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How long do voluntary lockdowns keep people at home? The role of social capital during the COVID-19 pandemic*

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Abstract

We create a city-by-day-level mobility index for the duration of the COVID-19 pandemic from data on over 80 million mobile devices to analyze how social distancing compliance varies with social capital levels. We find that in the second year of the pandemic, both voluntary preventative activities and policy compliance were substantially reduced in areas with low levels of social capital but not in areas with high levels of social capital. Additionally, in Japan, mobility was clearly reduced among those supporting a majority party, and there is little heterogeneity by political preference as related to ideology or position. This suggests that valuing conformity with others is an important driver of behavior that is beneficial to the community.

JEL classifications: H12, I18, Z18, A13, D91

Keywords: COVID-19, Stay-at-home orders, Social capital, Civic capital, Social distancing, Mobility, Compliance

1. Introduction

To fight the COVID-19 pandemic that began in early 2020, world governments have implemented various public health policies. Since social distancing is a primary policy used to control infectious disease outbreaks (Anderson et al. 2020; Hsiang et al. 2020), many governments adopted orders restricting mobility, such as lockdowns, stay at home (SAH) orders, and shelter-in-place orders (SIPOs). In the early stages of the pandemic, mobility restrictions were viewed as a containment strategy to be used until a vaccine was developed and distributed, but even after vaccination was underway, many serious and fatal cases of COVID-19 were still being reported worldwide. As a result, the fight against COVID-19 has turned into a protracted affair. Many studies have found that from the very beginning, mobility reductions and policy compliance varied by region (e.g., Allcott et al., 2020; Bargain and Aminjonov, 2020; Barrios and Hochberg, 2021), but gradually, changes were also observed over time. Understanding who will or will not comply with policy during which stages of a pandemic is a critical concern, not only during the current COVID-19 pandemic but also for future public health matters.

When faced with a public health problem and the risk of infection, individuals take self-defense actions to protect themselves, and they often comply with the government's prevention policies. However, in the case of infectious diseases, because of the critical externality of spreading the disease to others, the societal benefits resulting from individual preventive actions are greater than those that accrue to the individual. Since individual prevention can be considered a public good that benefits the community as a whole, prevention simply due to fear for one's own health cannot provide a socially desirable level of prevention (Jones et al., 2021). Because there are many asymptomatic COVID-19 carriers and the severity of symptoms varies widely across demographic groups, reducing mobility and enforcing social distancing have considerable positive externalities (Bethune and Korinek, 2020). Furthermore, the difference between the expected subjective benefits to an individual and the benefits to society can increase over time, as increased knowledge of the virus allows people to more accurately understand whether they are at high or low risk of infection (Chang et al., 2020).

If community members have a stronger interest in public welfare, they are more likely to voluntarily practice social distancing and even comply with government orders in a straightforward manner. Moreover, members of communities with strong reciprocity and social solidarity norms are more likely to reduce their mobility because of the higher psychological costs of infecting others (Alfaro et al., 2020). Members of such communities also monitor each other and stigmatize behavior that violates norms, which can increase the cost of engaging in risky behavior (Borgonovi and Andrieu, 2020; Herrmann et al., 2008; Putnam, 1993). We follow related studies (e.g., Bartscher et al., 2021; Durante et al., 2021) and define social capital as the beliefs and norms by which communities value collective actions and pursue socially valuable activities. The commitment of individuals to social systems is also known as civic capital (e.g., Barrios et al., 2021; Gusio et al., 2011; Lichter et al., 2021), and both concepts refer to the shared values, norms, mutual bonds, trust, etc., within a community and encourage individuals within that community to help other members and to work together to solve community-wide problems. Social capital can also be considered a resource necessary for the provision of public goods, as previous studies have found that it is positively associated with the efficient provision of public goods (Gächter et al., 2004). In the context of the COVID-19 pandemic, social capital can also overcome the free-rider problem by increasing the willingness to contribute to social welfare, thereby effectively overcoming the lack of self-defense and policy compliance related to the spread of infectious diseases.

This study analyzes how the reduction in people's mobility during the COVID-19 pandemic varies with the social capital of their region of residence using data from early 2020 to the end of September 2021 in Japan. We generate various indices of daily and city-level mobility from the location data of approximately 80 million mobile devices. We use principal component analysis to combine proxies commonly used in related studies (e.g., Barrios et al., 2021; Bartscher et al., 2021; Borgonovi and Andrieu, 2020), such as voter turnout and number of community centers per capita, in order to create a new proxy variable for social capital. We estimate the differences in people's mobility and policy compliance across social capital levels by strictly controlling for daily and city-level fixed effects, as well as by further controlling for the interactions between each phase of the pandemic and local geographic, demographic, and socioeconomic characteristics. The analysis reveals several important findings. First, in the early stages of the pandemic, areas with high levels of social capital areas (i.e., high social capital areas) reduced their mobility faster and to a greater extent, but the reductions were not very large (approximately a 1.5-percentage point difference in the rate of decline relative to the prepandemic baseline). Over time, however, the differences by social capital level increased, as individuals in high social capital cities continued to reduce their mobility and comply with government orders, while those in low social capital areas rarely complied with government orders. After mid-2021, individuals in areas with high levels of social capital were approximately 5 percentage points less mobile than individuals in areas with low levels of social capital, even in the absence of government orders, and an additional 10 percentage points less mobile if policies were introduced. These results are robust to 1) adding a prefecture–date interaction term, 2) controlling for potential confounders such as population density, taxable income, age, and education, and 3) using alternative measures of social capital and mobility.

We also examine the effects of political beliefs and ideologies, which have been emphasized in the context of policy compliance under COVID-19. Unlike previous studies on the United States (Allcott et al., 2020; Barrios and Hochberg, 2021), no significant differences or trends by political belief or ideology were found in Japan. Instead, the results suggest that whether the party an individual supports is in the majority may be an important determinant of compliance. Since people who conform to their surroundings are more concerned about being observed and their reputation, it is plausible that they participate in social activities, practice social distancing during pandemics, and comply with policies. In contrast, in areas where many people are not afraid to act differently from those around them (or who dare to act differently in retaliation against peer pressure), such forces may be weakened.

