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Abstract

Since the occurrence of the first outbreak of COVID-19 in a year ago, various interventions have been implemented to prevent its spread across the globe. 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 severe mobility control that restricts 90% of domestic travels on a national level decreases the peak cases by a half, compared to when no interventions are undertaken. The effectiveness of this strategy is more than 20% compared to all other types of contact restrictions. Therefore, mobility control that only limits movement from and to highly populated regions is as effective as nationwide travel restrictions. This finding rationalizes region-specific mobility control that does not restrict travel among less populated regions, which are less conducive to the spread of the virus. Furthermore, shortening of restaurants' opening hours is the most effective of all interventions taken in a state of emergency, thus, it should be utilized even after the emergency is lifted. However, working from home has limited effects.

Keywords: mobility control, travel restriction, COVID-19, targeting policies, restaurants' opening hours, working-from-home

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1 Introduction

Since the outbreak of the coronavirus disease (COVID-19), numerous interventions have been adopted to prevent its spread [1, 2]. 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 [3] for review). Notably, this mechanism is a frequently utilized intervention in many countries. Empirical evidence highlights that travel restriction, at least in the early stage of a virus outbreak, had a significant effect in preventing the spread of the virus [4, 5, 6]. Furthermore, tracing and quarantine of symptomatic contacts is renowned for its effectiveness against epidemics even before the outbreak of COVID-19 [7, 8]. Such contact tracing is more effective than sole mass-testing [9], although its effectiveness depends on the accurate and rapid detection of the contacts [10], which could be enhanced through app-based tracing [11]. 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 [12]. In contrast, the effects of other interventions, such as working from home and closure of restaurants, are still unclear[1] although they have been widely implemented in many countries [14, 15]. Moreover, understanding the degree of effectiveness of each intervention is necessary, since the interventions entail economic costs [16].[2]

To compare the effectiveness of mobility control, both on a nationwide and region-specific level, through restaurant closure and working from home, the present research constructs 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

[1]Among the few studies analyzing the effectiveness of working from home on COVID-19 cases, [13] report that cases in regions where many people can easily work from home were less than that in other regions.

[2][16] considers several types of measures, but, several major interventions, such as mobility control and working from home, have been ignored.

those of the real population. These attributes are used to construct daily contacts at home, workplaces, schools, and nursing homes, which account for more than a half of all observed contacts [17]. Non-daily fluid contact, such as while traveling and during leisures, that account for 20% of all observed contacts [17] is constructed by modeling the eight largest metropolitan cities of Japan, since most infections were reported from these areas (see Figure 2 in section 2.3). Using mobility data of 80 million people, provided by NTT DOCOMO,[3] movement patterns from each prefecture concerning each metropolitan area were reproduced. Fluid contacts were created by random matching in each metropolitan area, which is updated every day. It was found that more than 98% of all samples are likely to stay indoors every day. The remaining people, accounting for only a small fraction in each prefecture, undertook long distance travel. In this way, the mobility data automatically reproduces the partial independence of regions. Generally, people do not have free access to everyone in every region, as assumed in [18] and [19], 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 aggregates the point of interests (POIs) at the prefecture-level to determine the correspondence between each person's residence prefecture and their location at a certain time. Such aggregation enables the model to reproduce the metropolitan area, a concept of a large city that unites prefectures, which allows the model to restrict domestic long-distance travel.

The findings reveal that, first, severe mobility control that restricts 90% of domestic travels at the nationwide level is effective to the extent that it decreases the peak cases by half, compared with the scenario where no interventions are undertaken. The 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 a nationwide mobility control. Third, mobility control that only restricts 90% of the travel from and to the Tokyo metropolitan area—the largest 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 regional-specific mobility control that targets movement involving highly populated areas while ignoring the travels among less populated regions. Such mobility control

[3]The largest cellular phone career company in Japan.

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 [20] since 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 [21]. If the restaurants' shortening of their opening hours is still in place even after the state of emergency is lifted, cases will not increase even if travel restrictions and working from home are eased.

