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The effectiveness of mobility control, shortening of restaurants' opening hours, and working from home on control of COVID-19 spread in Japan

Asako Chiba

Tokyo Foundation for Policy Research, 3-2-1 Roppongi, Minato-ku, Tokyo, 1066234, Japan

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ABSTRACT

Since the first outbreak of COVID-19, various interventions have been implemented to prevent the global spread of the virus. Using an agent-based model that describes the attributes and mobility of the Japanese population, the present research evaluates the effectiveness of mobility control, shortening of restaurants' opening hours, and working from home. Results show that early and severe mobility control that restricts 90% of domestic travel decreases the peak cases by 40%, compared to no intervention implementation. Mobility control that only limits movement to and from highly populated regions is as effective as nationwide travel restrictions. Furthermore, shortening of restaurants' opening hours is the most effective intervention in a state of emergency; it should be utilized even after the emergency. However, working from home has comparatively limited effects.

1. Introduction

Since the outbreak of the coronavirus disease (COVID-19), numerous interventions have been adopted to prevent its spread (Bo et al., 2021; Wu et al., 2020). These non-pharmaceutical interventions include testing, mobility control, shortening of restaurants' opening hours, working from home, restriction on the size of events, and contact-tracing. Some of these interventions have been comprehensively studied, including nationwide travel restrictions, which had already been recognized as an effective policy tool to prevent the spread of diseases even before the outbreak of COVID-19 (see, for instance, Ferguson et al., 2006; Germann et al., 2006; Aledort et al., 2007). Empirical evidence highlights that travel restrictions, at least in the early stage of a virus outbreak, had a significant effect in preventing the spread of the virus (Fang et al., 2020; Kraemer et al., 2020; Lau et al., 2020). Furthermore, tracing and quarantine of symptomatic contacts were renowned for their effectiveness against epidemics even before the outbreak of COVID-19 (Fraser et al., 2004; Klinkenberg et al., 2006). Such contact tracing is more effective than sole mass-testing (Kucharski et al., 2020), although its effectiveness depends on the accurate and rapid detection of the contacts (Keeling et al., 2020), which could be enhanced through app-based tracing (Ferretti et al., 2020). Additionally, testing and tracing have good cost performance because these mechanisms do not impose restrictions on the economic activity of the entire society, as opposed to total lockdown and working from home (Aleta et al., 2020). Conversely, the effects of other interventions, such as working from home and shortening of restaurants' opening hours, are still unclear,[1] although they have been widely implemented in many countries (De Vos, 2020; Kim and Lee, 2020). Moreover, understanding the degree of effectiveness of each intervention is necessary, as the interventions incur economic costs (Flaxman et al., 2020). Flaxman et al. (2020) considers several types of measures, but several major interventions such as mobility control and working from home, have been ignored. Similarly, Courtemanche et al. (2020) and Li et al. (2021), who provide broad analyses on the effects of various interventions, do not include shortened restaurants' opening hours.

To compare the effectiveness of mobility control, both on a nationwide and region-specific level, through shortening of restaurants' opening hours and working from home, the present research develops an agent-based model that describes the attributes and mobility of the population in Japan, using individual census and mobility data. The results show the relatively high effectiveness of restaurants' shortened opening hours in preventing the spread of the virus. Mobility control decreases the peak cases by 40%, if it is implemented early and severely, such that it decreases travel by 90%. Mobility control that only targets highly populated regions is as effective as nationwide mobility control, suggesting that such region-specific mobility control has better cost effectiveness. The effectiveness of working from home is weak, even if people who can work from home reduce commuting by 70%.

E-mail address: chiba@tkfd.or.jp.

[1] Among the few studies analyzing the effectiveness of working from home on the number of COVID-19 cases, Fadinger et al. (2020) report that cases in regions where many people can easily work from home were less than that in other regions.

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2. Materials and methods

To compare the effectiveness of mobility control, both on a nationwide and region-specific level, through shortening of restaurants' opening hours and working from home, the present research develops an agent-based model that describes the attributes and mobility of the population in Japan using individual census and mobility data. In particular, the joint probability distributions of people's age, sex, residence prefectures, jobs, industries, the size of the firm they work for, and family types in the model reflect those of the real population. These attributes were used to construct people's contacts with each other.

The model is based on Covasim, an open-source platform to simulate the expansion of epidemics, proposed by (Kerr et al., 2020). In their model, viruses transmit through people's contact with each other, which happen at four different places: homes, workplaces, schools, and communities. The probability of transmission of viruses and the transition probability and duration in each stage of symptoms depend on each person's age (Kerr et al., 2020). have also provided intervention tools to deactivate contacts in places where people meet. Although their novel model describes a virus outbreak that would occur in a real world, several factors that determine the virus transmissions are missing. First, although their model assumes that the probability of virus transmission is determined only by people's attributes and the category of places where they meet, it is now known that a large proportion of infections can be explained by a small number of situations, classified as super-spreading environments (Cave, 2020). Second, virus transmissions can also occur in places other than the four places assumed in their model; a substantial fraction of positive cases are reported at nursing homes and restaurants. Third, people's mobility has not been fully considered; in reality, physical contact is affected by geographical constraints. People living in the same region come in contact with each other in their daily lives more frequently than those who live in different regions. Due to the inconsideration of this factor, travel restriction, one of the major interventions, cannot be directly implemented. The present study's model introduced the following factors for a more holistic understanding of the spread of the virus: super-spreading environments, detailed specification of places where people meet, people's mobility, and the implementation of travel restrictions. In addition, an artificial society that replicated the real one in Japan was constructed by allocating detailed attributions using the data from real distribution. The role of these factors in the transmission mechanism and the construction of data, which are newly introduced in the present paper, are explained in the following subsections.

2.1. Virus expansion including super-spreading environment

Table 1 illustrates each status as the infected people develop symptoms. The probability with which a susceptible person catches the virus from an infected person depends on three factors: likelihood of transmission where the two people meet, the relative transmissibility of the infected person, and whether the contact is under a super-spreading hotspot. Table 7 signifies the age-dependent probability and duration of developing symptoms.[2] Besides, the transmissibility in the early stage is set twice as high as that in the later. Super-spreading environments refer to the phenomena that only a small fraction of all cases account for a large amount of all transmissions (Cave, 2020). They are described in the model by specifying that the likelihood of transmission in the randomly selected 4% of all contacts is 2000 times higher than the rest of the contacts.[3]

2.2. Attributes of population in Japan

To create an artificially small society that reflects the attributes of people in Japan, the following steps were taken:

1. Randomly select 25,000 people from the individual census data as of 2015.[4]
2. Allocate family members to each of the selected people, according to their attributes regarding family members (e.g., having or not having a spouse, number of children, and presence of association with three-generation families).
3. Adjust distortion generated in step 2: the proportion of young people who live with families becomes larger than the population selected in step 1. Thus, to render the age distribution close to that in reality, in step 3, people over 60 years of age and living alone are doubled.
4. Give attributes to the members added in step 2 and 3, following the joint probability distribution of attributes obtained from the whole individual census data.