This study adds to a growing body of literature on social distancing and policy compliance during pandemics.[1] Previous studies in the United States and European countries investigating the early stages of the COVID-19 pandemic have shown that areas with higher social capital levels reduced mobility voluntarily and/or in compliance with policy (Bargain and Aminjonov, 2020; Barrios et al., 2021; Borgonovi and Andrieu, 2020; Brodeur et al., 2021; Ding et al., 2020; Durante et al., 2021), which in turn reduced the spread of infection and decreased excess mortality (Bartscher et al. 2021). Previous studies have suggested that in addition to social capital, mobility changes and policy compliance vary depending on socioeconomic characteristics such as income and occupation (Brough et al. 2021; Dave et al. 2021), political trust and beliefs (Allcott et al., 2020; Bargain and Aminjonov, 2020; Barrios and Hochberg, 2021), level of individualism (Bazzi et al., 2021; Bian et al., 2022), religion (Laliotis and Minos, 2022), culture as defined by language (Deopa and Fortunato, 2021), and ethnic diversity (Egorov et al., 2021). Because these cultural differences are interrelated (Bazzi et al., 2021), it is difficult to strictly separate the effects of each, and potential confounding factors may result in the impact of social capital being over- or underestimated. However, unlike the U.S. and European countries, which have been covered by previous studies, Japan, which we analyze, is highly homogeneous in terms of race, ethnicity, religion, language, culture, and other characteristics that are difficult to quantify (Central Intelligence Agency, 2022). In addition, Alexander and Karger (2021) note that the heterogeneity observed when using state-level variation is not found when using county-level variation, while our study finds heterogeneity by social capital levels at the Japanese city-level (there are approximately 1900 Japanese cities, a classification similar to counties in the United States). We contribute to the literature by providing robust evidence of heterogeneity by social capital level through the use of an index of social capital within a small geographic area in a culturally homogeneous country.

Additionally, most existing studies on social capital and social distancing have focused only on the early stages of the pandemic. While many studies have suggested that mobility and compliance vary across regions, Alexander and Karger (2021) find that in the early stages of the pandemic, there is little heterogeneity in the response to stay-at-home orders by regional characteristics, perhaps because of the lack of information on COVID-19 at the beginning of the pandemic. If people do not have information about what characteristics increase vulnerability to severe illness or death, they will proactively social distance to reduce their own risk of infection, regardless of their willingness to benefit others. Subsequently, as knowledge of COVID-19 increased, individuals could their own risk for severe illness, and the incentives for low-risk individuals to change their behavior were primarily altruistic. In this scenario, civic-minded individuals continuously practiced social distancing even if their own risk was low, while others may not have social distanced or complied with the policy at all. Therefore, differences in responses by social capital level may have increased with the passage of time since the beginning of the pandemic. Because it is impossible for governments to heavily restrict people's behavior for long periods, understanding the changes in community responses over time is crucial to developing effective strategies for dealing with prolonged infectious diseases.

By creating mobility indices from estimated population data that include information on area of residence, this study is able to analyze not only travel outside of a city but also, conversely, the travel into the city from somewhere else. Our results suggest that while government orders may prevent people living in high social capital areas from moving away, they may have a limited effect on reducing the number of people coming into those areas. Thus, imposing stricter restrictions on low-compliance areas may not increase social distancing, as people change their behavior to avoid such restrictions.

Our findings have important implications for the current multiyear struggle against COVID-19 and for new public health crises that may arise in the future. First, policies that explicitly inform people about the externalities of collective action to improve policy compliance are less effective in areas with low social capital levels and become even more attenuated over time. In such cases, financial policies such as penalties or subsidies may be necessary for individuals to internalize the externalities. Second, understanding that policy compliance varies by social capital levels and that this variation increases over time, will contribute to the development of public health models that more effectively predict the spread of disease. Accurate forecasting is critical for deploying resources appropriately, flattening the curve, and preserving hospital viability.

The paper proceeds as follows. Section 2 details the data related to policy, mobility, social capital and other control variables used in the analysis. Section 3 presents the empirical strategy. Section 4 presents the main results and a series of robustness checks. Section 5 discusses the underlying mechanisms and policy implications, and Section 6 concludes.

2. Data and institutions

We use four main types of data: 1) data related to COVID-19, such as government declarations and the number of cases, 2) indicators measuring mobility, 3) variables representing regional characteristics, and 4) other variables that may affect mobility. The analysis period is the 638 days from January 1, 2020, to the end of September 2021, and the data cover almost all 1889 cities in Japan.[2] Summary statistics for the major variables used in this analysis are presented in Appendix A1.

2.1. COVID-19 and policy in Japan

Japan was one of the first countries outside of China to confirm a case of COVID-19 infection, which occurred on January 16, 2020. After that, the number of infected people increased, exceeding 100 on February 22, at which time the government began full-scale countermeasures. In contrast to China, the U.S., and European countries, which adopted strict policies that restricted civil liberties by ordering citizens to stay home with penalties for violations, Japan attempted to control outbreaks by declaring a state of emergency, a measure with no legal binding force. Watanabe and Yabu (2021) called this situation in Japan a "voluntary lockdown", but despite the softness of the policy, Japan survived its first wave with very few cases by significantly reducing mobility.[3] Barrios et al. (2021) state that "Japan was able to contain COVID-19 with voluntary social distancing and without either large-scale testing or rigid lockdowns.” This may be an example of social capital working effectively. However, after the first wave, the government encouraged people to travel within the country in an effort to reactivate the stagnant economy, which led to another wave of infection. With the second and third waves, mobility gradually increased, and the number of cases and deaths increased as in other countries. Moving into 2022, the outbreak has continued, and the end of the COVID-19 epidemic in Japan is not yet in sight.