2 Model

The model to analyze human society and the spread of viruses is based on the agent-based model proposed by [18]. Their novel model describes the development of symptoms in different types of people, with the transition probability and duration in each stage of symptoms depending on each person's age. The following subsections explain features of the present model, which are newly introduced.

2.1 Virus expansion including super-spreading environment

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 superspreading hotspot. Table 1 signifies the age-dependent probability and duration of developing symptoms.[4][5] Besides, the transmissibility in the early

[4] The transition probabilities of illness were computed primarily using the number of people in each stage, as reported on June 10 [22]. 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% [23]. Thus, the model assumes that the true number of the infected in each age group is three-fold of reported cases.

[5] ~LN(a,b) in Table 1 depicts that the parameter follows the Log-normal distribution with the expected value of a, and the standard deviation of b.

stage is set twice as high as that in the later. Super-spreaders (see [24] and [25]) are described in the model by specifying that the likelihood of transmission in the randomly selected 4% of all contacts is 2000 times as high as that in the rest.

	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
(Recover)										
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 1: Probability and duration of developing symptoms depending on age.

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:

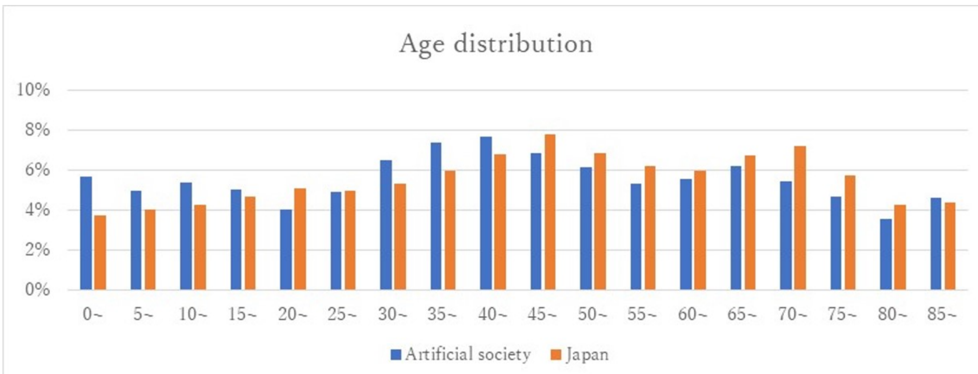
1. Randomly select 25,000 people from the individual census data as of 2015.

2. Allocate family members to each of the selected people, according to their attributes regarding family members (e.g., whether having a spouse or not, number of children, and association with three-generation families or not.).

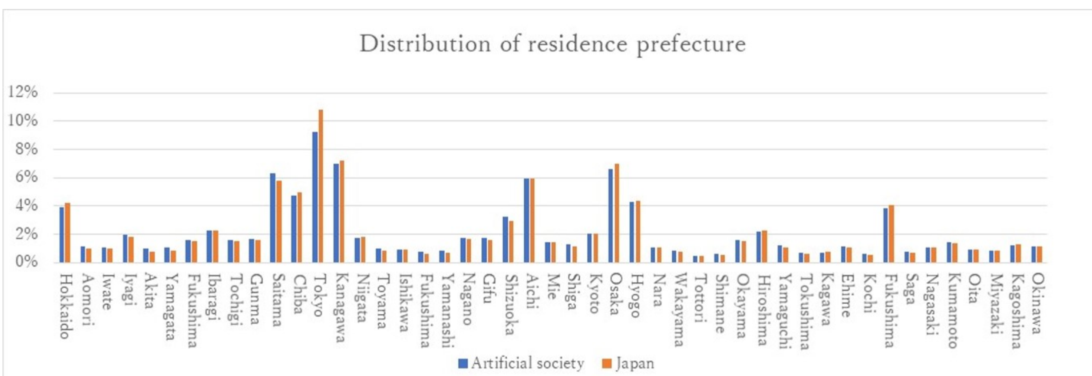
3. Adjust distortion generated in step 2: the proportion of young people who live with families becomes larger than the population selected in step 1. Thus, to render the age distribution close to that in reality, in step 3, people over 60 years of age and living alone are doubled.