These steps created an artificial population that copied Japan, scaled down to 1/1500: the size of the population was 76,178, and the attributes of people included age, sex, residence prefecture, job, industry, and size of the employing firm. The panels in Fig. 1 show the distribution of age and residence prefectures of the artificial society in comparison with the real one in Japan.

2.3. Contacts

People's attributes were used to construct patterns of daily contacts at home, workplaces, schools, and nursing homes, which account for more than half of all observed contacts (Mossong et al., 2008). Non-daily fluid contacts, such as contacts made while traveling and during leisure, that account for 20% of all observed contacts (Mossong et al., 2008), were constructed by modeling the eight largest metropolitan cities of Japan, as most infections were reported from these areas (see Fig. 2).

Daily fixed contacts considered four places: home, workplace, school, and nursing home. In each place, people were selected and grouped according to the methods described in Table 2. Since family members had already been created, as described in the previous section, contacts through workplaces, schools, and nursing homes were created here. For instance, contacts in the workplaces were created by grouping people who work for a certain firm in a certain industry and live in a certain prefecture with the size equivalent to their firm size. Similarly, children of school-age in each prefecture were grouped into units of size 25 (Ministry of Education, Culture, Sports, Science and Technology, 2004). In each student group, two workers who work for educational services in the prefecture were randomly selected and added to denote the existence of teachers (Ministry of Education, Culture, Sports, Science and Technology, 2008). People over the age of 65 years and who lived in nursing homes in each prefecture were grouped into units of size 20

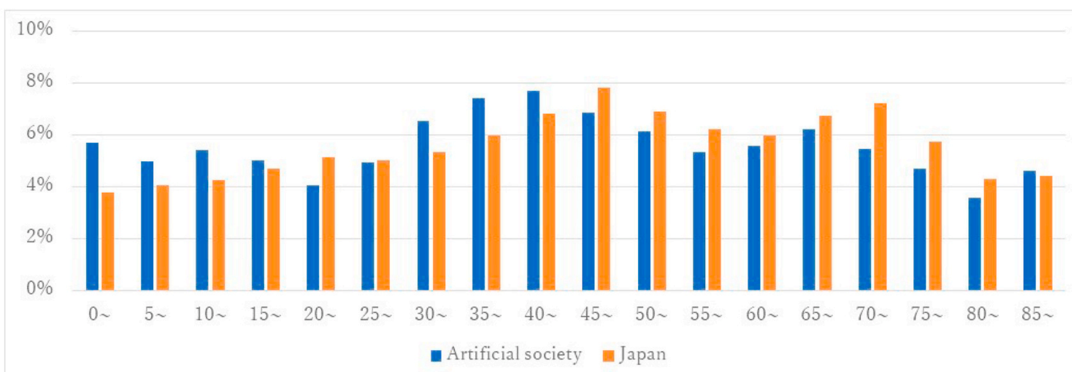
[2] The transition probabilities of illness were computed primarily using the number of people in each stage, as reported on June 10 (Ministry of Health, Labour and Welfare, 2020a). The fact that the reported cases only include confirmed positive individuals, and that even a small fraction of the symptomatic people could not get tested due to limited testing capacity, suggests that the true number of the infected persons should be much higher. According to the report on antibody-testing conducted in Tokyo from June 1 to 7, 0.10% of the population were positive, whereas the cumulative number of the confirmed positive cases as of May 30 accounts for 0.038% (Tokyo Metropolitan Government, 2020). Thus, the model assumes that the true number of the infected people in each age group is three-fold of the reported cases.

[3] Although literature argues that the law of 80-to-20 might hold, that is, around 20% of all cases account for 80% of secondary infections (Bi et al., 2020; Endo et al., 2020), the precise probability that such super-spreading environments take place has not been found. Evidence suggests that such environments may be highly extremal, occurring with a probability far less than 20% and accounting for more than 80% of the secondary infections (Vazquez et al., 2021; Wong and Collins, 2020). The parameters in the present study's simulations were chosen to describe this extremality.

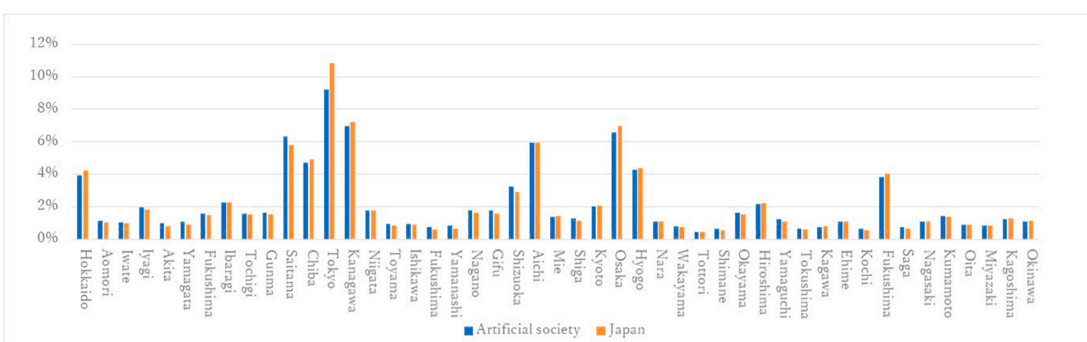
[4] The latest data that can be obtained as of writing the present study.

Table 1
Definition of each status.

State	Definition	Detected by tests	Infectious	Infected	Symptomatic
Uninfected	Not infected	—	—	—	—
Noninfectious	Infected but not infectious yet	×	×	○	×
Pre-symptomatic	Infectious but not symptomatic yet	○	○	○	×
Moderate	Symptomatic but not in need for hospitalization	○	○	○	○
Severe	In need for hospitalization	○	○	○	○
Critical	In need for intensive care	○	○	○	○



(a) Distribution of age.



(b) Distribution of residence prefectures.

Fig. 1. Distribution of attributes in the simulation and in reality.

(Ministry of Health, Labour and Welfare, 2016). In each age group, six randomly selected nursing workers were included.[5]

Fluid contacts take place in restaurants, theatres, and activity rooms, most of which are located in urban areas. These contacts were introduced in the model because they generated many clusters of COVID-19 cases. In general, such clusters occurred in the urban areas of large cities. As demonstrated in Fig. 2, among all the cases reported in the clusters of restaurants, activity facilities, and other places in each prefecture, cases in the prefectures belonging to the eight largest metropolitan areas in Japan accounted for more than 70% cases. Hence, describing infections through non-daily contacts required describing large, highly-populated urban areas, where anonymous people have contacts with each other. Moreover, these areas have other features whereby the people around the country are more likely to visit metropolitan areas than small rural areas.

[5] The guidelines issued by the Ministry of Health, Labour and Welfare set the standard for the number of care workers in each nursing home to be one-third of the number of the residents.