We obtained information on the daily number of cases (and deaths) in each city from the official websites of the public health departments located in those cities. Figure 1-(1) plots the number of daily confirmed infections per person, divided into cities with above-median and below-median social capital. The figure also shows when different states of emergency were declared in Tokyo, Japan's capital and the most heavily infected city. There were four large waves of infection during the analysis period, with a state of emergency declared in all 47 prefectures in the first wave and in prefectures with particularly high infections in the second and subsequent waves. The prefectures where states of emergency were declared and the timing of implementation are shown in Appendix A2. Figure 1-(1) shows that both cities with high and low levels of social capital followed similar trends but that cities with high social capital levels had fewer confirmed cases of infection overall. Of course, these differences are not necessarily caused by social capital levels, as they are the result of a combination of various geographic, demographic, and socioeconomic characteristics. We can also see that the peak of each wave increased over time.

We divide the analysis period into 13 phases based on the introduction of various policies, such as state of emergency declarations. Policy dates related to the start and end of each phase were obtained from government and local municipality websites. Table 1 shows the start date, domestic conditions, and expected impact on mobility for each phase. The start dates for phases 1 and 2 are the same for all prefectures, but for subsequent policies, there is a lag ranging from a few days to a few weeks in the start and end of the policy. Additionally, the second, third, and fourth state of emergency declarations covered 11, 10, and 21 prefectures, respectively. Additionally, the policy to promote domestic travel and consumption in Phase 5 (known as the "GoTo Campaign" in Japan) excluded only Tokyo until September 30, 2020. Taking advantage of the differences in the timing and presence of policies across prefectures, we analyze the change in mobility during each phase, that is, the change in mobility due to the introduction of the policy, while controlling for time fixed effects.

Since not all prefectures declared a state of emergency after the second wave, we use two methods for generating our data. The first is to skip the relevant phase in cities without a declaration, divide the period in half at an approximately median date, and allocate those dates to the phases before and after. For example, a prefecture without a phase 8 emergency declaration (from January 8, 2021, to March 21, 2021, in Tokyo) would be in phase 7 from the end of November 2020 to mid-February 2021 and in phase 9 from mid-February 2021 to the end of April 2021. The second method is similar to the triple-differences method, which creates a cross term between a dummy variable indicating the phase and a dummy variable indicating whether a declaration had been made. In this case, the variation in cities with emergency declarations during Phase 8 is identified with the interaction term "phase 8 x has a declaration", and the variation in cities without declarations is identified with "phase 8". Since both methods produce almost identical results, for ease of interpretation, we use the first method as our main strategy and the second method as a robustness check. While there is concern that areas with declarations might include only cities with high or low social capital levels, we have confirmed that such bias is small and does not affect the results.[4]

A state of emergency declaration is an endogenous response to the number of COVID-19 cases, the level of social capital, and other local characteristics. The number of cases and the declaration of a state of emergency are related, but higher social capital levels may make it easier to declare a state of emergency, and the characteristics associated with social capital (e.g., average age and occupation) may be correlated with the number of cases. However, in Japan, relatively strong interventions, such as state of emergency declarations, are implemented by prefectures, and except for very weak interventions, cities do not set policies on their own initiative. Because we exploit the variation in social capital and mobility among cities within a prefecture, we avoid the problem of policy endogeneity.

However, one set of policies for which the timing does not overlap with that of the state of emergency declarations is the “preemergency measures” issued at the city level. This is an even less enforceable policy that made “requests”, but areas with particularly high case rates were designated “priority areas,” and those with low rates were designated “normal areas” where people were encouraged to cooperate with voluntary prevention measures. To control for the effects of these measures, we add the explanatory variables “preemergency measures: normal” and “preemergency measures: priority.”

2.2. Mobility measures

We use population data estimated hourly, Mobile Spatial Statistics, obtained from NTT DOCOMO, Inc., the largest wireless carrier in Japan with over 80 million subscribers, to measure changes in mobility during the pandemic. These data are generated based on the location of the subscriber's device, which is continuously and automatically aggregated from the cellular operational network. Japan is divided into 500 m x 500 m meshes, and hourly mesh-level information about where a person who lives in a given city is currently located is reported.

A detailed and technical description of Mobile Spatial Statistics can be found in the Technical Journal published by NTT DOCOMO, Inc. (NTT DOCOMO, Inc., 2013). We use data from 2019 to define each mesh and to measure “normal” mobility before the pandemic. Each main analysis use data from January 1, 2020, to September 30, 2021.

We generated several mobility variables from the raw data. The first is the number of people outside their residential city, which is the most straightforward measure of people's mobility behavior. The second is the average distance traveled by the residents of a city, calculated as the distance between the center of gravity of their current mesh and the center of gravity of their city of residence. The third is the number of people visiting commercial areas; a similar definition is used by Mizuno et al. (2021), who also use Mobile Spatial Statistics. This is created by defining a “commercial area” as a mesh with an average nighttime population of at least 1 and a day/night population ratio of at least 1.5 in 2019 and taking the difference between the number of people in the defined mesh and the resident population. While the second and third indicators exhibit wide regional variation, the first, travel out of the city, is highly homogeneous across the country. In addition to these three measures, we also measure the number of people going out of the prefecture, the number of people around train stations, and the number of people in hotspots where people from various cities gather, which we use for robustness checks. Each variable is created at the city level for each hour, and its average value between 09:00 and 17:00 is used to calculate daily values. Detailed definitions and replication instructions are reported in Appendix B.

We also generated each mobility index for 2019 and used the average values for each weekday and holiday in 2019 as a measure of mobility during normal times. Taking averages allows for a more uniform measure of each city's mobility, alleviating extreme swings in 2019 due to major events, natural disasters, or other factors. We do not analyze the absolute level of mobility but rather use the percentage change after the pandemic relative to normal mobility as our explained variable. Because our identification relies on within-city variations in mobility over time rather than on comparisons of mobility between cities, the effect of the absolute magnitude of the original mobility measure is not a concern.

