazkuday (2020) showed that COVID-19 cases and deaths are lower in counties where a higher share of people have stayed in the same county in U.S. by using a difference-in-difference design.

We will also review the evidence reported for Japan. First, Figure 1 shows the number of cases in Japan until the end of May (Ministry of Health, Labour and Welfare, 2020). This period is called the first wave of the COVID-19 pandemic in Japan, which is the target of this study. As the number of cases increased, the government declared a state of emergency, and it lifted this declaration when the number of new cases began settling down. The details of the situation in this period are summarized in the appendix.

Arimura et al. (2020) analyzed behavioral changes in Sapporo City during this period using cell phone location data. As a result, they reported that the statement of reducing 70%–80% of contact between people in line with the purpose of the emergency declaration. Although these indicators are not simply comparable, the level of behavioral change is likely to be the same as that of countries with stronger lockdown measures as described above. Parady et al. (2020) developed a behavior change model based on the results of a panel web-survey in the Tokyo metropolitan area. As a result, they conclude as following about soft measures without penalties: “These findings suggest that in the context of non-binding requests, soft measures such as campaigns to promote a reduction of non-essential travel might be more effective if they (i) properly convey the severity of the threat posed by COVID-19 as well as its coping mechanisms, and (ii) appeal to the group, rather than the individual, emphasizing the behavior (or at least the perception of behavior) of others.” Based on this conclusion, it is likely that the Japanese residents as a group may have changed its behavior against the promotion of government, even

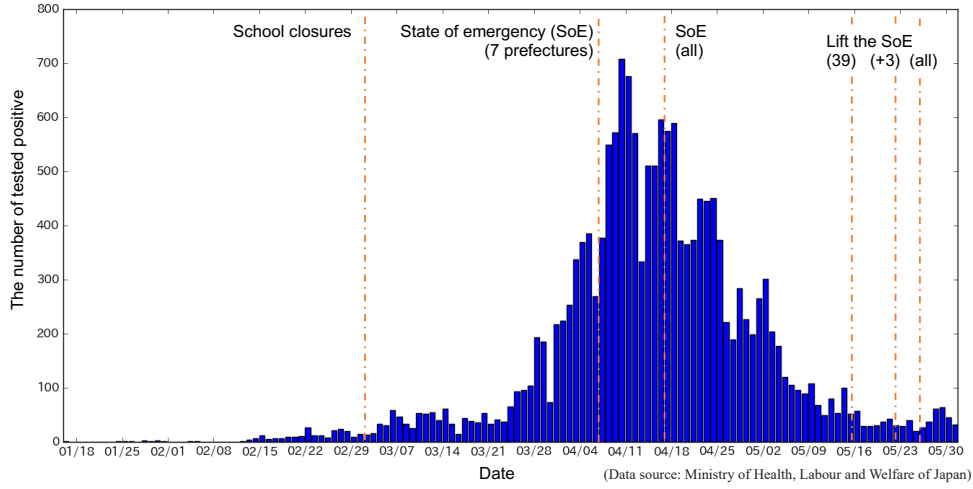


Figure 1: Number of individuals who tested positive until the end of May.

in areas where the number of infected people (or risk of infection) was small.

This paper is characterized by the following two points. First, by a large sample of nationwide data, the behavioral changes of people due to soft measures under pandemic conditions are discussed quantitatively from a broader perspective. Here, several indices are proposed to derive quantitative changes in movement and population density from a time series of aggregated population distribution data. Second, while applying the same approach, differences between regions under the same national government policies will also be discussed. This difference is important because it shows the characteristics of people's behavioral change toward the risk of infection under the same policy. This study will add new evidence on behavioral change under the COVID-19 pandemic in the above focus points.

### 3. Data

Mobile spatial statistics (MSS) is a new type of population statistics; it estimates the actual population in areas throughout Japan based on operational data from the mobile phone network of NTT DoCoMo (DOCOMO InsightMarketing, 2013; Terada et al., 2013). In a classification of mobile phone data by Wang et al. (2018), the original data of MSS are classified as cellular network-based data. This data has already been used in several transportation studies (Nakanishi et al., 2018; Yamaguchi and Nakayama, 2020; Kubo et al., 2020; Arimura et al., 2020).

Okajima et al. (2013) explains the features of MSS. MSS use operational data from a mobile terminal network to make population estimation depending on the properties of the mobile terminal network. Since MSS makes estimations based on the operational data from a mobile terminal network, the coverage of the estimates is essentially the same as the mobile terminal service area. The service area for NTT DOCOMO mobile terminal includes 100% of local government offices for cities, towns and villages in Japan. MSS has equivalent coverage. The characteristics of MSS are different from conventional residential population statistics. The first benefit of MSS is that it is easier to survey over wide areas. MSS are created automatically from operational data generated by a mobile terminal network, so the additional cost and time are much lower than conventional statistics. The second benefit is that results can be estimated much more quickly than conventional statistics. MSS are created 24-hour-a-day and 365-days-a-year, so statistics at one-hour intervals can be implemented at practical costs. On the other

hand, there are limitations on the age-groups over which MSS can estimate data. Since MSS are estimated from the operational data, estimates cannot be made on age groups where mobile terminal penetration is particular low. Specifically it cannot be applied to the age group of 80 and over or 14 and under. Thus, population estimations currently possible using MSS are limited to age ranges between 15 and 79. Another limitation is precision of the estimation compared to data such as the national census. In principle, the national census involves distributing questionnaires to all residents of Japan, so population estimates from it cover the entire population, while MSS are estimated from the operational data of NTT DOCOMO mobile terminal network, so values are subject to estimation error.

Okajima et al. (2013) also explains the data production process of MSS. The first process removes the identifying information, such as names and telephone numbers. Additionally, this stage also converts the date of birth to age groups, then summarizes it in the output. The second step has the role of counting the number of devices by age groups and gender for a specific time and area. Finally, the last process will remove the areas that have a few persons to prevent the identification of individuals based on their location. Thus, personal identity is again protected as a second security layer. Consequently, the final data exhibits the distribution of population by area, gender, age group, and moving patterns at the multilevel within cities, from prefecture to prefecture or from foreign countries to Japan, etc. Note that the data with higher dimensions of information will have a lower quantity compared with data with only spatial information.

As seen above, MSS indicates population statistic information indicating only the number of members of a group in a particular time zone and area. Figure 2 shows an example of MSS. MSS provides population statistics of standard grids (e.g., 1 km and 500 m grids) by gender, age, and prefecture-level (or city-level) residence in each hour.

Estimated population		
103	212	88
121	257	189
125	235	148

Estimated population includes gender, age groups, and residential city.

Gender: F: 97, M: 92  
 Age: 15-19: 14, 20-29: 48, 30-39: 31, ...  
 Residential: Tokyo: 132, Kanagawa: 39, ...