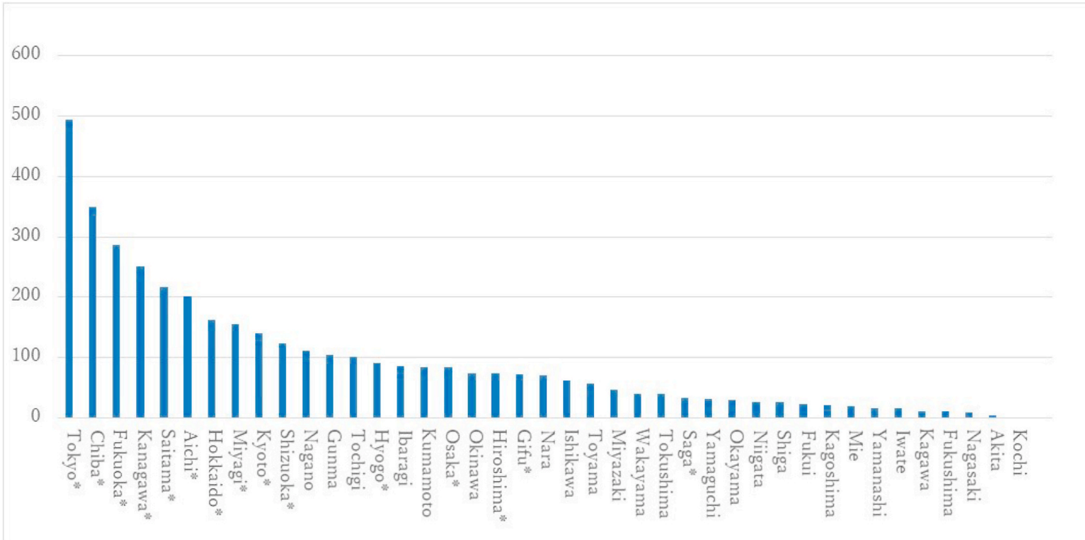


Fig. 2. Number of infections in clusters reported from restaurants and activity facilities in each prefecture. * prefectures belong to one of eight largest metropolitan areas.

Table 2
Description of daily fixed contacts in the model.

Layer	Methods to develop networks	Average size	Relative likelihood of transmission
Home	Developed automatically when family members are added.	3	4
Workplace	For each prefecture, a group of working individuals— working for the same industry— of a size that follows the firm-size distribution in the industry should be developed.	5	1
School	For each prefecture, a group of up to 25 educated individuals, with 2 teachers in each group, should be developed.	25	1
Nursing home	For each prefecture, a group of up to 20 older adults, over 60 years of age, adding up to 6 care workers in each group, should be developed.	18	4

To create fluid contacts reflecting such features in the transfer procedure, the model assumed that the population in each of the eight largest metropolitan areas was shuffled every period; in each time-step, people gathered in each metropolitan area depending on their own travel destinations and the probability of whether they travelled or stayed at their hometowns. People who happened to be in the same metropolitan area were randomly grouped and had contact with each other.

To obtain the distribution of travel destinations and the probability that residents in each prefecture travelled or stayed at their hometowns, the following steps were taken:

1. Obtain the probability of a resident in each prefecture to visit every prefecture using the location data of mobile phone as of February 1st, 2019.[6]
2. Obtain the structure of each of the eight largest metropolitan areas: The Statistic Bureau of Japan defines the metropolitan area and key prefecture in each zone (Statistic Bureau of Japan, 2008). For each of the eight metropolitan areas, its member prefectures are defined as follows. The prefectures whose residents visit the key prefecture of that metropolitan area with a probability of more than 2% is defined as the member prefectures of that metropolitan area. The results are presented in Table 3.
3. Using the correspondence between metropolitan areas and prefectures obtained in step 2, the probability of transfer from one prefecture to another is obtained in step 1 with regards to the probability of transfer from a prefecture to each metropolitan area (see Table 8).
4. Assuming that people have preferences in choosing traveling destinations, allocate travel destination to each resident in each prefecture, using its distribution obtained in step 3. In addition, determine the probability that a resident in each prefecture travels, that is, moves to the metropolitan area that is designated as their travel destination, or stays at their hometown, that is, the metropolitan area which their residence prefecture belongs to, using the probability of transfer obtained in step 3.

Thus, the mobility data automatically reproduced the partial

[6] The data, which contain the information on the location of 80 million people, was provided by NTT DOCOMO, the largest cell phone company in Japan. They included the number of people in each mesh per hour, distinguishing the prefecture where people bought the cell phone. Therefore, by naturally assuming that the place where people bought the cell phones are their residence, one can obtain the proportion of people from regions at a certain place and time, and as a result, the probability of the residents of each prefecture visiting every prefecture is estimated.

independence of regions; generally, people do not have free access to everyone in every region, as assumed by Kerr et al. (2020) and Liu et al. (2018), nor are they completely independent from other regions. The reproduction of human activity in high accuracy, due to these features of the model, enables comparing the effects of various interventions. The model aggregated the point of interests at the prefecture-level to determine the correspondence between each person's residence prefecture and their location at a certain time. Such aggregation enabled the model to reproduce the metropolitan area, a concept of a large city that unites prefectures, which allowed the model to restrict domestic long-distance travel.

Fluid contacts in each metropolitan area are shuffled every day. The process of shuffling utilized the following steps:

1. At the beginning of each day, determine who visits which metropolitan area following the previous steps.
2. Determine the contact group: assuming that each person has contact with N people,[7] create a contact group in each metropolitan area.
3. In each contact group in every metropolitan area, add three people who work as hospitality or service workers, and live in the member prefecture of the metropolitan area, reflecting the high frequency of contacts of service and sales workers (Ministry of Health, Labour and Welfare, 2020b).

2.4. Interventions

Simulations presented in the following part test the effects of three measures: travel restrictions, working-from-home, and shortening of restaurants' opening hours.

Travel restrictions reduce the number of domestic long-distance travel in a particular region or at a nationwide level. Notably, the long-distance travel targeted in such a measure was defined in the model as a person visiting a metropolitan area other than the one that their residence prefecture belonged to. To illustrate, a visit of a resident in Kanagawa prefecture to the Osaka metropolitan area was considered long-distance travel, whereas a visit to the Tokyo metropolitan area was not. When travel restrictions targeting a certain metropolitan area were in place, contacts of outside residents that took place in the target metropolitan area were randomly selected with a certain probability and cancelled. At the same time, contacts of residents of the target metropolitan area that took place in the other metropolitan area were also randomly selected with a certain probability and cancelled. Thus, by deactivating those contacts, decrease in the number of travels from and to the target area was reproduced, while other long-distance travels, which did not involve the target areas, were left unrestricted.[8]

When working-from-home was in place, workers who were in teleworkable jobs[9] were assumed to work from home with a certain probability, which corresponded to the partial deactivation of such workers' contacts in their workplaces and anonymous contacts in metropolitan areas. When restaurants' opening hours were shortened, contacts in metropolitan areas decreased by a certain probability.

[7] N follows a Poisson distribution with an expected value of 10 (Ibuka et al., 2016).