4. Give attributes to the members added in step 2 and 3, following the the joint probability distribution of attributes obtained from the whole individual census data.

These steps create an artificial population that copies Japan, scaled down to 1/1500: the size of the population is 76,178, and the attributes of people include age, sex, residence prefecture, job, industry, size of the employing firm. The panels in Figure 1 shows the distribution of age and residence prefectures of the artificial society in comparison with the real one in Japan.



(a) Distribution of age.



(b) Distribution of residence prefectures.

Figure 1: Distribution of attributes in the simulation and in reality.

2.3 Contacts

The model reproduces people's contacts using their attributes. Altogether, two types of contacts are created: daily fixed contacts (i.e., households, workplaces, nursing homes, schools) and fluid contacts (i.e., restaurants, shopping, activities, etc.)

Daily fixed contacts consider four places: home, workplace, school, and nursing home. In each place, people are selected and grouped according to the methods described in Table 2. Since family members have already been created, as described in the previous section, the contact through workplaces, schools, and nursing homes are created here. For instance, contacts in the workplaces are 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 are grouped with size 25 [26]. 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 [27]. People over the age of 65 years and who live in nursing homes in each prefecture are grouped with size 20 [28]. In each age group, six randomly selected nursing workers were included.[6]

Layer	Methods to construct networks	Average size	Relative likelihood of transmission
Home	Constructed automatically when family members are added in the previous section.	3	4
Workplace	For each prefecture, construct a group of working individuals working for the same industry of a size that follows the firm-size distribution in the industry.	5	1
School	For each prefecture, construct a group of up to 25 educated individuals, adding 2 teachers in each group.	25	1
Nursing home	For each prefecture, construct a group of up to 20 elderly persons over the age of 60 years, adding up to 6 care workers in each group.	18	4

Table 2: Description of daily fixed contacts in the model.

Fluid contacts take place in restaurants, theatres, and activity rooms, most of which are located in urban areas. These contacts are introduced in the model because they have generated many clusters of COVID-19. In general, such clusters occur in the urban areas of large cities. As demonstrated in Figure 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 account for more than 70%. Hence, describing infections through non-daily contacts requires 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

[6]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.

than small rural areas. To create fluid contacts reflecting such features in the transfer procedure, the model assumes that each person has a probability of visiting each of the eight largest metropolitan areas. In each timestep, people gather in each metropolitan area depending on their probabilities, and people who happen to be in the same metropolitan area are randomly grouped and have contact with each other. To obtain the probability of a resident in each prefecture visiting every designated metropolitan area, the following steps were conducted.

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.[7]

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 [29]. 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 4).

[7] The data are provided by NTT DOCOMO. They include the number of people in each mesh per hour, distinguishing the prefecture where they bought the cell phone. Therefore, by naturally assuming that the place of the contact is the 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.

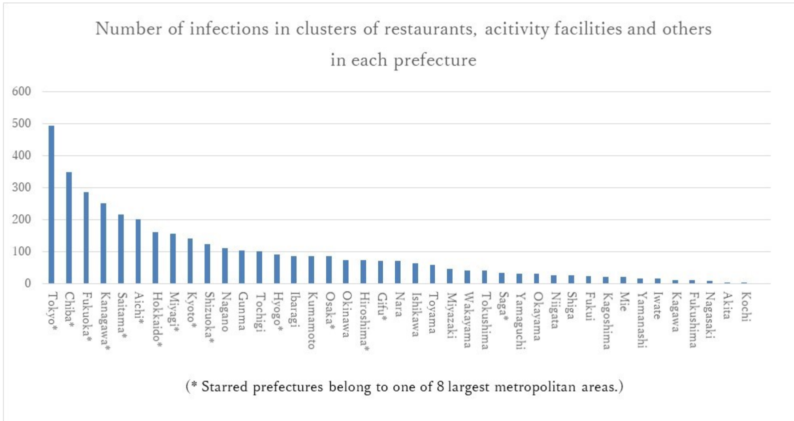


Figure 2: Number of clusters in each prefectures.