Figure 2: An example of MSS. Each standard grid has population statistics by gender, age, and residence in each hour.

Here, MSS is provided by the information of 80 million devices (DOCOMO InsightMarketing, 2013). The total population of Japan is 126 million, so even if we take into account the possibility that each person has multiple devices and the spatial difference of the share, we can say that the accuracy is better than the order of several hundred. In addition, the share of each residential area and age group is used to estimate the population (Terada et al., 2013). In this process, bias by the different share of age and residence place is corrected. The only situation we should be concerned about is when there is a large difference in behavior among the user groups of mobile phone operators. However, such a difference is unlikely for behavioral changes to COVID-19 pandemic, therefore this data can be expected to be sufficiently accurate for the this study.

In this paper, we use five-month MSS data for the entire Japan. The period is from January 1 to May 31, and it is considered to be the first wave of COVID-19. The spatial resolution is 500 m grids. As mentioned above, these data include gender, age, and city-level residence in each 500 m grid, but it does not include movement itself and trip-based statistics. This study excludes data from January 1 to 5 because the travel behavior in this period, which is the new-year holiday, is

quite different from normal.

#### 4. Temporal trends of trips

Here, we show how the number of daily trips across Japan changed. As the MSS is an aggregate population in a 500 m grid per hour, we cannot directly know the number of trips. In order to know the tendency of trips, we assume the minimum trip assumption in Figure 3.  $x_{m,t}$  indicates a population of a grid  $m$  at time zone  $t$ ,  $m$  is a 500 m grid, and  $t$  is a time zone (e.g., 14:00 on January 6). In the example, to determine the number of trips is ill-posed problem because there is lack of constraints. Therefore, we assume that the number of trips is the minimum number of trips that will satisfy the population at the next time slot.

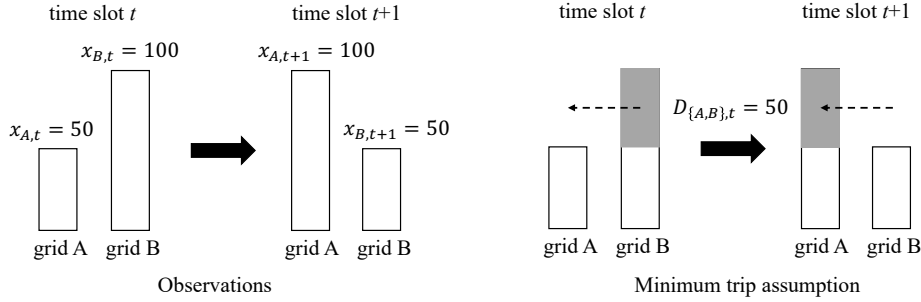


Figure 3: An illustrative example of the minimum trip assumption.

We call the trips that will satisfy the population at the next time slot “approximate trips” of target area. We calculate the number of “approximate trips”  $D_{M,t}$  using the following equation:

$$D_{M,t} = \frac{\sum_{m \in M} |x_{m,t} - x_{m,t+1}|}{2} \quad \forall t \in T, \quad (1)$$

where  $M$  is a target set of 500 m grids,  $T$  is a set of time zones. Naturally, this number of “approximate trips” is an underestimate of the actual number of trips because of the minimum trip assumption, but we can identify the trend of increase or decrease in the number of actual trips.

Figure 4 shows the change in the number of “approximate trips” in Japan from January to May. Red line indicates 7-day moving average. We can see a periodic pattern for weekdays and weekends. With January assumed to be normal, the school closures in March reduced trips by 4% compared with the normal number, and the “state of emergency” declaration by the Japanese government in April reduced trips further by 4.6%. The number of trips was the lowest during Japan’s major holiday period in early May, but it increased again with the lifting of the state of emergency. This result shows that the total number of “approximate trips” in Japan decreased significantly around the school closures and the declaration of a state of emergency.

Then, we focus on the “approximate trips” in each prefecture. Table 1 shows the change rate of “approximate trips” and the number of cases by prefecture as of May 31. Figure 5 shows the change in the number of “approximate trips” in Tokyo. The number of “approximate trips” reduced significantly in the Tokyo metropolitan area (MA), Osaka MA, Nagoya MA, Sapporo MA, and Fukuoka MA. In particular, Tokyo reduced its number of trips by about 45%, which is an excellent decreasing rate. The temporal pattern of trips in Osaka was the same as that in Tokyo. In both prefectures, the first trigger was the school closures, and the second was the declaration of the state of emergency. By contrast, local cities, especially those in the countryside, did not reduce their numbers of trips as much. Some cities even increased them. Figure 6 shows the change in the number of “approximate trips” in Iwate, whose number of cases was 0. The timing

of both school closures and the declaration of the state of emergency shows that the number of “approximate trips” in Iwate Prefecture did not decrease, but rather increased. Nonetheless, as the numbers of cases in these cities were small, the increase in trips was not necessarily linked to an increase in cases. These results suggest that, in addition to the number of trips, the population density of each city can have a significant impact on that city’s number of cases.

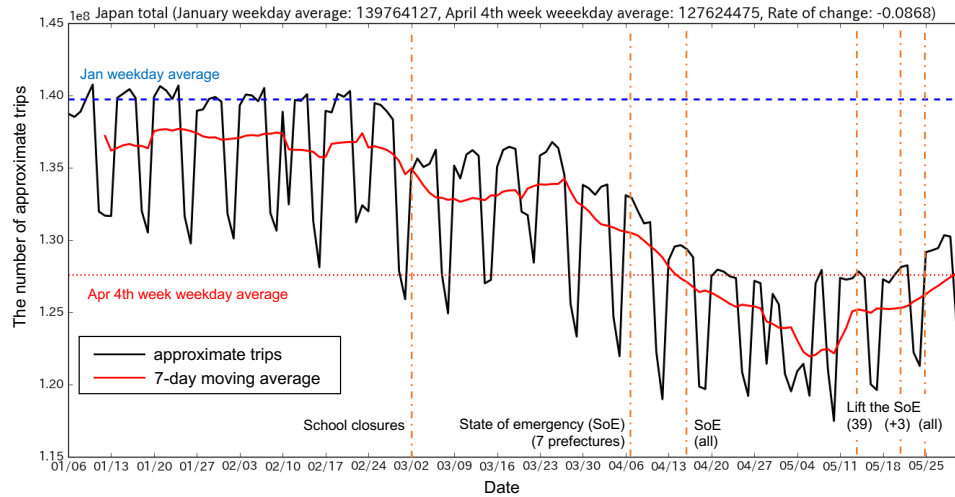


Figure 4: Number of approximate trips in Japan from January to May.