[8] Lee et al. (2021) found that a reduction in mobility was strongly correlated with a reduction in income and occupation. Parady et al. (2020) and Irawan et al. (2021) showed that the activities undertaken during a virus outbreak depended on psychological aspects and descriptive norms, which vary among people. The present analysis assumed that people homogeneously followed the decrease in the travel frequency under travel restriction policy by abstracting away from such bias for simplicity.

[9] Teleworkable jobs include managerial positions, specialized and skilled workers, office workers, and the uncategorized workers; sales staffs, service workers, farmers, factory workers, and operators in construction and transportation industry were assumed as unable to work from home.

3. Simulations

Simulations presented in Section 4 were conducted in the following steps: initialization, running, and averaging.

3.1. Initialization

Kerr et al. (2020) assumed that the initial state of the simulation was the first importation of the virus. This assumption led the model to generate zero new cases in the first several days followed by a gradual increase in cases; it took time for the first infected people to turn infectious, and other people had not been infected yet. In estimating future cases at a certain point of time, when the infections had already expanded, the simulation reflected not only the initial cases but also the initial speed of virus expansion. That is, the initial state should be selected to match the case on that day, and at the same time, reproduces the presymptomatic people who were not infectious on the first day of the emergency but were bound to develop symptoms a few days later.[10] At this point, the initial state of each simulation was obtained through the following steps:

(i) First, starting from the same proportion of the recovered population as of the initial date of the target horizon, the increase in cases was reproduced under the scenario that the daily tests were conducted on the randomly selected 30% of all symptomatic people.[11]
(ii) The snapshot of the simulation in 3.1, when the proportion of the number of newly diagnosed cases in the population matched the one observed in reality, was stored. The number of snapshots were equal to the number of iterations for each scenario conducted in 3.1.
(iii) Starting from the snapshot stored in 3.1, it was assumed that the interventions that were taken in the target horizon were introduced from the first day. Thus, by reproducing the initial state, the model can be applied to estimate future cases as of any point of time.

The number of iterations for each scenario was set to 300 in the following simulations.

3.2. Running and averaging

After obtaining the initial states, the historical data under each scenario were simulated. Every day, each person's status and contacts were updated, and actual transmissions were determined. Interventions were implemented on the day designated by the scenario. On the days of implementation, each person's status and contacts were adjusted by the interventions before the actual transmissions took place. Thus, each scenario, defined as a set of interventions, affected the likelihood of each transmission taking place.

Simulations were run 300 times for each scenario. After the run, the average number of people in each stage of the illness was computed, as shown in Section 4.

4. Results

4.1. Comparing the effects of interventions

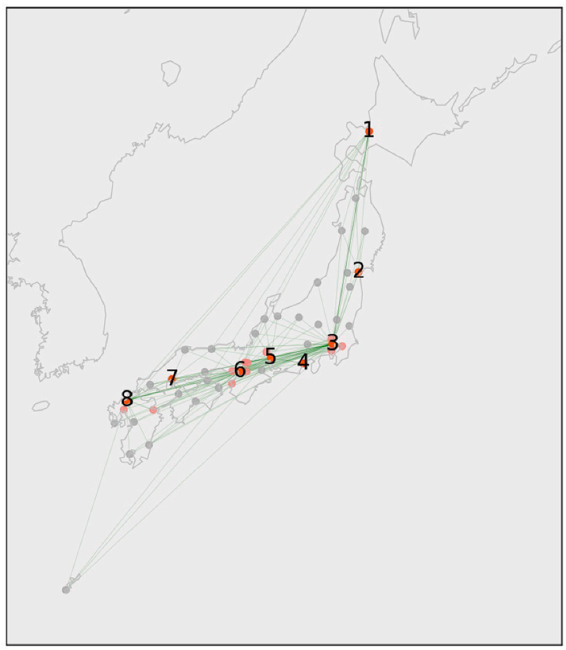
First, the effects of mobility control, both nationwide and region-

[10] In the model, the schedule of each infected person developing symptoms was determined by the infection, following the probability and duration presented in Table 7.

[11] The tested people received the test results the following day. If they tested positive, they were quarantined. The test sensitivity was set to 70%.

Table 3
Structure of metropolitan areas.

No.	Metropolitan area	Key prefecture	Member prefectures
1	**Sapporo**	Hokkaido	Hokkaido
2	**Sendai**	Miyagi	Miyagi
3	**Tokyo**	Tokyo	Chiba, Saitama, Tokyo, Kanagawa
4	**Shizuoka**	Shizuoka	Shizuoka
5	**Nagoya**	Aichi	Gifu, Aichi
6	**Osaka**	Osaka	Shiga, Kyoto, Hyogo, Osaka, Nara, Wakayama
7	**Hiroshima**	Hiroshima	Hiroshima
8	**Fukuoka**	Fukuoka	Fukuoka, Saga, Oita



specific, shortening of restaurants' opening hours, and working from home were compared. Table 4 portrays these scenarios. The baseline scenario assumed that testing was conducted on 30% of the symptomatic people that were randomly selected. To compare the effects of the interventions, each scenario assumed that on the day the daily confirmed cases at the national level hit 3,000, only one of the interventions was taken on top of daily testing.[12] A hypothetical simple measure, reducing all types of contacts, was also considered to obtain intuition on that level. In every scenario, it was assumed that (i) a randomly selected person became infected on the first day; (ii) each intervention was taken the following day, and; (iii) it was in place until the last day.

During the nation-level travel restriction scenario, the contact of long-distance travelers to all metropolitan areas decreased by 90%, a figure similar to the real decrease in May 2020, during the first state of emergency (Ministry of Land, Infrastructure, Transport and Tourism, 2020b). Region-specific travel restrictions decreased long-distance travelers to and from the target areas by 90%. In working-from-home scenario, workers who were in teleworkable jobs worked from home with a decrease in contact probability by 49%, similar to the averaged real decrease from June to September 2020.[13] This corresponded to a decrease in the contacts of teleworkables at their workplaces by 70%, and their contacts in metropolitan areas reduced by 40%. In the scenario of shortening restaurants' opening hours, contacts in metropolitan areas decreased by 36% in Tokyo during August 2020 when restaurants were required to shorten their opening hours.[14]

Fig. 3 shows the proportion of daily diagnosed people, that is, confirmed cases in population under the scenarios. It can be inferred that strong nationwide travel restrictions lower the peak cases by around 40% if they decrease no less than 90% of all travels. Further, travel restrictions only on Tokyo and Osaka, the first and second-largest metropolitan areas, can achieve the same decrease as a nationwide restriction. This outcome rationalizes travel restriction only on highly populated regions, suggesting that restricting travels between less populated regions has only a limited contribution to flattening the curve. In other

[12] Although multiple interventions are simultaneously implemented in reality, the simulation here counterfactually compared the results for when each one of the major interventions were taken for simplicity.

[13] Source data were surveys regarding teleworking that were confidentially provided by the Cabinet Office.

[14] Sources were the mobility data confidentially provided to the author by NTT DOCOMO.

Table 4
Scenarios to compare the effects of mobility control, shortening of restaurants' opening hours and working from home.