Graphs (2), (3), and (4) in Figure 3 show the changes in the mobility index (7-day moving averages) from January 2020 to September 2021. If mobility is unchanged compared to the prepandemic period, the index takes on a value of 0; if it is halved, the index takes on a value of -0.5. The figure shows that mobility was declining even before the state of emergency was declared. We note, however, that this trend includes both voluntary behavior and reactions to policies such as school closures. Although the patterns in each of the mobility indicators suggests an association between social capital and mobility, this may be due to any number of factors that could be correlated with both social capital and mobility.[5] The empirical strategy described in the next section aims to exclude the effects of confounding factors on the relationship between social capital and pandemic responses.

Mobile Spatial Statistics provide information on the estimated population, not travel, so we cannot identify who has moved or by what routes. However, the nature of the data can be used to create indicators of incoming as well as outgoing activity in a given area. We use the residential location information in the data to generate the following variables for each mobility indicator: 1) the mobility of people who reside in a given area and 2) the mobility of people who are currently in a given area. The first variable shows, for example, how many people living in Minato-ku are now traveling to other cities, and the second shows how many people currently staying in Minato-ku are from other cities. This allows us to distinguish between cities with high social capital levels whose residents either do not leave the city or reject outside visitors.

2.3. Social capital measures

We assume that residents in communities with high social capital levels exhibit strong social responsibility and therefore are more likely to defend themselves and comply with policies. To measure social capital, the literature uses voting rates (Barrios et al., 2021; Bartscher, 2021; Bauernschuster et al., 2014; Guiso et al., 2004: Putnam, 1993), blood and organ donations (Buonanno et al., 2009; Guiso et al., 2004; Guiso et al., 2016; Satyanath et al., 2017), association densities (Giuliano and Wacziarg, 2021; Satyanath et al., 2017), newspaper readership (Durante et al., 2021; Gusio et al., 2004), historical literacy rates (Tabellini, 2010), and the number of civil offices and religious organizations (Rupasingha et al., 2006). Following Rupasingha et al. (2006) and the related literature, we use turnout in national elections, participation in the volunteer fire brigade, the number of community centers per capita, and the number of meeting facilities per capita. We use the first principal component of these four factors as the composite social capital measure in our analysis. We also use each indicator separately in our estimation and confirm the robustness of the results to changes in the social capital proxy variables. Each variable is described below.

Voting is the most representative example of an activity that is privately costly and has no direct reward but is socially useful. We obtain national election data from the Ministry of Internal Affairs and Communications. Voter turnout has the analytical advantage of being highly representative, accurately observed, and specific to geographic areas. We use the average turnout in the last three (prepandemic) national elections (held in 2012, 2014, and 2017) as a measure of social capital. For each city and election, turnout is the number of votes divided by the number of eligible voters.

The number of fire brigades in each city is based on data published by the Fire and Disaster

Management Agency of the Ministry of Internal Affairs and Communications. In Japan, volunteer fire brigades (also known as the fire corps) are the emergency firefighting organizations for each city, and its members hold other jobs while training part-time to perform firefighting and disaster management activities during emergencies. Headquarters are located in each city, and anyone over the age of 18 may join. In 2021, there were approximately 810,000 volunteer fire brigades in Japan. Since participation is voluntary rather than mandatory, there is wide variation in participation rates from city to city. Because participation in the volunteer fire brigade contributes to the community but receives a small compensation (the national average is approximately $300 per year), participation rates can measure the willingness to contribute to society and levels of community connectedness.

We also use the number of community centers and meeting facilities in each city based on the Social Education Survey of 2008. The number of such facilities does not increase or decrease over short periods, and it is also well known that cultural characteristics such as social capital are strongly persistent over time (Alesina et al., 2013; Bisin and Verdier, 2000; Tabellini, 2008). The number of community centers per capita is a good measure of the strength of community connections and the willingness to provide public goods. Meeting facilities include health care clubs, martial arts halls, and multipurpose meeting spaces, which can be used to measure the level of community activity.

Figure 2 shows the variation in the composite social capital variable at the city level, color-coded by quintile. In Japan, urban areas tend to have relatively low social capital levels. Since urban areas attract people from rural areas in search of education and employment, it can be assumed that few people are born and raised in the city and, therefore, have a low sense of community. However, it is important to note that some urban areas do have high levels of social capital and that there is variation in social capital levels within a single prefecture. We use the city-level variation in social capital within prefectures in our empirical approach.

2.4. Other control variables

We control for local characteristics related to mobility, social capital, and the response to the virus. We use the share of the population 65 or over, population density, the share of white-collar workers, the unemployment rate, and the share of those with a college education or above, all obtained from the national census.[6] Additionally, the number of hospital beds in each city, based on the 2015 Survey of Medical Institutions, and the average taxable income for each city as published by the Ministry of Internal Affairs and Communications are included. These variables are used as control variables in the main estimation and for creating subsamples when checking for robustness.

To account for the risk of exposure to COVID-19, the number of new confirmed cases and deaths in a given city on a given day as reported by that city’s health department is used. We control for the previous day's values because we are interested in the impact of the reported number of cases and deaths on people's behavior. If a health center manages more than one city, the number of cases and deaths are prorated according to the population ratios. Although the impact of mobility on the number of cases is important, the number of cases is used only as a control variable in our analysis because of measurement error arising from the upper limits on inspections, false positives and negatives, and patients who do not receive medical attention.

Data from the Automated Meteorological Data Acquisition System, known as AMeDAS, operated by the Japan Meteorological Agency, are used to control for the weather, an important determinant of mobility. We use the precipitation level, average temperature, wind speed, and snowfall information reported by the weather station closest to each city office to represent the daily weather conditions for each city. If data from the nearest station were missing, the weather conditions reported by the second or third nearest station were used instead.

We also measure the share of votes cast for the major parties in each city (the number of votes cast for each party divided by the total number of votes cast) on the basis of the proportional representation vote for national elections. Because proportional representation voting is for parties rather than candidates, it provides information about preferences for each party as a whole rather than for a particular politician. We define the six parties that are on the ballot in all prefectures as the major parties in Japan and use them in our analysis. Each party's average vote share, percentage of seats in the House of Representatives, ideology, and position (right or left) are reported in Appendix A8.[7] These variables are not included in the main analysis but are used as independent variables in place of social capital to analyze the impact of local party preference on mobility and policy compliance.