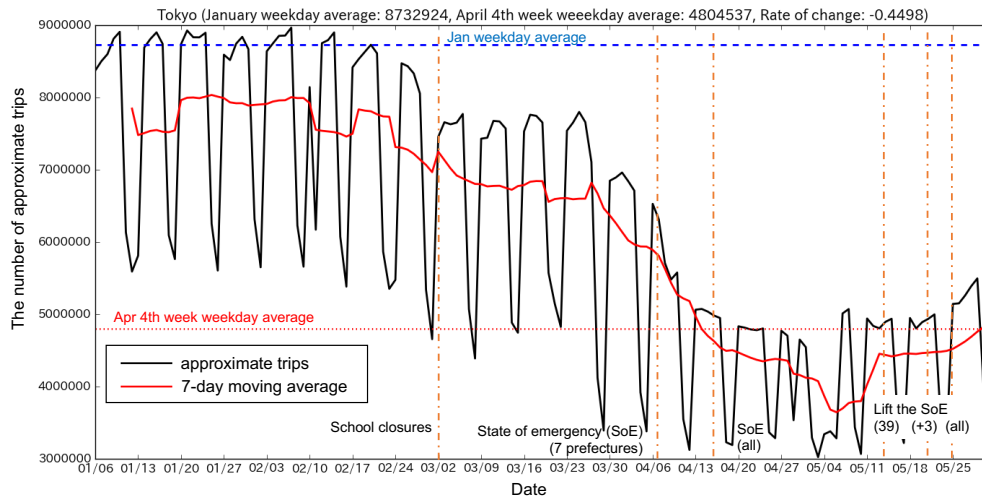


Figure 5: Number of approximate trips in Tokyo from January to May.

## 5. Temporal trends of inter-prefectural travel

Next, we focus on trends in inter-prefectural travel. The more people there are who travel long distances, the more likely COVID-19 will spread over a large area. Fauver et al. (2020) examined whether international or domestic travel contributed to the COVID-19 epidemic in the United



Table 1: Change rate of trips and the number of cases by prefecture.

Region	Metropolitan area (MA)	Prefecture	Rate of change	Number of cases	Population density (per km <sup>2</sup> )
Kanto region	Tokyo MA	Tokyo	-44.98%	5236	6367.67
		Kanagawa	-26.06%	1359	3813.30
		Saitama	-13.80%	1003	1933.63
		Chiba	-12.60%	909	1217.89
		Ibaraki	-2.46%	168	468.09
		Tochigi	-3.12%	65	301.51
		Gunma	-4.51%	149	302.78
Kinki region	Osaka MA	Osaka	-26.90%	1783	4627.76
		Kyoto	-10.82%	358	556.88
		Hyogo	-8.59%	699	647.41
		Nara	-5.52%	92	358.44
		Shiga	-4.90%	100	351.58
		Wakayama	-1.20%	63	193.47
		Mie	-3.64%	45	306.11
Chubu region	Nagoya MA	Aichi	-12.73%	507	1457.77
		Gifu	-3.02%	150	185.87
	Shizuoka MA	Shizuoka	-5.40%	76	465.32
		Yamanashi	-1.34%	64	180.55
		Nagano	-2.46%	76	149.99
		Niigata	-2.37%	83	174.80
		Toyama	-2.94%	227	243.59
		Ishikawa	-4.85%	298	269.97
		Fukui	-2.00%	122	182.00
Kysyu region	Fukuoka MA	Fukuoka	-10.46%	746	1024.12
		Saga	-1.46%	47	331.39
		Nagasaki	-1.31%	17	317.28
		Kumamoto	-1.68%	48	234.28
		Oita	-1.01%	60	177.42
		Miyazaki	-1.59%	17	137.52
		Kagoshima	-1.68%	10	172.78
		Okinawa	-14.15%	142	639.12
Hokkaido region	Sapporo MA	Hokkaido	-3.03%	1085	66.47
Tohoku region	Sendai MA	Miyagi	-3.74%	88	314.83
		Aomori	-0.17%	27	127.57
		Iwate	0.24%	0	79.36
		Akita	0.38%	16	81.81
		Yamagata	-0.83%	69	114.23
		Fukushima	-0.82%	81	132.77
Chugoku region	Hiroshima MA	Hiroshima	-4.74%	167	329.60
		Yamaguchi	-1.36%	37	219.47
		Okayama	-1.76%	25	264.59
		Tottori	1.05%	3	157.22
		Shimane	0.73%	24	99.43
Shikoku region		Tokushima	-1.37%	5	173.94
		Kagawa	-3.08%	28	505.55
		Ehime	-1.93%	82	233.69
		Kochi	-0.24%	74	97.10

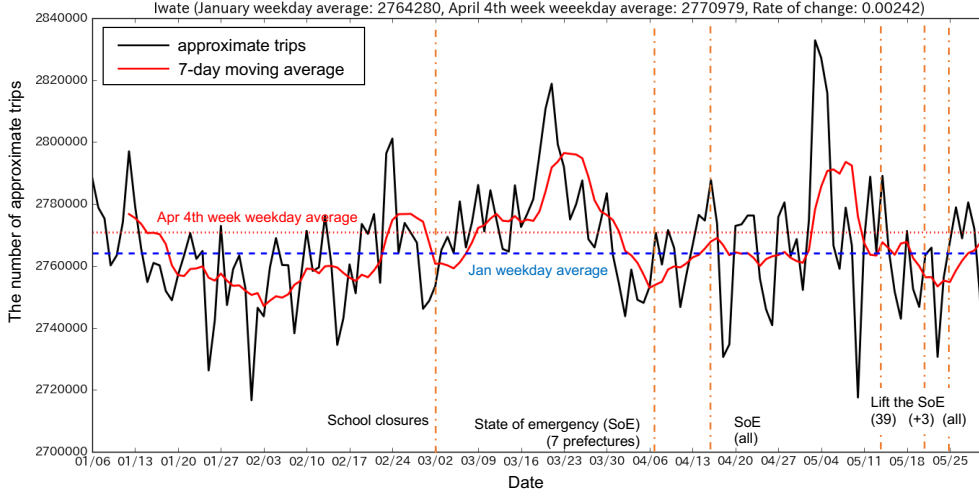


Figure 6: Number of approximate trips in Iwate from January to May.

States and they reported that domestic travel spread the epidemic more. In an analysis of cases in San Francisco during the early stage of the COVID-19 epidemic, Gu et al. (2020) reported that travel history is a risk factor for COVID-19; travel within the United States, particularly New York, the epicenter of the epidemic at the time, was a greater risk than international travel. These previous studies suggest that domestic travel is a risk factor for the spread of COVID-19 infection.

In some countries, lockdowns are being used as a strong policy to suppress COVID-19. In Japan, under a declared state of emergency, people were discouraged from going out, especially traveling across prefectures. However, because there was no lockdown, public transportation, such as airplanes and high-speed rail, was operational, and inter-city expressways were available. Naturally, there was no penalty for traveling across prefectures.