Scenario	Description
Baseline	—
Travel restriction (nation-wide)	The number of contacts of long-distance travelers in all metropolitan areas is decreased by 90%.
Travel restriction (only from/to Tokyo)	The number of contacts of long-distance travelers in Tokyo and those from Tokyo to other metropolitan areas is decreased by 90%.
Travel restriction (only from/to Tokyo and Osaka)	The number of contacts of long-distance travelers in Tokyo and Osaka, and those from Tokyo or Osaka to other metropolitan areas is decreased by 90%.
Work from home	Workers who have teleworkable jobs work from home with a 49% probability.
Shortening of restaurants' opening hours	The number of contacts in metropolitan areas is decreased by 36%.
Reduce all types of contacts (X%)	The number of both fixed and fluid contacts of all people is decreased by X%.

words, imposing mobility control only on large urban areas effectively prevents the spread of the virus, suppressing the domestic travel demand to only a minimum but necessary level.[15]

The results show multiple peaks in travel restriction scenarios because the contacts people have with each other differ in each region; even if one region experiences its peak cases, the outbreak rarely expands to other regions, due to the restriction in people's free travels. If no travel restriction is imposed, people's contacts exhibit inter-regional patterns. Thus, the outbreak in one region tends to transmit to other regions, and peak cases in different regions coincide. As a result, the nation-wide cases shown in Fig. 3 in the scenarios without travel restrictions had only one high peak. As for the other measures, shortening restaurants' opening hours is as effective as nationwide travel restrictions. Alternatively, compared with travel restrictions and reduced restaurants' opening hours, working from home has comparatively limited effects. This is because the proportion of people who can work from home is limited, accounting for 43% of all workers,[16] and 19% of the total national population.

The effectiveness of the interventions depends on the timing of their implementation, as pointed out by Matrajt and Leung (2020). Fig. 4 compares peak cases under the different interventions when the timing of implementation was varied: when the daily domestic confirmed cases hit around 3,000, the true number of infected people was around 17, 000, and when the confirmed cases hit around 9,000, the true number of infected people was around 50,000. Each peak value was normalized in the results in the baseline scenario. Among the interventions considered, reduction of peak cases under travel restrictions compared to the baseline scenario was sensitive to the timing of implementation. This was because once the virus spread to multiple regions, it transmitted within those regions. This could not be restrained by controlling inter-regional travels. These results were consistent with the results shown by Kraemer et al. (2020).

4.2. Estimated rate of decrease in positive cases during the state of emergency in January 2021

The model can also be applied to estimate the required duration of the state of emergency. In Japan, while facing an increasing number of infections, a state of emergency was introduced for the second time on January 7th, 2021. The reported number of the newly diagnosed cases was 7,639, and 211,900 recoveries were reported on that day (NHK, 2020). Here, the rate of decrease in positive cases was estimated assuming that the same figures and interventions had been realized in the same proportion on the first day of the state of emergency. Travel restrictions are assumed to decrease long-distance travels by 50% (SankeiBiz, 2021). Additionally, it is assumed that the possible workers work from home with probability 70% (Japan Business Federation, 2021), and shortened restaurants' opening hours reduce the fluid contacts in metropolitan areas by 75%.[17] Tests are conducted on 30% of the symptomatic cases, which is the same as before the state of emergency. Event restriction refers to the upper bound of the size of the fluid contact groups.[18] Fig. 5 indicates the estimated daily cases diagnosed during the state of emergency (Table 5). While assuming that the conversion rate of the number of newly diagnosed cases nationwide in relation to that in

[15] After the first wave was over, Japan introduced a large campaign that provided a discount on domestic travel. The campaign excluded travels from/to Tokyo in the first two months, followed by including all domestic travels because cases in Tokyo were still high when the campaign started (Ministry of Land, Infrastructure, Transport and Tourism, 2020c). The result of the simulations weakly rationalizes excluding Tokyo, given that the campaign significantly increased the number of trips.

[16] This proportion is close to the estimated figures in other countries: 37% in the US (Dingel and Neiman, 2020), 42% in Germany (Fadinger et al., 2020).

[17] Mobility in Tokyo decreased by roughly 50% according to V-RESAS (https://v-resas.go.jp/prefectures/13), which corresponds to a 75% decrease in the number of contacts in this study's results.

[18] In Japan, the government has restricted the size of the event to be less than 5000 people. In the simulation, the limit size was interpreted as a large number that would rarely be realized. Since the model assumed that the number of contact groups in the metropolitan area followed a Poisson distribution with a probability of 10, such a large size corresponded to 17, which achieved a probability of 1%.

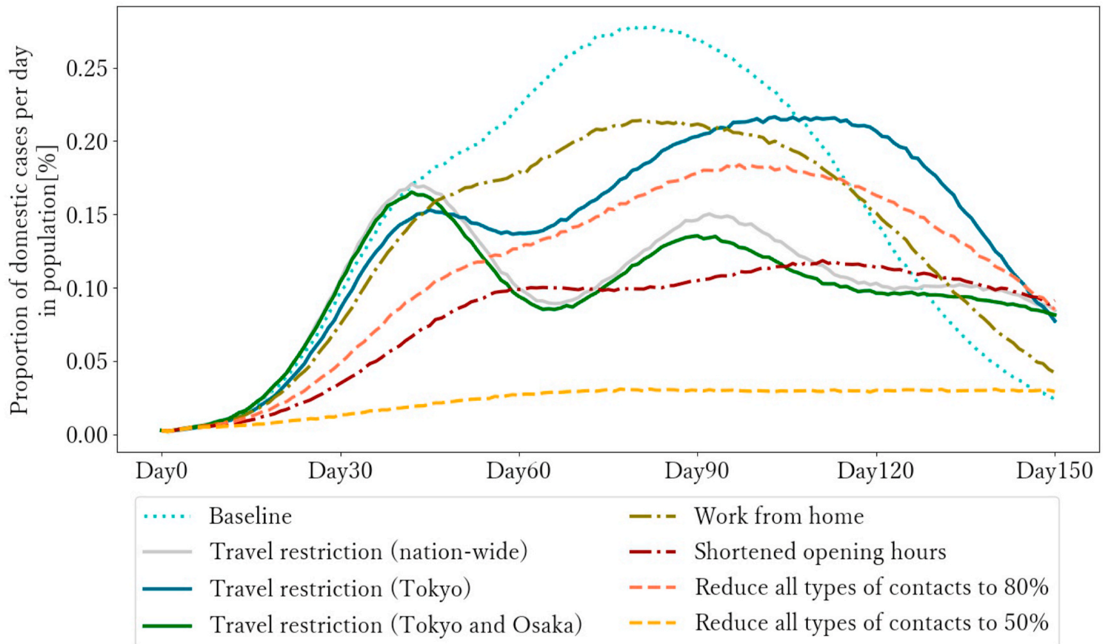


Fig. 3. COVID-19 cases under different interventions.