When analyzing COVID-19 and mobility, it is important to consider the vaccination coverage data published by each prefecture. However, to avoid statistical discrimination, vaccination rates are published only at the prefectural level. Additionally, all prefectures began vaccination on almost the same day (up to two days later), and vaccination rates increased at similar speeds across prefectures, with little variation. Therefore, vaccination rates are not used for the main estimation but simply to confirm the descriptive statistics and provide suggestive evidence.

3. Empirical strategy

We aim to identify the role of social capital in postpandemic changes to mobility and policy compliance over time. The defined phases are used as temporal variables to measure the average effects in those phases. We begin by dividing the sample into high- and low social capital cities as a baseline to see how their respective mobility changed during each phase. We then use the interaction between the phase dummy and the high social capital dummy to identify heterogeneity by social capital level.

Our baseline specification is expressed by the following equation:

$$Y_{it} = \alpha + \sum_{j=1}^{j=13} \beta_j Phase_{jit} + \theta_i + \gamma_t + \delta_{it} + \varepsilon_{it}, \tag{1}$$

where the explained variable Y_{it} is the measure of mobility, such as traveling outside the city or distance traveled and measured as the percentage change relative to prepandemic levels, on day t in city i. Our explanatory variable of interest is $Phase_{jit}$, a dummy variable that takes on a value of 1 when day t in city i corresponds to phase j and that identifies the average change in mobility in each phase. Phase 1, which corresponds to the prepandemic period, is the baseline. θ_i represents the city fixed effects, which control for all time-invariant observable and unobservable city characteristics and their impact on mobility. γ_t comprises date-related variables such as holiday dummies and day-of-week fixed effects. δ_{it} includes the following variables for day t in city i: the natural logarithm of the number of cases and deaths (on the previous day), the weather, and the dummy variable representing the city's status under the preemergency measures issued. In all specifications, we report cluster-robust standard errors clustered at the city level. We examine changes in mobility in high- and low social capital areas separately by estimating equation (1) using two subsamples obtained by dividing the full sample into cities with above-median and below-median social capital.

Our identification assumption is that other factors correlated with social capital have no systematic effect on changes in mobility. However, regional characteristics, including social capital, risk for infectious diseases, changes in mobility, and the implementation of policy, interact in various ways. We apply the following specification to address the possibility that various unobservable variables may confound our estimates.

$$\begin{aligned} Y_{pit} = \alpha + \sum_{j=1}^{j=13} \beta_{1j} Phase_{jit} + \sum_{j=1}^{j=13} \beta_{2j} Phase_{jit} \times High_i \\ + \sum_{j=1}^{j=13} Phase_{jit} \times X_i + \theta_i + \gamma_t + \delta_{it} + \mu_{pt} + \varepsilon_{pit}, \end{aligned} \tag{2}$$

where $High_i$ is a dummy variable that equals 1 if the social capital of city i is above the median for all cities. The estimates of β_{2j} indicate whether the average percentage change in mobility in each phase depends on the level of social capital. For example, if the estimated value of β_{22} is -0.1, mobility in Phase 2 is reduced in cities with higher social capital by an average of 10 percentage points more than in those with lower social capital.

We consider several factors in addition to the variables included in equation (1). By adding interaction terms between each phase and major regional characteristics X_i, we control for the time-varying effects of those characteristics. Specifically, we add 1) the share of the population over age 65 (as the elderly are at higher risk of infection), 2) population density (as infection is more likely to spread in urban areas), 3) the share of white-collar workers (as they are more likely to work at home), and 4) the number of hospital beds per capita (as a better health care infrastructure lowers the risk of infection). We further include date fixed effects in γ_t to control for changes in mobility that are common to all cities on a given day. Additionally, since many of the policies other than declarations of a state of emergency (e.g., subsidy payments and other requests) are implemented at the prefectural level, we absorb their effects by adding an interaction term between prefecture p and date t: μ_{pt}. In the main analysis, social capital is a binary variable for ease of interpretation, but an analysis using social capital quintiles is also performed to capture any nonlinear effects. Our main results are robust to the addition and removal of these control variables, which are presented in Appendix A3.

To identify differences between areas that did and did not declare a state of emergency after the second wave of the pandemic, we also use the following triple-difference-like framework.

$$\begin{aligned} Y_{pit} = \alpha + \sum_{j=1}^{j=13} \beta_{1j} Phase_{jit} + \sum_{j=1}^{j=13} \beta_{2j} Phase_{jit} \times High_i \times Declar_i \\ + \sum_{j=1}^{j=13} Phase_{jit} \times X_i + \theta_i + \gamma_t + \delta_{it} + \mu_{pt} + \varepsilon_{it}, \end{aligned} \tag{3}$$

where $Declare_i$ is a dummy variable that equals 1 if the city declared a state of emergency during the second, third, or fourth wave of infection (phases 8, 10, and 12). This allows us to investigate how mobility differed between cities with and without declarations during the second and subsequent waves of the pandemic. Of course, our specifications do not strictly identify voluntary prevention and policy compliance, since the declaration of a state of emergency is endogenously determined by the number of cases. The purpose of this specification is to verify that the definition of the phases does not cause the under- or overestimation of the impact of the state of emergency declarations. Since the results from equation (3) are almost the same as those from equation (2), equation (2) is our primary specification.

4. Results

4.1. Main results

We first estimate equation (1) using two subsamples, obtained by dividing the full sample into two parts: cities above the median social capital level and cities below. The results of this estimation are shown in Figure 3. The explained variables for mobility are (1) people traveling outside their city of residence, (2) distance traveled, and (3) people visiting commercial areas, and the dots in the graph indicate the estimated coefficients for each phase. The 95% confidence intervals for each estimate are plotted and are constructed on the basis of standard errors clustered at the city level. Although these results must be interpreted with caution because a number of regional characteristics are not controlled for, they provide us with important insights into changes in mobility during the pandemic. First, regardless of social capital level, all estimates are negative, indicating that mobility was always lower than normal after 2020. Mobility was greatly reduced when the first state of emergency was declared (Phase 3) but had already declined as a result of voluntary preventative activities during Phase 2. During Phases 4 through 6, after the end of the first wave, mobility increased slightly, partly because the government encouraged domestic travel and consumption, but it did not return to normal levels. Subsequently, after the end of 2020 (Phase 7), each explained variable and the composite social capital measure exhibit different movements.