Metropolitan area	Key prefecture	Member prefectures
Sapporo	Hokkaido	Hokkaido
Sendai	Miyagi	Miyagi
Tokyo	Tokyo	Chiba, Saitama, Tokyo, Kanagawa
Shizuoka	Shizuoka	Shizuoka
Nagoya	Aichi	Gifu, Aichi
Osaka	Osaka	Shiga, Kyoto, Hyogo, Osaka, Nara, Wakayama
Hiroshima	Hiroshima	Hiroshima
Fukuoka	Fukuoka	Fukuoka, Saga, Oita

Table 3: Structure of metropolitan areas.

	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

Table 4: Probability of the residents in each prefecture (in the first column) visit each metropolitan area (in the first row).

Fluid contacts in each metropolitan area are shuffled every day using the probability of transfer from each prefecture to each metropolitan area. The process of shuffling utilizes the following steps:

1. At the beginning of each day, determine who visits which metropolitan area following the conditional probability obtained in the previous steps.
2. Determine the contact group: assuming that each person has contact with N people[8], 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 [31].

2.4 Definition of long distance travels

Simulations presented in the following part test the effects of various measures, including mobility restrictions that restrict domestic travel in a particular region or at a nationwide level. Notably, the long-distance travel targeted in such a measure is defined in the model as a person visiting a metropolitan area that is outside of their residence prefecture. To illustrate, a visit of a resident in Kanagawa prefecture to the Osaka metropolitan area is considered long-distance travel, whereas a visit to the Tokyo metropolitan area is not.

2.5 Validation

Figure 3 outlines the proportion of cases in each contact place in the baseline case, where no interventions are taken. The result proves 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. Further, reports confirm that the detection of the place where the infections took place succeeded in roughly half of the cases, and household transmission and workplace transmission account for 43% and 15% of all detected cases, respectively [32]. Assuming that

[8]N follows a Poisson distribution with an expected value of 10 [30].

all of the infections whose places were not detected belong to the fluid contacts in metropolitan areas, the proportion of cases in each contact place generated by the model and parameters is consistent with the reported figures.

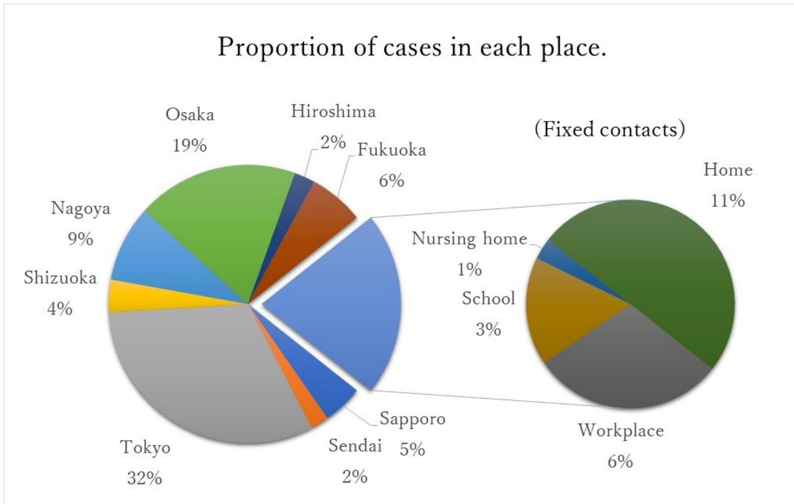


Figure 3: Number of infections through fluid and fixed contacts.

3 Results

The results presented in this section shows the transition of cases averaged over 300 trials.