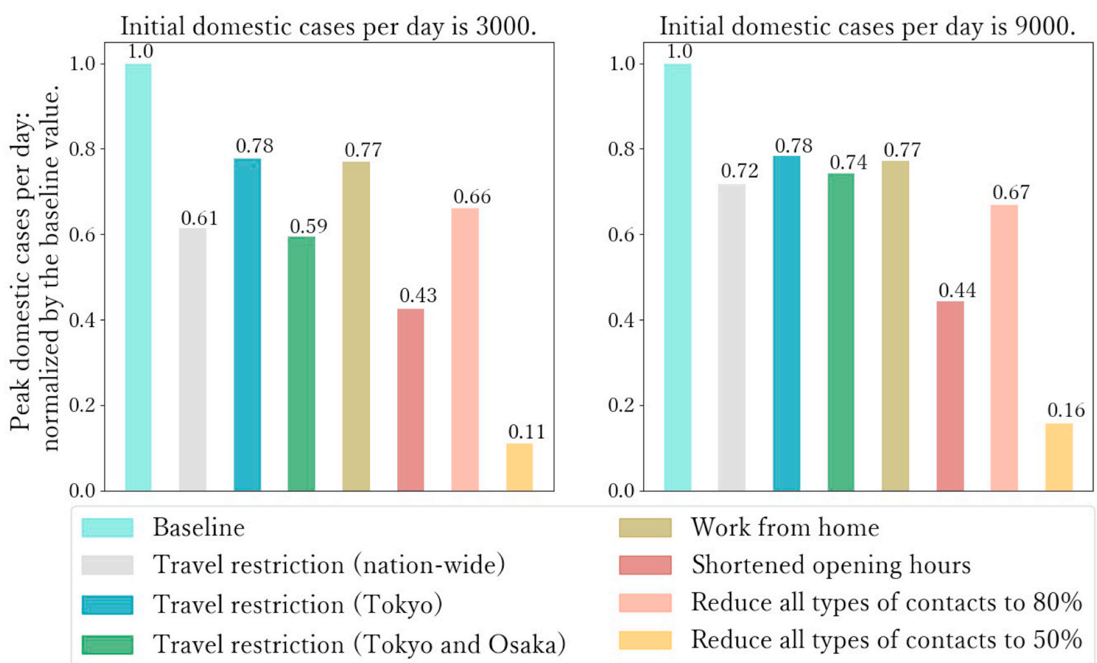


Fig. 4. Effectiveness of each intervention implemented at different timings.

Tokyo is six to one, the estimation shows that it takes more than a month for the number of diagnosed cases to decrease to 250 per day in Tokyo.[19] Notably, the results averaged over multiple runs have the tendency to decrease at a fast speed in the long horizon. This is because the averaged path includes the path where the cases converges to zero right after the initial day. Since zero infection is an absorbing state in the sense that the spread of the virus ends and no more infections occur thereafter, and that the results are more likely to hit such absorbing state in a long horizon, the estimation is under a strong downward pressure. Thus, the estimated decrease should be interpreted as the fastest possible one.

4.3. Slowing down the expansion

The state of emergency is expected to be lifted when the government judges that the new cases have decreased to a sufficiently low number. Nevertheless, a major problem that arises is how to reopen the economy; if people's activity suddenly returns to the normal level right after the state of emergency is lifted, cases that have decreased due to the strict

[19] As presented in the previous section, the model does not distinguish the place of infection at the prefecture-level but at the level of the metropolitan area. Thus, it is impossible to directly count the cases in a certain prefecture, including Tokyo.

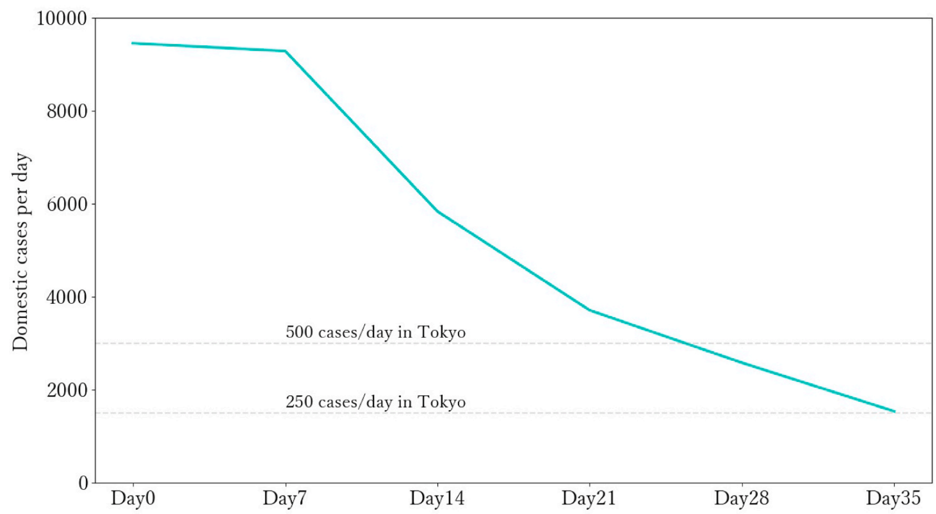


Fig. 5. COVID-19 cases estimated upon the introduction of emergency.

interventions would start to increase again at a high speed (Leung et al., 2020). On the other hand, keeping all the interventions implemented during the state of emergency would generate a heavy economic cost (Aleta et al., 2020), even if it may further decrease the number of cases. Fig. 6 reveals the transition of diagnosed cases under various scenarios of easing of interventions. The initial state is set to a situation where the newly diagnosed cases decrease during the state of emergency and match the number corresponding to 250 per day in Tokyo. In all scenarios, daily tests and event restrictions are assumed to be continued, as in the state of emergency; travel restrictions, working from home, and restaurants' shortening of their opening hours are assumed to be moderately lifted depending on the circumstances (see Table 6 for the degree of easing). An increase in domestic travel out of the state of emergency reflects what is observed right after the first state of emergency in 2020 (Ministry of Land, Infrastructure, Transport and Tourism, 2020a). Extending restaurants' opening hours increases the number of contacts in metropolitan areas, assuming that mobility recovers to the level when the restaurants are required to close at 22:00 in August 2020. The findings validate that the most effective measure is the shortening of restaurants' opening hours: With this measure still in place after the state of emergency is lifted, cases do not increase even if travel restrictions and working from home are eased. Lifting travel restrictions has a limited effect because it increases travels only by a mere 15%.

5. Conclusion

In the present study, the effectiveness of various interventions was analyzed by developing an agent-based model that utilized census and mobility data of Japan.