During the first state of emergency, (1) travel outside the city of residence were down approximately 25% to 30% in both high- and low social capital cities. However, the difference gradually increased in the second year, with the those from high social capital cities traveling out as much as they did under the first declaration, while those from low social capital cities reduced their mobility by only approximately 10%. Viewed differently, it may be surprising that voluntary preventative activity continued for a year and a half in high social capital cities, despite the absence of any legal restraints. For (2) travel distance, there appears to be little difference by social capital level, with both groups of cities exhibiting a 30-40% drop at the time of the outbreak. Regarding (3) visitors to commercial areas, we see that not only do individuals from high social capital cities always visit fewer commercial areas, but they also respond more strongly to the third and fourth state of emergency declarations. In contrast, the impact of the second and subsequent emergency declarations in the low social capital cities was almost negligible. It is important to note, however, that the estimated results capture only the average change in mobility during each phase, so the decrease in mobility during the state of emergency declarations reflects both private precautions and public restrictions. The purpose of Figure 3 is to observe the changes in mobility in cities with high and low social capital levels, not to identify the causal effects of social capital. We therefore provide more robust evidence for the differences produced by social capital, controlling for a variety of confounding factors.

Figure 4 presents the estimation results for equation (2) on the left and equation (3) on the right.[8] The explained mobility variables are (1)-(2) the number of people who leave their city of residence, (3)-(4) the distance traveled, and (5)-(6) the number of visitors to commercial areas, and are measured in terms of the percentage change relative to normal times. Although each mobility measure varies in the magnitude of its coefficient due to differences in variance, the overall trend is consistent. There is no significant difference between high- and low social capital cities in the first year of the pandemic (up to Phase 7), but from the second year onward, individuals from high social capital cities are significantly less mobile. Focusing on (1) and (2), the number of people leaving their city of residence, individuals from high social capital cities reduced their mobility by 5 percentage points more than those from low social capital cities outside the state of emergency declarations. Additionally, the emergency declarations increased the resident mobility gap between high- and low social capital cities by an additional 10 percentage points.

The main findings of this study are consistent with those of Barrios et al. (2021), who found that regions with high civic capital take voluntary precautions and follow government orders. Barrios et al. (2021), who analyzed the first wave of infection in the U.S., found an additional 1.3% reduction in mobility in areas with high levels of civic capital when states had a stay-at-home order. Although our definitions of social capital, our mobility indicators, and the policies studied also differ and the results should be interpreted with caution, our results for the first wave are similar (an additional 1.4% reduction in travel outside the city). However, our novel evidence shows that the differences increased greatly after the second wave of the pandemic. During a state of emergency declaration, noncompliance is more costly because the probability of infection is higher due to the increased number of infected people and because it is easier to detect and sanction violations. Therefore, one would expect that reliance on social capital would be lower during a declaration, but our results suggest the opposite. This indicates that there are significant differences in policy compliance as well as voluntary preventative activity depending on social capital levels.

4.2. Robustness checks

4.2.1. Nonlinear impact of social capital on changes in mobility

We use dummies for the quintiles of social capital to estimate the nonlinear effects of social capital on changes in mobility, and the results are reported in Appendix A4. Estimates using travel outside of cities as the explained variable show that individuals from cities with particularly high levels of social capital (80-100th percentile) reduced their mobility by 15 to 20 percentage points relative to the baseline in the second year of the pandemic. In contrast, there is little change among those from cities with lower social capital levels, which means that cities with particularly high levels of social capital were more responsive to the pandemic. The results using the other mobility indicators are also roughly consistent, although the magnitude and significance of the coefficients vary. Comparing the magnitude of the coefficients on the quintile dummies in each phase, we see that in almost all phases, the higher the social capital level is, the more mobility is reduced. This reinforces the argument that the results are not driven by the threshold used to define a high level of social capital.

4.2.2. Above- and below-median subsamples by each characteristic

The main results are robust to the inclusion of controls for city fixed effects and of interaction terms between regional characteristics and phases, suggesting that geographic, demographic, and socioeconomic characteristics are unlikely to be important confounders. As further robustness checks and to obtain insight into the underlying mechanisms, we partitioned the sample by the median of several regional characteristics and estimated the specification in equation (2) for each. In the following, we present results using travel outside of the city of residence as an explanatory variable, which universally expresses mobility regardless of city scale or geographic size. Appendix A5 presents the results of the analysis using the above- and below-median subsamples for (1) population density, (2) the percentage of the population over 65, (3) the percentage of white-collar workers, (4) the percentage of residents with a college degree or above, (5) average taxable income, and (6) the number of hospital beds per capita. All results are consistent with the main results, indicating that in the second year of the pandemic, there were significant differences in mobility by social capital. This indicates that the main results are not driven by the potential confounding factors presented here.

Looking at each of the results, first, the impact of social capital is greater in areas with lower population densities. In less populated areas, the risk of becoming infected oneself is low, but the psychological cost of infecting others is high because residents are more likely to know each other. Additionally, social capital has a stronger effect on mobility in areas where people are more vulnerable (a higher percentage over age 65) or that have a worse medical infrastructure (fewer beds) because the risk and psychological costs of spreading infection are greater. The impact of social capital is stronger in areas with a smaller percentage of white-collar workers, lower education levels, and lower income, possibly because culture plays a smaller role in more developed and urbanized areas and the impact of community linkages and culture is greater in less urbanized areas.

4.2.3. Results using alternative measures of social capital

To ensure that our results do not depend on the construction of our social capital index, we reestimated our model using each social capital variable in place of the principal components. The results are presented in Appendix A6 and are consistent with the results using the principal components for (1) voter turnout in national elections, (2) participation in volunteer fire brigades, (3) the number of community centers per capita, and (4) the number of meeting facilities per capita. Therefore, our main results are robust to changes in alternative indicators of social capital.