3.1 Comparing the effects of interventions

First, the effects of mobility control (i.e., nationwide and region-specific), shortening of restaurants' opening hours, and working from home are compared. Table 5 portrays the tested scenarios. To compare the effects of interventions, each scenario assumes that only one of the interventions is taken from the first day when the first infection appears. [9]In the travel restriction scenario, the contact of long-distance travelers to all metropolitan areas decreased by 90%, the real decrease in May 2020, during the first state of emergency [34]. Region-specific travel restrictions decreased long-distance travelers to and from the target areas by 90%. All other long-distance travel was not

[9]The effectiveness of the interventions depends on the timing of their implementation [33].

restricted. In the working-from-home scenario, workers who are in teleworkable jobs[10] work from home with a probability of 49%, the averaged real decrease from June to September 2020.[11] This corresponds to a decrease in the contacts of teleworkables at their workplaces by 70%, and their contacts in metropolitan areas reduced by 40%. In the store-closure scenario, contacts in metropolitan areas decreased by 36% in Tokyo during August 2020 when restaurants were required to shorten their opening hours.[12] A hypothetical simple measure, reducing all types of contacts, is also considered to obtain the intuition on that level. In every scenario, it is assumed that (i) a randomly selected person becomes infected on the first day, (ii) each intervention is taken the following day, and (iii) it is in place until the last day.

Figure 4 shows the results of the cases under the scenarios. It can be inferred that strong nationwide travel restriction lowers the peak cases by half if it decreases no less than 90% of all travels. Also, travel restriction 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 have only a limited contribution to flattening the curve. In other 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.[13] As for the other measures, shortening restaurants' opening hours is as effective as nationwide travel restriction. Alternatively, compared with travel restrictions and reduced restaurants' opening hours, working from home has limited effects. This is because the proportion of people who can work from home is limited, accounting for 43% of all workers[14], and 19% of the total population.

[10]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.

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

[12]Sources are the mobility data confidentially provided to the author by NTT DOCOMO.

[13]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 [35]. The result of the simulations weakly rationalizes excluding Tokyo, given that the campaign significantly increased the number of trips.

[14]This proportion is close to the estimated figures in other countries: 37% in the US [36], and 42% in Germany [13].

Scenario	Description
Baseline	—
Travel restriction (nation-wide)	Number of contacts of long distance travelers in all metropolitan areas decreases by 90%.
Travel restriction (only from/to Tokyo)	Number of contacts of long distance travelers in Tokyo decrease by 90%. In addition, number of contacts of long distance travelers from Tokyo in metropolitan areas other than Tokyo decreases by 90%.
Travel restriction (only from/to Tokyo and Osaka)	Number of contacts of long distance travelers in Tokyo and Osaka decreases by 90%. In addition, number of contacts of long distance travelers from Tokyo or Osaka in metropolitan areas other than Tokyo decreases by 90%.
Work from home	Workers who are in teleworkable jobs work from home with probability 49%.
Store closure	Number of contacts in metropolitan areas decreases by 36%.
Reduce all types of contacts (X%)	Number of both fixed and fluid contacts of all people decreases by X%.

Table 5: Scenarios to compare the effects of mobility control, store closure, and working from home.

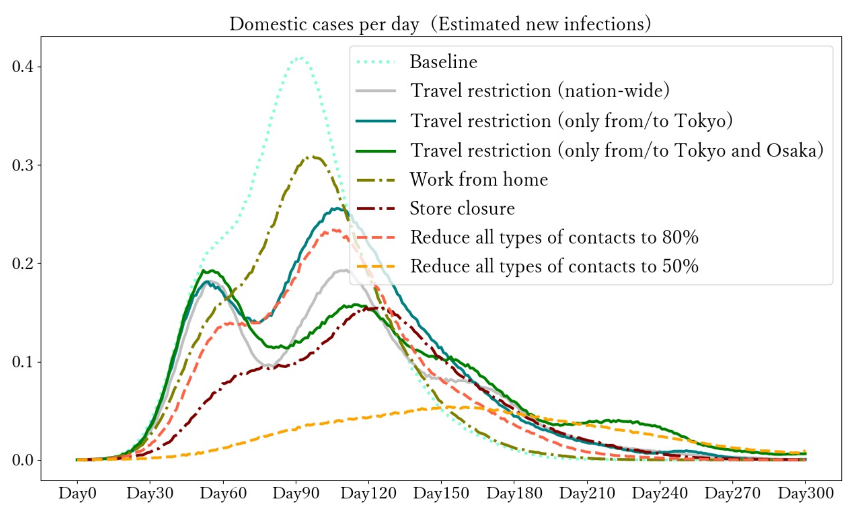


Figure 4: Cases under each intervention.