The findings reveal that, first, early and severe mobility control, that restricts 90% of domestic travels at the nationwide level, is effective to the extent that it decreases peak cases by 40%, as compared to the scenario where no interventions are undertaken. This effectiveness exceeds that of all other types of contact restrictions by more than 20%. Second, region-specific mobility control that restricts 90% of travel from and to the Tokyo and Osaka metropolitan area—the two largest regions in Japan—is as effective as nationwide mobility control. Third, mobility control that only restricts 90% of the travel from and to the Tokyo metropolitan area—the largest metropolitan area in Japan—is more effective than nationwide mobility control but is less effective than travel restrictions involving Tokyo and Osaka. These results rationalize the introduction of region-specific mobility control that targets movement involving highly populated areas while ignoring travels between less populated regions. Such mobility control does not impose limitations irrelevant to the nationwide spread of the virus, and thus, reduces peak cases with a lower economic and social cost. Region-specific mobility control is simpler than the mobility control on high-risk contacts suggested by (Chang et al., 2021) as the detection of high-risk contacts would be costlier in reality. Fourth, working from home has a mild effect compared to restaurants' shortening of their opening hours and severe mobility control.

Likewise, the simulations also suggest an effective policy for a nation not in a state of emergency, which should be adopted to curb the spread of the disease (Leung et al., 2020). If the restaurants' shortened opening hours is still in place after the state of emergency is lifted, cases will not increase even if travel restrictions and working from home are eased.

The model features an accurate description of reality by reflecting people's attributes and mobility, and by using parameters rationalized by reports. Nonetheless, the model has abstracted several issues, mainly to reduce the time for simulation. For instance, although the model incorporates major places where contacts take place, hospital transmission is missing. In fact, a substantial proportion of infection is reported to take place in hospitals (Wang et al., 2020). Besides, fluid contacts could be disaggregated into more detailed levels, such as contacts between friends that take place at a certain frequency and contacts that happen in a theatre. In addition, given the scarcity in literature focusing on the contacts that occur in the specific places considered in the model, the numbers of daily contacts, along with data on other parameters, were extracted from data of different years, as cited in Section 2.3. However, as these data should have changed over time, contact networks described in the model possibly misinterprets the reality, which is a limitation of the analysis. A more detailed and realistic description of contacts would enhance the accuracy of the model's prediction.

Aside from these issues regarding the detailed description of reality, a possible extension is to incorporate adaptiveness in people's behavior. For instance, historical data validates that mobility decreased sharply when the possibility of implementing a state of emergency is reported in media, even before the state of emergency begins. Introducing such behavioral aspects affects the relationship between interventions and the number of contacts in each place.

Declaration of competing interest

None.

Table 5
Interventions implemented in the emergency scenario.

Interventions	Description
Travel restriction (nation-wide)	The number of contacts of long-distance travelers in all metropolitan areas is decreased by 50%.
Work from home	Workers who have teleworkable work from home, with a 70% probability.
Shortening of restaurants' opening hours	The number of contacts in each metropolitan area is decreased by 75%.
Tests	Symptomatic people, who are selected randomly with a 30% probability of selection, get tested every day.
Event-size restriction	The size of the contact networks in the metropolitan area is restricted.

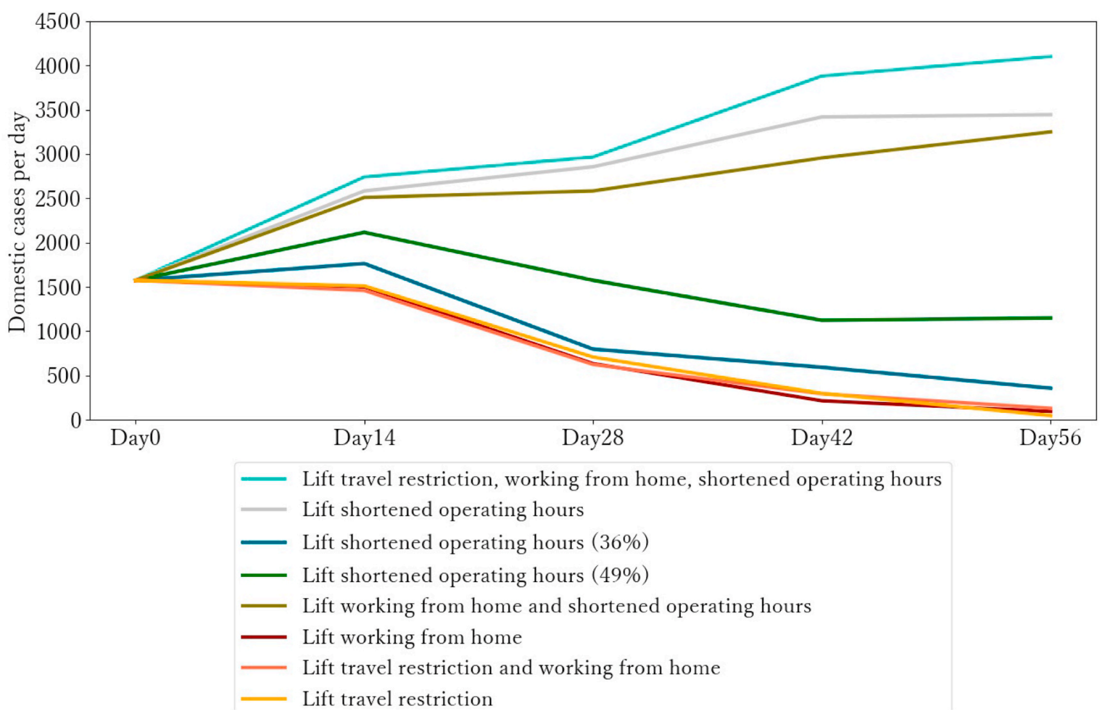


Fig. 6. COVID-19 cases after partial easing of the post-emergency interventions.

Table 6
Changes in interventions post-emergency.

Interventions	State of emergency	Lifting
Travel restriction (nation-wide)	The number of contacts of long-distance travelers in each metropolitan is decreased by 50%.	50% → 35%
Work from home	Workers who are in teleworkable jobs work from home, with a 70% probability.	70% → 50%
Shortening of restaurants' opening hours	The number of contacts in metropolitan areas is decreased by 75%.	75% → 36%

Appendix

A. Proportion of infections in each places

Fig. 7 outlines the proportion of cases in each contact place in the baseline case, where no interventions are taken. The result shows that about 80% of all infections take place through fluid contacts in metropolitan areas. Infections through fluid contacts in Tokyo metropolitan area and those in the Osaka metropolitan area account for a third and a fifth of all cases, respectively. Among cases determined through fixed contacts, contacts at home accounts for half of all reported cases.