In order to understand the inter-prefectural travel trends, we propose a day-level average inter-prefectural travel flow by using MSS. As mentioned above, The MSS includes the population that currently exists in a 500 m grid, and it can be divided by the people's prefecture of residence in Figure 2. In this study, we calculate the number of day-level average number of people staying in a prefecture from other prefectures. It means that when a person who lives in prefecture  $a$  stays for 12 hours in prefecture  $b$ , we regards day-level average flow from  $a$  to  $b$  as 0.5 person per day. The reason why the number of trips between prefectures cannot be calculated directly is due to the limitation of the MSS. Therefore, we use the average number of people staying per day. The day-level average flow  $f_{a,b,d}$  from prefecture  $a$  to  $b$  on day  $d$  is as follows:

$$f_{a,b,d} = \frac{\sum_{t \in T_d} \sum_{m \in M_b} x_{m,t,a}}{24} \quad \forall a, b \in A, \forall d \in D_{all}, \quad (2)$$

where  $x_{m,t,a}$  is the number of people on a 500 m grid  $m$  at time zone  $t$  who live in prefecture  $a$ ,  $M_b$  is a set of grids belonging to prefecture  $b$ ,  $T_d$  is a set of time zones on day  $d$ ,  $A$  is a set of prefectures, and  $D_{all}$  is a set of observed days. Hence,  $f_{a,b,d}$  means the 24-hour average number of people who live in prefecture  $a$  and stay in prefecture  $b$ .

Figure 7 shows the day-level average inter-prefectural travel flow. The figure shows how the total volume of inter-prefectural travel in Japan evolved. In January, the inter-prefectural travel flow was about 5.5–6 million, but near the school closures, it suddenly decreased to about 4.5–5 million. Interestingly, a decreasing trend was already observed a few days before the

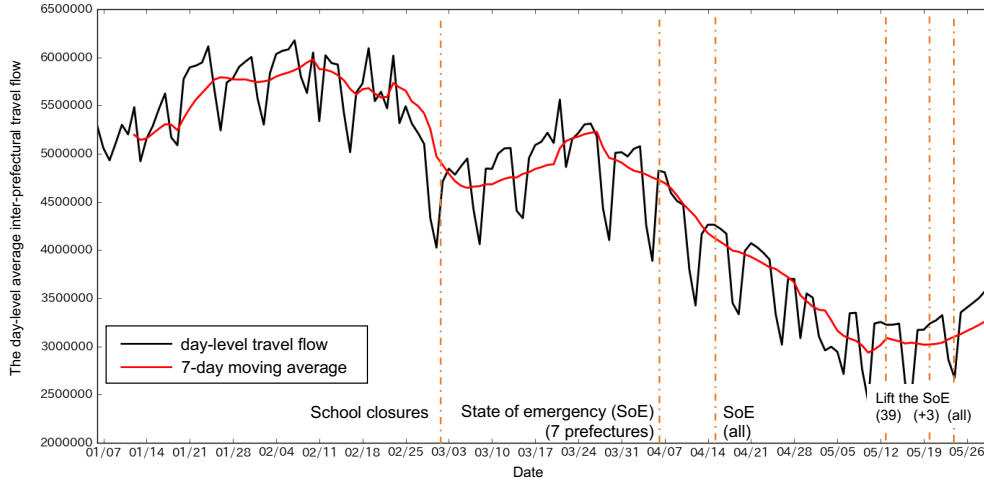


Figure 7: The day-level average inter-prefectural travel flow: the 24-hour average number of people staying in a prefecture other than the one they live in.

school closures. Near the timing of state-of-emergency declaration, the inter-prefectural travel flow continued to decline further. At the end of April, the number was about 3 million, which is approximately half of January’s figure. As Figure 7 shows, there was a clear decrease in inter-prefectural travel flow after the declaration of the state of emergency despite the lack of penalty for travel across prefectures.

Figure 8 and 9 show the inter-prefectural travel inflow to Tokyo and the outflow by Tokyo residents. Each color indicates the origin (destination) prefecture. In Figure 8, we can see the weekday and weekend cycles by plenty of commuters from neighboring prefectures (Kanagawa, Saitama, and Chiba). These commuters decreased significantly in inflow. At the end of April, the number of inflow was approximately half of January’s figure. Figure 9 shows the day-level average inter-prefectural travel outflow from Tokyo to other prefectures. It also shows a significant decrease in the number of Tokyo residents traveling to other areas on weekends and holidays. These results indicate that the declaration of the state of emergency has forced people to refrain from commuting to neighboring prefectures, engage in remote work, and avoid weekend trips. In particular, late April and early May constitute a long holiday known as the Golden Week in Japan, a period when many people would normally travel across Japan or overseas, but the results show that many people did not leave their places of residence in the same period 2020.

As these results show, near the school closures and emergency declarations, inter-prefectural travel flow significantly reduced. We estimate that the number of commuters to Tokyo from neighboring prefectures on weekdays decreased by up to 1 million. Furthermore, about 200,000 outflow trips from Tokyo to other prefectures were eliminated due to a decrease in weekend vacation trips and weekday business trips. In terms of inter-prefectural travel, we conclude that the school closures and emergency declarations with the spread of COVID-19 contributed to the reduction in the number of trips across prefectures.

## 6. Temporal trends of population density index

### 6.1. Definition of target index

In this section, we focus on the population density and understand its temporal change under the COVID-19 “state of emergency” declarations. Here, the average number of people who

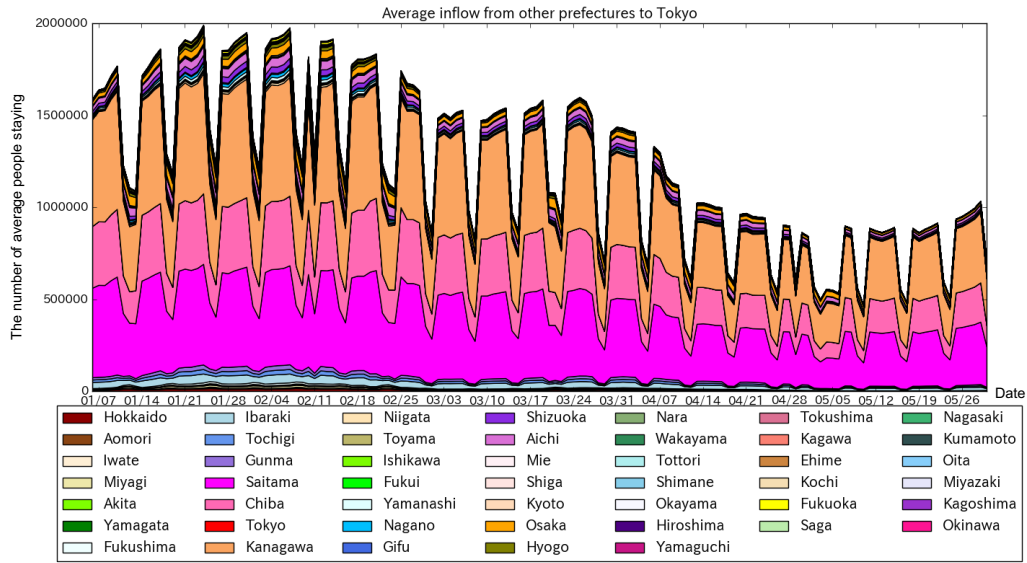


Figure 8: The day-level average inter-prefectural travel inflow to Tokyo from other prefectures.