3.2 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 [37]. Here, the rate of decrease in positive cases is estimated assuming that the same figures and interventions have been realized in the same proportion on the first day of the state of emergency. Unlike the previous simulation, the initial state should not only be selected to match the data but also reproduce the presymptomatic people who are not infectious on the first day of the emergency but are bound to develop symptoms a few days later.[15] At this point, the initial state of this simulation is obtained by the following steps: (i) First, starting from the same proportion of the recovered population, the increase in cases is reproduced under the scenario that the daily tests are conducted on the randomly selected 30% of all symptomatic people.[16] (ii) For each of the 300 trials, the snapshot of the simulation in (i) when the proportion of the number of newly diagnosed cases in the population matches the one observed in reality is stored. (iii) Starting from the snapshot stored in (ii), it is assumed that the interventions listed in Table 6 are simultaneously introduced from the first day. Travel restrictions are assumed to decrease long-distance travels by 50% [38]. Additionally, it is assumed that the possible workers work from home with a probability of 70% [39], 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] Figure 5 indicates the estimated daily cases

[15] In the model, the schedule of each infected person developing symptoms are determined by the infection, following the probability and duration presented in Table 1.

[16] The tested receive the results in the following day. If they turned positive, they get quarantined. The test sensitivity is set to 70%.

[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.

[18] The government has restricted the size of the event to be less than 5,000 people in reality. In the simulation, the limit size is interpreted as a large number that would rarely be realized. Since the model assumes that the number of contact groups in the metropolitan area follows a Poisson distribution with a probability of 10, such a large size should correspond to 17, which achieves a probability of 1%.

diagnosed during the state of emergency. While assuming that the conversion rate of the number of newly diagnosed cases nationwide in relation to that in Tokyo is 6 to 1, 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.

Interventions	Description
Travel restriction (nation-wide)	Number of contacts of long distance travelers in all metropolitan areas decreases by 50%.
Work from home	Workers who are in teleworkable work from home with probability 70%.
Store closure	Number of contacts in each metropolitan area decreases by 75%.
Tests	Symptomatic people who are randomly selected with probability 30% get tested every day.
Event-size restriction	The size of the contact networks in metropolitan area is restricted.

Table 6: Interventions implemented in the scenario of the state of emergency.

[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.

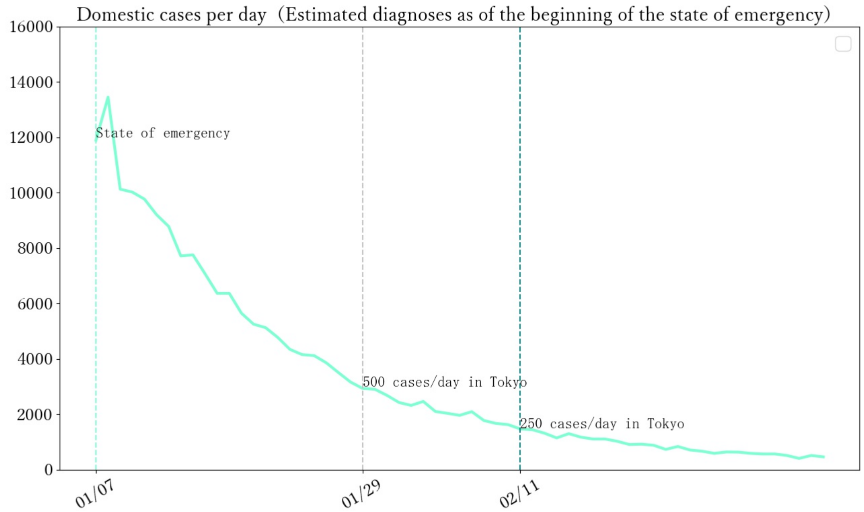


Figure 5: Cases estimated upon the introduction of emergency.