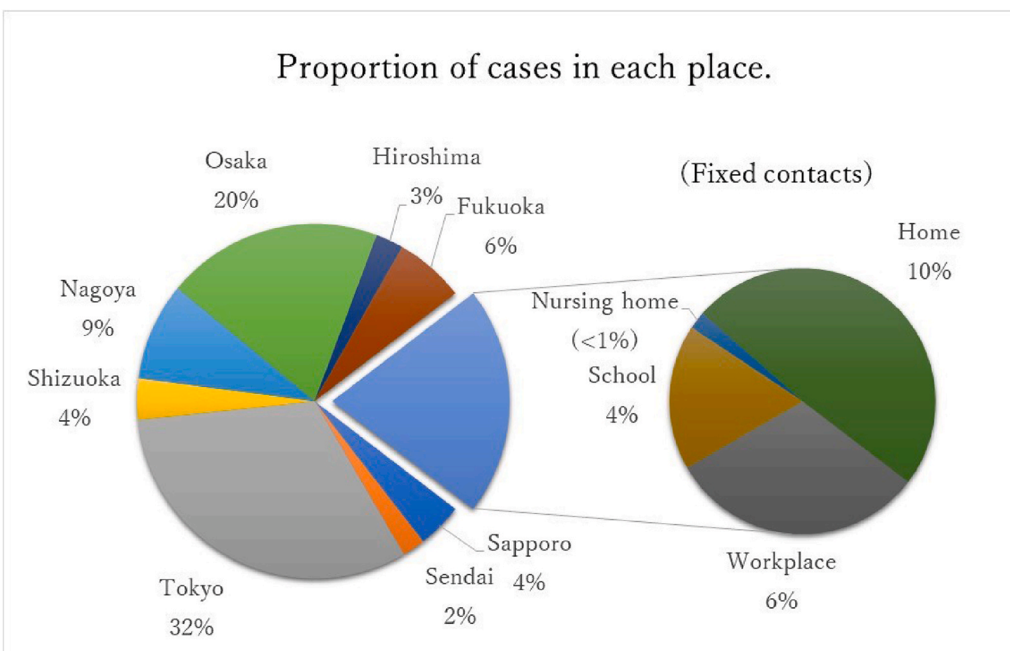


Fig. 7. Proportion of COVID-19 cases in each place of contact.

B. Parameters

Table 7
Probability and duration of developing symptoms depending on age. ~LN(a,b) depicts that the parameter following the Log-normal distribution with the expected value of a, and the standard deviation of b.

	Duration of transition (days)	Probability of transition								
		~9	10~	20~	30~	40~	50~	60~	70~	80~
(Worsen)										
Not infectious → Pre-symptomatic	~LN(4.6, 4.8)	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Pre-symptomatic → Moderate	~LN(1.0, .9)	0.500	0.550	0.600	0.650	0.700	0.750	0.800	0.850	0.900
Moderate → Severe	~LN(6.6, 4.9)	0.000	0.000	0.000	0.155	0.151	0.198	0.365	0.360	0.408
Severe → Critical	~LN(3.0, 7.4)	0.000	0.000	0.000	0.029	0.029	0.147	0.368	0.491	0.490
Critical → Death	~LN(6.2, 1.7)	0.000	0.000	0.000	0.146	0.182	0.218	0.255	0.291	0.327
(Recovery)										
Pre-symptomatic → Recovered	~LN(8.0, 2.0)	0.500	0.450	0.400	0.350	0.300	0.250	0.200	0.150	0.100
Moderate → Recovered	~LN(8.0, 2.0)	1.000	1.000	1.000	0.845	0.849	0.802	0.635	0.640	0.592
Severe → Recovered	~LN(14.0, 2.4)	1.000	1.000	1.000	0.971	0.971	0.853	0.632	0.509	0.510
Critical → Recovered	~LN(14.0, 2.4)	1.000	1.000	1.000	0.854	0.818	0.782	0.745	0.709	0.673

Table 8
Probability of the residents in each prefecture (in the first column) of visiting each metropolitan area (in the first row).

	Sapporo	Sendai	Tokyo	Shizuoka	Nagoya	Osaka	Hiroshima	Fukuoka
Hokkaido	0.9987	0.0001	0.001	0	0	0.0001	0	0
Aomori	0.0001	0.001	0.001	0	0	0	0	0
Iwate	0	0.0041	0.0008	0	0	0	0	0
Miyagi	0	0.9958	0.0012	0	0	0	0	0
Akita	0.0001	0.0011	0.0006	0	0	0	0	0
Yamagata	0.0001	0.0025	0.001	0	0	0	0	0
Fukushima	0	0.0023	0.0017	0	0	0	0	0
Ibaragi	0	0	0.0251	0	0	0	0	0
Tochigi	0.0001	0	0.0058	0	0	0	0	0
Gunma	0	0	0.0214	0	0	0.0001	0	0
Saitama	0	0	0.9949	0	0.0001	0.0002	0	0
Chiba	0	0	0.9941	0	0.0001	0.0002	0	0.0001
Tokyo	0.0001	0.0001	0.998	0.0001	0.0003	0.0007	0	0.0001
Kanagawa	0.0001	0	0.9979	0.0011	0.0001	0.0003	0	0.0001
Niigata	0	0	0.001	0	0	0	0	0
Toyama	0	0	0.0011	0	0.0003	0.0001	0	0
Ishikawa	0	0	0.0012	0	0.0003	0.0004	0	0
Fukui	0	0	0.0004	0	0.0001	0.0012	0	0
Yamanashi	0	0	0.0103	0.0004	0	0	0	0
Nagano	0	0	0.0018	0	0.0004	0.0001	0	0
Gifu	0	0	0.0005	0	0.9974	0.0004	0	0
Shizuoka	0	0	0.0029	0.9941	0.0025	0.0002	0	0
Aichi	0	0	0.0009	0.0016	0.995	0.0004	0	0
Mie	0	0	0.0005	0	0.0122	0.0064	0	0
Shiga	0	0	0.0003	0	0.0014	0.9975	0	0
Kyoto	0	0	0.0005	0	0.0002	0.9984	0	0
Osaka	0	0	0.0009	0	0.0002	0.9985	0.0001	0.0001
Hyogo	0.0001	0	0.0013	0	0.0002	0.9977	0.0001	0.0002
Nara	0	0	0.0006	0	0.0001	0.9986	0	0
Wakayama	0	0	0.0003	0	0	0.9889	0	0
Tottori	0.0002	0	0.0005	0	0.0001	0.0013	0.0004	0
Shimane	0	0	0.0005	0	0	0.0004	0.002	0
Okayama	0	0	0.0005	0	0.0001	0.0012	0.0045	0.0001
Hiroshima	0	0	0.0007	0	0	0.0006	0.9859	0.0002
Yamaguchi	0	0	0.0004	0	0	0.0002	0.0085	0.0044
Tokushima	0	0	0.0004	0	0	0.0009	0.0001	0
Kagawa	0.0007	0	0.0011	0	0.0002	0.0013	0.0002	0.0001
Ehime	0	0	0.0008	0	0.0002	0.0008	0.0014	0.0001
Kochi	0	0	0.0011	0	0	0.0008	0.0001	0
Fukuoka	0.0001	0	0.0008	0	0	0.0003	0.0001	0.9955
Saga	0.0002	0	0.0005	0	0	0	0	0.9948
Nagasaki	0	0	0.0008	0	0	0.0001	0	0.0051
Kumamoto	0	0	0.0005	0	0	0.0002	0	0.0051
Oita	0	0	0.0008	0	0.0001	0.0003	0	0.9977
Miyazaki	0	0	0.0007	0	0.0001	0.0002	0	0.0021
Kagoshima	0	0	0.0014	0	0	0.0001	0	0.0019
Okinawa	0	0	0.0006	0	0.0001	0.0002	0	0.0003

Author statement

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