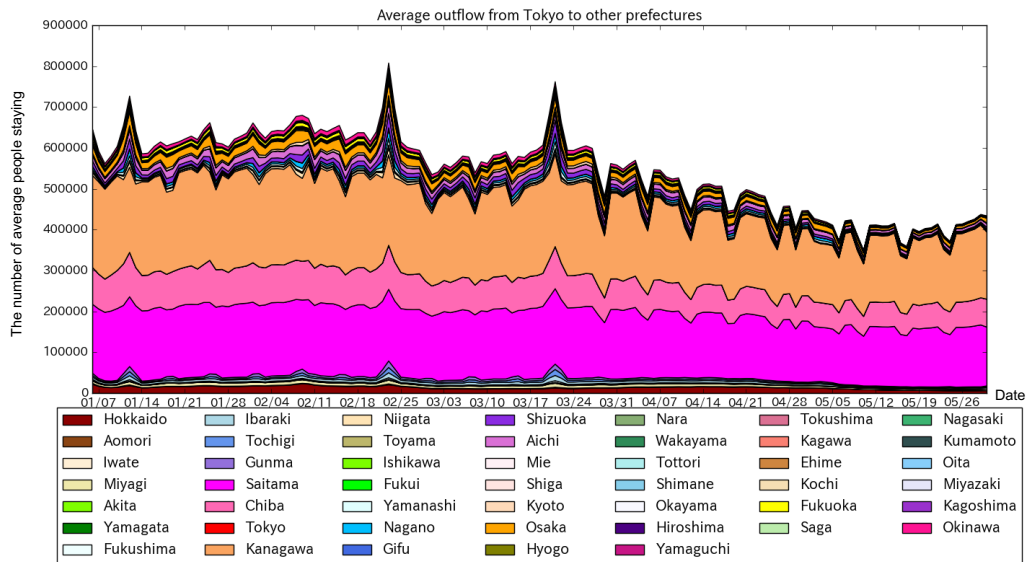


Figure 9: The day-level average inter-prefectural travel outflow from Tokyo to other prefectures.

stayed in the same 500 m grid  $C_{d,t}$  is used as the index of density. This index is calculated by dividing all pairs staying in the same grid by the total population.

$$C_{d,t} = \frac{\sum_{m \in M} (x_{d,t,m})^2}{\sum_{m \in M} x_{d,t,m}} - 1 \quad \forall (d, t) \in D_{\text{all}} \times T \quad (3)$$

where  $m$  is a 500 m grid,  $M$  is a set of 500 m grids in area  $z$ ,  $d$  is a date,  $D_{\text{all}}$  is a set of dates ( $D_{\text{all}} = [1/06, 1/07, \dots, 5/31]$ ),  $t$  is a time zone,  $T$  is a set of time zones ( $T = [0:00, 1:00, \dots, 23:00]$ ),  $x_{t,m}$  is the population of grid  $m$  at time zone  $t$ .

Here, for each person staying in grid  $m$ , the number of people staying in the same grid is  $x_{d,t,m} - 1$ . The index  $C_{d,t}$  is the average number of people staying in the same 500m grid at a given time  $(d, t)$  for all people. This index can be roughly interpreted as the average number of people staying at a perimeter of  $282 \text{ m} \sim \sqrt{\frac{500 \times 500}{\pi}} \text{ m}$  around each person. Therefore, this index takes a small value when many people avoid staying in a dense place. When we assume that a pair who stays in the same 500 m grid contacts in a certain probability, the index  $C_{d,t}$  becomes proportional to the number of contacts among people.

In order to calculate the number of contacts at risk of infection, it is desirable to calculate  $C_{d,t}$  using smaller size grid. Because the distance related to the infection is only several meters. The 500m grid used in this study is the smallest unit in which the data accuracy of MSS is sufficiently reliable on a national scale in Japan. This grid size may be difficult to predict the risk of infection, but it is sufficient to determine the degree of behavioral change avoiding dense areas.

## 6.2. Temporal changes in density index of whole Japan

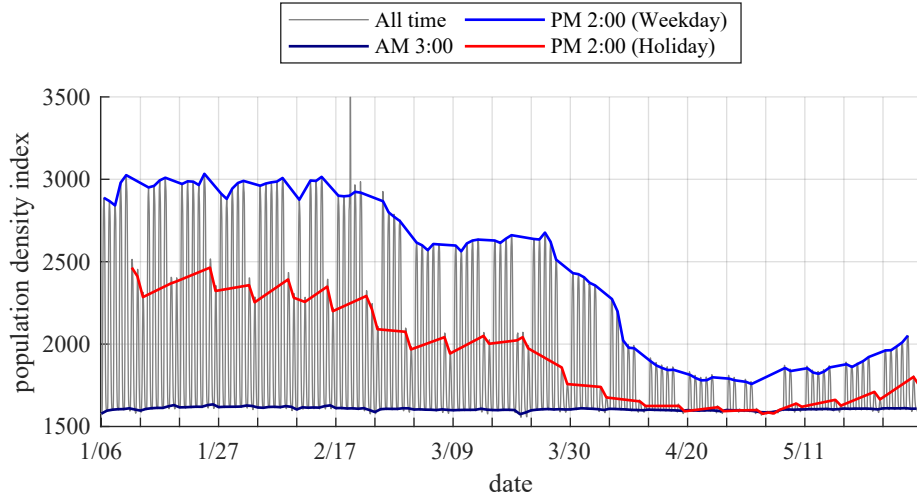


Figure 10: Population density  $C_t$  index of whole Japan

Figure 10 shows the time-series change of the density index  $C_{d,t}$ , which is calculated by using all 500 m grid data in Japan. The thin black line in this figure shows the hourly time-series change of the density index. Basically, this density index fluctuates greatly during a day. Specifically, it typically takes a small value at night and a large value at daytime because people stay in dense places during the day for work.