4.2.4. Results using alternative measures of mobility

To improve the robustness of the main results, different mobility measures are also considered. Given the limited data sources available, our best option was to create several mobility measures with different definitions and use them as explained variables. The results are shown in Appendix A7. The mobility measures used are (1) the number of people visiting from other cities, (2) the distance traveled by people visiting from other cities, (3) the number of people visiting commercial areas from other cities, (4) the number of people leaving their prefecture of residence, (5) the number of people in hot spots, and (6) the number of people near train stations. The results using these alternative measures of mobility are presented in (4), (5), and (6) and are consistent with the main results, indicating that our results are not sensitive to the mobility measure used.

Columns (1) through (3) capture the impact of people coming from outside the city, indicating that it is easier for high social capital cities to reduce (1) the number of people visiting from outside the city and (3) the average distance those visitors had traveled. This may be due to the stronger level of mutual monitoring among residents and the increased criticism of violators in high social capital cities, which may suppress visits from outsiders. Alternatively, it could be explained by local cooperation, such as encouraging telework or voluntarily closing stores and facilities. However, the results in (3) indicate that the number of people visiting commercial areas (areas with particularly large daytime populations) from other cities does not vary with social capital levels. This suggests that high levels of social capital may keep the residents of those areas from traveling away but may have a limited effect on reducing the number of people visiting from other cities. Since the overall number of visitors has decreased, visitors may be concentrated in certain commercial areas, which is problematic from the standpoint of controlling the spread of infection.

We attempt to explain these results in terms of Japanese policy and actual conditions. People are attracted to commercial areas because business activities take place there and because bars, restaurants, and other establishments are in operation. A state of emergency declaration includes a "request" that bars and restaurants reduce their hours of operation or refrain from serving alcohol. However, it is not a legal prohibition, and there are no legal penalties for noncompliance, but store managers have a financial incentive to cease operations to receive compensation for their closure. However, if only one store was open while the others were closed, the operating profits would likely exceed the compensation for closure because it would attract all potential customers. In such cases, if the indirect effects of negative reviews, etc., are not considered, management may make the rational decision to keep the business open and to continue to attract people. It was frequently reported in Japan that pachinko parlors, bars, and restaurants remained open and drew crowds even during the declared states of emergency (The Japan Times, 2020). There is also anecdotal evidence that when a state of emergency was declared in an area and many stores were closed for business, people would travel to stores in neighboring cities and prefectures (Asahi Shinbun, 2021). Therefore, a strong policy with enforceable penalties may be important to keep people from congregating in commercial areas rather than relying on social capital and individual voluntary efforts.

4.2.5. Political preferences

Although social capital is the primary concern of this paper, the impact of political preferences on mobility and policy compliance is also important, as previous studies (Allcott et al., 2020; Barrios and Hochberg, 2021) have identified. Here, we confirm that our results are not driven by political preferences. We create dummies that equal 1 for cities where the share of votes cast for each party is above the 25th percentile and use those dummies in place of our social capital measure. The results are reported in Table 5, and a summary of each party is provided in Appendix A8. Unlike previous studies covering the U.S., our results find no specific trends by ideology (e.g., conservative or liberal) or position (right or left) in Japan. For example, (1) the Liberal Democratic Party (LDP, Japan's ruling party, conservative, right-wing) and (2) the Democratic Party of Japan (DP, the largest opposition party, liberal, center-left) often propose contradictory policies, but the impact of support for those parties on mobility and policy compliance is similar. However, support for (3) Komeito, which is close to the LDP in its political leanings, exhibits a trend in its effects opposite that of the LDP. In areas with relatively large numbers of supporters of the (5) Japan Communist Party, which advocates communism, mobility was less likely to decline, and policy compliance was lower.

The finding that areas with more supporters of the two largest parties, the LDP and the DP, are more likely to exhibit reduced mobility suggests that supporting the "majority party" may be more important than party ideology or agenda in Japan. It is plausible that those who prefer a party that many people support rather than a party that conforms to their personal principles and beliefs are more likely to take voluntary precautions and comply with policies to avoid acting differently from the majority in their community. Cato et al. (2020), who used a questionnaire to analyze mobility behavior during the pandemic in Japan, reported that respondents who believed that "it is important to always avoid doing anything people would say is wrong" were less likely to eat out during the pandemic. Thus, a culture in which people care more about how others perceive them than their own beliefs may affect their mobility choices during the pandemic. An alternative explanation might be that resistance to the preventative measures may be due to a backlash against the existing hierarchy and elites and a distrust of authority and science. Such defiant attitudes toward the current regime may reduce perceptions of the risk of COVID-19 and discourage engaging in voluntary prevention and complying with policy (Brzezinski et al., 2021).

5. Discussion and policy implications

Our results have several important policy implications. As the pandemic has continued for more than a year, the impact of social capital on mobility and policy compliance has gradually become stronger, with decreases in mobility being less likely in cities with lower social capital levels. In contrast, in high social capital cities, both mobility reductions and policy compliance have continued for a long time, but it is difficult to prevent visits from outside the city. Thus, unenforceable (or weak) constraints meant to control the pandemic may be effective only in the short term. Japan managed its first year of the pandemic with a voluntary lockdown, but this became ineffective during the second year. Therefore, in the long fight against a highly infectious disease such as COVID-19, it may be less costly to suppress mobility in the short term with strict policies than with long periods of weak policies. Additionally, constant monitoring to see where mobility is declining or where policy compliance is highest is very important because initially effective policies may gradually become ineffective.