3.3 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 interventions would start to increase again at a high speed [21]. On the other hand, keeping all the interventions implemented during the state of emergency would generate a heavy economic cost [12], even if it may further decrease the number of cases. Figure 6 reveals the transition of diagnosed cases under various 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 restriction, working from home, and restaurants' shortening of their opening hours are assumed to be moderately lifted depending on the circumstances (see Table 7 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 [40]. The ease of store closure 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 travles only by a mere 15%.

Interventions	State of emergency	Lifting
Travel restriction (nation-wide)	Number of contacts of long distance travelers in each metropolitan area decreases by 50%.	50% → 35%
Work from home	Workers who are in teleworkable jobs work from home with probability 70%.	70% → 50%
Store closure	Number of contacts in metropolitan areas decrease by 75%.	75% → 36%

Table 7: Changes in interventions when out of the state of emergency.

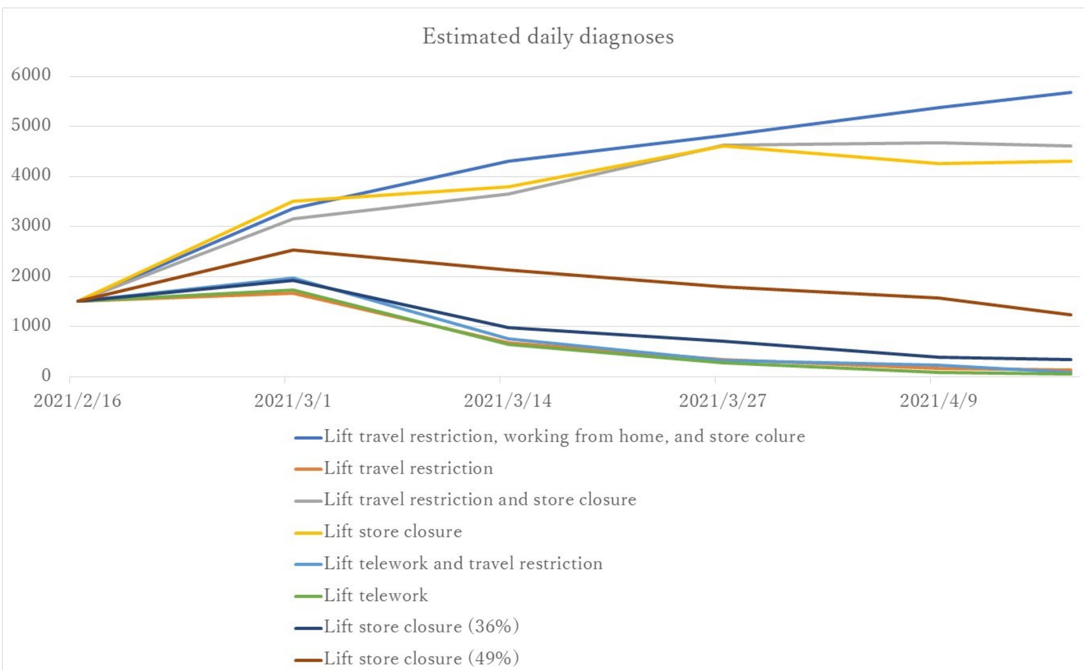


Figure 6: Cases under partial easing of the interventions after the state of emergency.

4 Conclusion

In the present study, the effectiveness of various interventions is analyzed by constructing an agent-based model that introduces census and mobility data in Japan. The results show the relatively high effectiveness of restaurants' shortening of their opening hours. Mobility control decreases the peak cases by half if it is severely implemented such that it decreases travel by 90%. The effectiveness of working from home is limited, even if people who can work from home reduce commuting by 70%. As for mobility control, interventions that only target highly populated regions are as effective as the nationwide one, suggesting that such region-specific mobility control has better cost effectiveness.

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 [41]. 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. Such a detailed 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.

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