The three thick lines in Figure 10 connect plots for the same time period. The thick black line shows the day-to-day temporal change of the density index at 3:00 AM. On many days, the density index takes a minimum value at 3:00 AM, when most people are sleeping at home. As

a result, this thick black line  $C_{d,3AM}$  is close to the lower bound of  $C_{d,t}$ . The minimum density index values of the days are constant during the entire analysis period, including COVID-19 “state of emergency” period. This is the expected result because the places where people stay at night (home) did not change.

The thick blue line in Figure 10 connects the plot for PM 2:00 on weekdays. On many weekdays, the density index takes a maximum value at 2:00 PM. As a result, this thick blue line is close to the lower bound of  $C_{d,t}$ . In January, which was not affected by COVID-19, the density index at PM 2:00 on weekdays is about 3,000. This means that the average number of people within a 280 m radius around a person is about 3,000 at PM 2:00 on weekdays. This blue line continues to decrease from late February to April, which was affected by COVID-19. This means that people had started gradually avoiding dense areas. The blue line has a minimum value on May 1. At this time, the average number of people within a 280 m radius around a person is 1,843, which is only 60% of the average in January.

The thick red line in Figure 10 shows the time-series change of the population density index at PM 2:00 on holidays (Saturday, Sunday and national holidays). In January, the density index at PM 2:00 on holidays is about 2,300, which is smaller than that on weekdays. This means that people spend their holidays in less dense places than on weekdays. Under the COVID-19 “state of emergency” declaration, this value on holidays also becomes smaller. In particular, the five weeks from April 13 to May 18 are almost the same as those at midnight. In other words, people either stayed home during the daytime on holidays or moved to places other than dense areas within these five weeks.

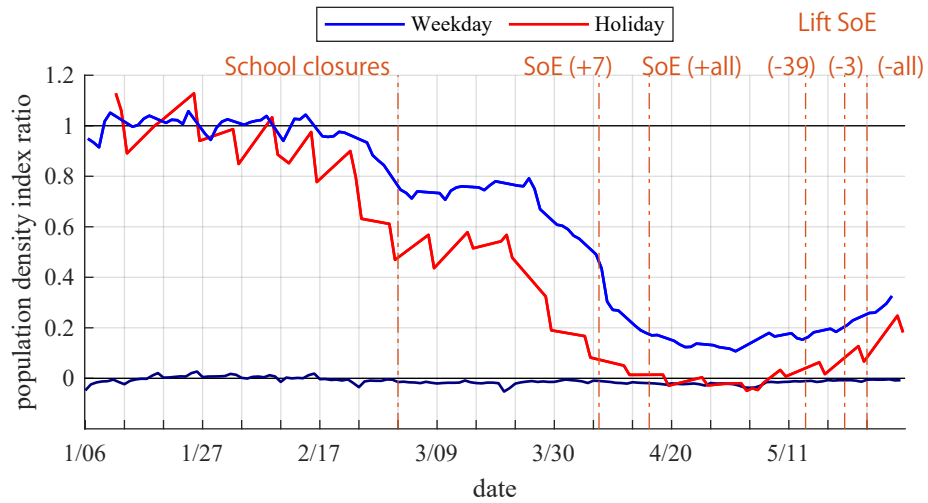


Figure 11: Population density index ratio  $R_d$  and implementation date of the main measures against COVID-19.

Let us analyze this time series of  $C_{d,t}$  in more detail to see its relationship to some of the government responses related to COVID-19. Here we focus on two representative points of time shown in Figure 10. In addition, to discuss the detailed time-series change ratio respect to before

COVID-19, we use  $R_d$ , defined as follows.

$$R_d = \begin{cases} \frac{C_{d,2PM} - \bar{C}_{\text{mid-night}}}{\bar{C}_{\text{weekday},2PM} - \bar{C}_{\text{mid-night}}} & \forall d \in D_{\text{weekday}} \\ \frac{C_{d,2PM} - \bar{C}_{\text{mid-night}}}{\bar{C}_{\text{holiday},2PM} - \bar{C}_{\text{mid-night}}} & \forall d \in D_{\text{holiday}} \end{cases} \quad (4)$$

$$\bar{C}_{\text{mid-night}} = \frac{\sum_{d \in D_{\text{normal}}} C_{d,3AM}}{N(D_{\text{normal}})} \quad (5)$$

$$\bar{C}_{\text{weekday}} = \frac{\sum_{d \in [D_{\text{normal}} \cap D_{\text{weekday}}]} C_{d,2PM}}{N([D_{\text{normal}} \cap D_{\text{weekday}}])} \quad (6)$$

$$\bar{C}_{\text{holiday}} = \frac{\sum_{d \in [D_{\text{normal}} \cap D_{\text{holiday}}]} C_{d,2PM}}{N([D_{\text{normal}} \cap D_{\text{holiday}}])} \quad (7)$$

where  $D_{\text{weekday}}$  is a set of weekday dates that satisfies  $D_{\text{weekday}} \subset D_{\text{all}}$ ,  $D_{\text{holiday}}$  is a set of holiday dates,  $D_{\text{normal}}$  is a set of dates when the impact of COVID-19 is assumed to be small enough ( $D_{\text{normal}} = [1/06, 1/07, \dots, 2/02]$ ), and  $N(S)$  is the number of elements in set  $S$ .  $\bar{C}_{\text{mid-night}}$  is the average of  $C_{d,3AM}$  before COVID-19, and the difference from this value represents the movement to high-density areas from nighttime stay places. In addition,  $\bar{C}_{\text{weekday}}$  and  $\bar{C}_{\text{holiday}}$  are the averages of  $C_{d,2PM}$  for weekdays and holidays, respectively, without the effect of COVID-19. Therefore,  $R_d$  shows the reduction rate of the movement to high-density areas based on the level before COVID-19 pandemic.

Figure 11 indicates the following features of the COVID-19-induced behavioral change in Japan. At first, the value of  $R_d$  decreases more rapidly and considerably on holidays than on weekdays. This indicates that the leisure behavior changed earlier and by a larger margin than the business behavior. Secondly, the major changes occurred before the government made policy decisions (school closure, “state of emergency” declaration). The only exception is that the  $R_d$  on weekdays decreased by about 20% on the day of the declaration of emergency (4/7). However, before the declaration, it was already 50% lower than the level in January. In other words, we can infer that such a decrease in density was done willingly by the people and not controlled by the government. The national government only implemented multiple measures after these changes in behavior. As a result, no significant recovery can be observed despite the lifting of the state of emergency.

### 6.3. Temporal changes in density index (prefectures)

We compare the regional difference in the population density index ratio  $R_d$ . Here, we compare the difference among six prefectures, as shown in Table 2. These include Tokyo Prefecture, which had the most serious situation in Japan, and Iwate Prefecture, where the number of individuals tested positive had become zero by the end of May. The multiple prefectures with different “state of emergency” periods are selected.

In Tokyo, the national government declared the state of emergency between April 7 and May 25. Large numbers of patients with COVID-19 were continuously detected from just before this period until its end. This time transition in Tokyo was almost the same as those in Osaka and Fukuoka. The only difference is that the declaration of emergency was lifted in Osaka and Fukuoka sooner than that in Tokyo, because the number of individuals tested positive decreased relatively early, as shown in Figure 12.

The time transition in Hokkaido is different from those in the other prefectures. First, the number of individuals who tested positive became relatively larger during February 24 to March 9. Therefore, the Governor of Hokkaido independently declared a state of emergency on February 28. At this time, he asked the citizens to refrain from going out on weekends. This original declaration of emergency continued until March 18. Second, the number of individuals who

Table 2: Basic information of target prefecture

Prefecture	Number of cases (until 2020/05/31)	Population (million)	State of emergency	
			Start	End
Tokyo	5,163	13.7	April 7	May 25
Osaka	1,702	8.8	April 7	May 21
Hokkaido	967	5.3	April 13	May 25
Fukuoka	743	5.1	April 7	May 14
Hiroshima	166	2.8	April 13	May 14
Iwate	0	1.3	April 13	May 14

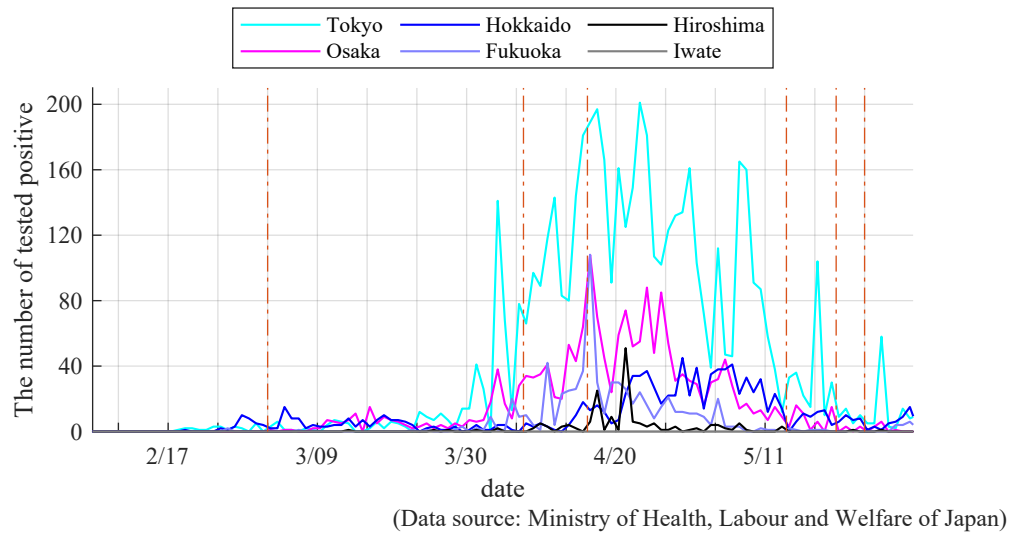


Figure 12: Number of individuals who tested positive in each prefecture.



tested positive increased again in the second half of April, slightly later than that in the other prefectures. During this period, the national government declared the state of emergency in Hokkaido.

In Hiroshima and Iwate Prefecture, as in many other rural areas, the number/ratio of individuals who tested positive was relatively smaller than those in the four other prefectures at the end of May. In particular, Iwate is the only prefecture where the number of detected COVID-19 patients was zero by May 31. Even in these prefectures, the national government applied school closures and declared a state of emergency (April 13 to May 14).

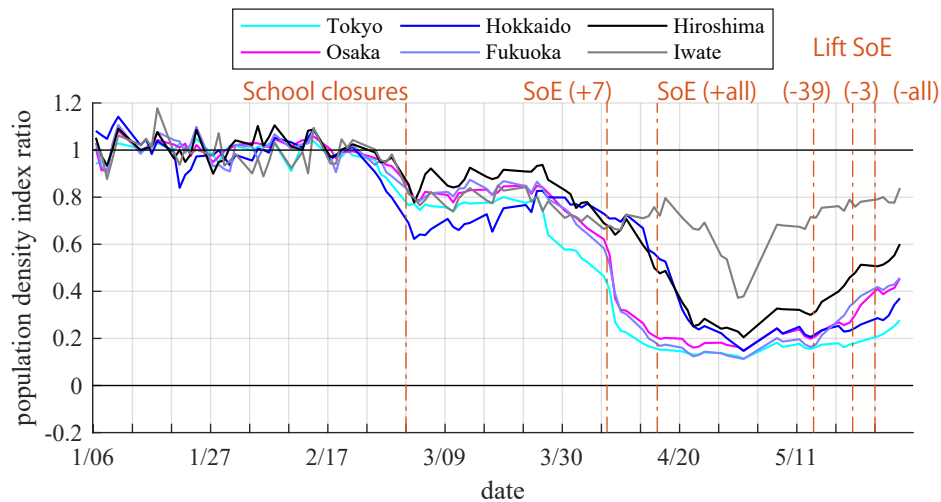


Figure 13: Population density index ratio  $R_d$  in six prefectures (weekday).

Figure 13 shows the time-series change of  $R_d$  on weekdays for six prefectures. Three differences are noted. First, from March 2 to March 23, the population density index ratio  $R_d$  in Hokkaido is different from those of the five other prefectures. During this period, the  $R_d$  in the other prefectures is about 80% of that in January. In Hokkaido, where the governor independently declared a state of emergency, the value of  $R_d$  is smaller than that of the other prefectures by about 10%. The value in Hokkaido then recovers to the same level as those of the other prefectures (80% of that in January) after the cancellation of the original state of emergency. Second, the time transitions of  $R_d$  are different among the prefectures in April, when the national government declared the state of emergency. In Tokyo, Osaka, and Fukuoka, where the national government declared an emergency relatively early, the value of  $R_d$  decreases to about 20% on the declaration date (April 7). In Hokkaido and Hiroshima, the value of  $R_d$  gradually decreases over two weeks before and after the date of emergency declaration (April 13). Moreover, their values of  $R_d$  decreases to the same level as those of Tokyo, Osaka, and Fukuoka around April 27. Third, in Iwate Prefecture, where there are no detected COVID-19 patients, the value of  $R_d$  is not as small as those in the other prefectures even after the national government declared the state of emergency.

Figure 14 shows the time-series change of  $R_d$  on holidays for the six prefectures. This figure indicates that the regional difference of  $R_d$  on holidays is smaller than on weekdays.

We can find the following regional differences in Figure 14. First, on and around March 1, the value of  $R_d$  in Hokkaido is smaller than that in the other prefectures. In particular, a value 20% of the January level is recorded for March 1. This difference seems to be a reaction to the request of the governor. Second, Iwate has relatively larger values recorded on holidays and weekdays than those in the other prefectures. Even in the relatively large Iwate, the level is 50% or less; thus, people may have been refraining from traveling to densely populated areas on holidays.

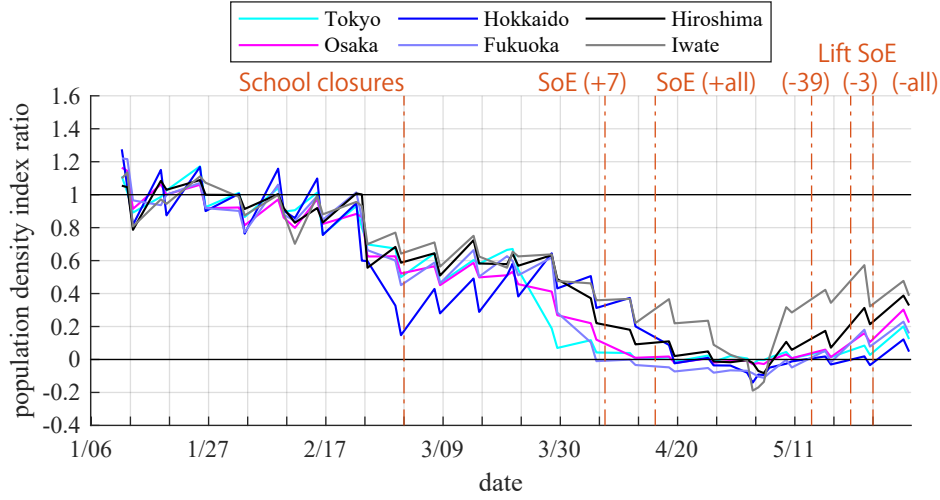


Figure 14: Population density index ratio  $R_d$  in six prefectures (holiday).

## 7. Summary of findings

This study empirically analyzed behavioral changes under COVID-19 in Japan by using MSS, which is based on mobile phone networks. Our contribution is the creation of certain indices for understanding nationwide behavioral changes in Japan from MSS data. This approach has the advantages of avoiding privacy violations and providing an overview of nationwide behavioral change with a small computational load.

An important fact related to the early stages of the COVID-19 epidemic in Japan is that a significant decline was achieved without strong governmental restrictions. The main triggers for behavioral change in Japan appear to have been school closures and the declaration of a state of emergency. These policies affected the entire country and significantly reduced intra- and inter-city trips, especially in MAs (45% in Tokyo and 27% in Osaka). In addition, the number of people coming to local cities from large cities was significantly reduced compared with the normal numbers because most people in MAs stayed home.

The second finding is that people changed their behavior even a few days before a school closure or a “state of emergency” declaration. A detailed analysis of the population density index shows that the index did not decrease with the declaration of these policies; rather, the index decreased as people spontaneously avoided moving to densely populated areas. This result suggests that the public opinion formed by the mass media and social media may have caused such behavioral change. This assumption requires further analysis, but it does not mean that behavioral change suddenly occurred as a result of the government’s declarations.

The third finding is the similarities and differences between prefectures. School closures and “state of emergency” declarations were implemented throughout Japan without taking into account the number of cases in each prefecture. The numbers of intra-city trips and travels across prefectures decreased significantly, especially in large cities with many cases. By contrast, in the countryside, the number of trips was not reduced. Nonetheless, even if the number of trips did not decrease, the population density index decreased significantly, indicating a significant change in people’s behavior in all cities.

The fourth finding is the inertia of behavioral change. Both the number of trips and the population density index did not recover to their normal levels immediately after the lifting of the “state of emergency” declarations. This result also suggests that people changed their behavior spontaneously.

These results and findings represent only the behavioral changes that occurred during the first wave of COVID-19 expansion in Japan, and it is not necessarily indicative of behavioral changes due to the pandemic in other countries, given differences in culture and politics. However, these results can provide some evidence of behavioral changes in people during a pandemic.

#### **Appendix: Timeline related to COVID-19 in Japan from January to May, 2020**

In January 2020, there was little interest in COVID-19 in Japan. One of the triggers for the increased interest in COVID-19 was the Japanese government's decision to send a charter flight to Wuhan, China, to repatriate its citizens. The second trigger was the COVID-19 outbreak on the cruise ship Diamond Princess. As passengers who were forced to stay in the cruise ship for two weeks returned to their homes (their places of residence are not only metropolitan areas, but also countryside), many people recognized COVID-19 as a familiar issue. The following timeline shows major events related to COVID-19 in Japan (Ministry of Health, Labour and Welfare, 2020).

- Jan. 16: A Chinese man living in Kanagawa Prefecture who has traveled to Wuhan, China, is infected. This is the first COVID-19 infection case in Japan.
- Jan. 29: Japanese citizens living in Wuhan return to Japan through a charter plane.
- Feb. 13: The first death caused by COVID-19 in Japan is reported.
- Feb. 19: The quarantine period of the passengers in the Diamond Princess ends. Those with negative test results start to disembark.
- Feb. 21: The cases in Japan exceed 100.
- Mar. 2: The Japanese government decides to temporarily close all elementary, middle, and high schools.
- Mar. 21: The cases in Japan exceed 1,000.
- Mar. 24: The International Olympic Committee (IOC) and the Tokyo Organising Committee of the Olympic and Paralympic Games announced that the Tokyo 2020 Olympic Games is postponed.
- Mar. 27: The cases per day in Japan exceed 100.
- Apr. 3: The cases in Japan exceed 3,000.
- Apr. 7: The Japanese government places seven prefectures (Tokyo, Saitama, Chiba, Kanagawa, Osaka, Hyogo and Fukuoka prefectures) under a state of emergency until May 6. Under this situation, the Japanese government asks people to avoid leaving their homes for non-essential reasons, and it requests many commercial establishments and restaurants to refrain from doing business. Many offices promote remote working. However, travel between cities remains unrestricted, and highways and public transportation are available.
- Apr. 8: Japan's cases per day exceed 500.
- Apr. 12: The death toll in Japan exceeds 100.
- Apr. 16: The government expands the "state of emergency" declaration to all of Japan.
- Apr. 18: The cases in Japan exceed 10,000.

- Apr. 22: The death toll in Japan exceeds 200.
- May 2: The death toll in Japan exceeds 500.
- May 3: Japan's exceed 15,000.
- May 4: The government announces the extension of the "state of emergency" declaration until May 31.
- May 14: The government lifts the "state of emergency" declarations in 39 prefectures.
- May 21: The government lifts the "state of emergency" declarations in three prefectures (Osaka, Kyoto, and Hyogo).
- May 25: The government lifts the "state of emergency" declarations in the entire country.

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