We have given several explanations as to why differences began to appear after the second year, which we summarize here. The first reason is a change in people's understanding of the virus. In the early stages of the pandemic, little was known about the virus, so everyone voluntarily restricted their mobility because of the uncertainty regarding who would be infected and who would become severely sick. This is plausible because the number of cases and deaths were lowest during the first wave when mobility was also reduced the most. However, as the risk of infection was gradually acknowledged as demographically heterogeneous, altruistic individuals with a low risk of infection may have continued to voluntarily restrain themselves for the sake of others, but egocentric low-risk individuals may have begun to ignore such restrictions. This hypothesis cannot be empirically tested with our data. However, an explanation relying on altruism is plausible in light of the finding by Cato et al. (2020) that people with more altruistic characteristics were more likely to reduce their social distance during the pandemic.

Another possibility is whether the areas covered by the state of emergency declarations are geographically large. The first wave necessarily reduced mobility because the state of emergency was declared for all of Japan, so no one could escape to areas not covered by the declaration. However, after the second wave, individuals had the option of moving to nonemergency areas, which may have caused the differences in mobility. However, this explanation is unlikely to hold given our sample and results. As mentioned above, some establishments remained open during the first state of emergency, allowing people to congregate there. This explanation is also not very convincing considering the differences in the impact of the third state of emergency declaration, which covered a small number of areas, and that of the fourth state of emergency declaration, which covered the entire area surrounding certain cities.

It is also difficult to use vaccination for any kind of explanation, since differences by social capital were present even before vaccination began. However, since vaccination has strong externalities and its social benefits are very large (White, 2021), it would be useful to consider the effect of vaccines. To avoid statistical discrimination, data on vaccination coverage is only published at the prefectural level in Japan and cannot be analyzed in detail. We developed a prefecture-level index of social capital and compared the vaccination coverage of prefectures with above- and below-median social capital levels. Appendix A9 indicates that vaccination is progressing more quickly in prefectures with high levels of social capital. It is interesting to note that vaccination progressed more quickly and widely in high social capital areas, even though, on average, infections were more common and the vaccine supply was greater in urban areas with lower social capital. This is very weak evidence of prefecture-level differences, so these results must be interpreted with caution, but they do suggest a relationship between vaccination and social capital.

6. Conclusion

In response to the global COVID-19 pandemic, countries around the world implemented various policies, both mandatory and voluntary, to enforce social distancing. To explain the large national and regional differences in social distancing and policy compliance, it is important to consider the role of culture from a sociological perspective (Bian et al.). Given that COVID-19 is still prevalent in 2022 and the threat of similar pandemics in the future is great, understanding the effects of cultural heterogeneity is of great value to public health.

We used a wealth of data on the Japanese context to investigate how the effect of social capital on mobility changed during the first year and a half of the pandemic. The results revealed that the differences in mobility and policy compliance between cities with high and low social capital levels increased as the pandemic continued. As Durante et al. (2021) predicted, social capital is more important during prolonged pandemics. They mention the possibility of faster economic recovery in communities with higher social capital levels, but according to our results, this may be spoiled by noncompliance and free riding among those from cities with lower social capital levels. Because the virus easily crosses community boundaries, successful prevention in one city may be offset and rendered meaningless by contact with people from another city.

Since collective action issues are important in human society (Ostrom, 2000), not only for COVID-19, our results have broader implications. Our finding that high social capital areas make longer-lasting contributions to the community highlights the importance of the social capital stock within the community. Although there are continuous and enormous costs associated with beautifying a community and improving public health, areas with high levels of social capital may be able to provide such services less expensively. While community bonding and peer pressure are sometimes viewed negatively from an individualistic viewpoint, encouraging community unity and strengthening social capital can be highly effective for addressing issues that require collective action.

A potential limitation is that we do not examine the external validity of our study. Compared to the areas covered by previous studies, Japan exhibits two main differences, its unique culture and its voluntary lockdowns, and the effects of these factors cannot be identified separately. However, it is interesting to find large heterogeneity by social capital level, even in a society with relatively little racial, religious, linguistic, and ethnic heterogeneity. Additionally, while this study used city-level characteristics, it is important to know about the impacts of individual-level demographics and their relationship to the community. More insight into individual-level characteristics such as knowledge of viruses, personality, and trust in the government and science could be obtained by analyzing individual-level data rather than population estimates. If individual characteristics such as cooperation and perseverance are associated with local social capital levels, those characteristics may provide better explanations for our results. This is an interesting issue for the future.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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[1] Brodeur et al. (2021) provides a comprehensive review of the economic research related to COVID-19.

[2] Seven cities in Fukushima were not included in the analysis because they were severely damaged by the nuclear power plant accident caused by the Great East Japan Earthquake and are still considered evacuation zones.

[3] A detailed analysis of the mobility changes during the early stages of the pandemic in Japan is provided by Watanabe and Yabu (2021).

[4] There are 1889 cities in the analysis, of which 616 (121), 649 (266), and 1114 (389) were covered by the second, third, and fourth state of emergency declarations, respectively (with the number of cities with high levels of social capital in parentheses).

[5] In Figure 2-(B), mobility among residents of high-social capital cities declines sharply at the end of February, which introduces a concern about some kind of error in the data preparation, but a closer examination of the data shows that this fluctuation actually occurred. This may be the result of a time lag during which infections spread first in areas with low levels of social capital and then spread to areas with high levels of social capital. In other words, the spread of infection may have reduced the high mobility of individuals from low social capital areas so that it was equal to the mobility of individuals from high-social capital areas. Then, the subsequent spread of infection in high-social capital areas caused a rapid decline in mobility.

[6] The Japanese census is conducted every five years, with the latest data being from 2020, but to avoid the effects of the pandemic, we used the 2015 census. Because surveys on education

are conducted only every 10 years, we use data from the 2010 census for the share of individuals with a college degree or above.

[7] Descriptions of each party's ideology and standing are determined based on information from each party's website, election-related materials, and Taniguchi and Winkler (2020).

[8] The estimation results presented in Figure 4 are listed in Appendix A4, and estimation results excluding some fixed effects are also reported.

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Phases	Start date	Conditions	Expected impact on mobility
1	January 1, 2020	Before the number of confirmed cases of COVID-19 exceeded 100	Baseline
2	February 22, 2020	Early stages of outbreak (Schools were closed)	Negative
3	Early April, 2020	First state of emergency (47 prefectures)	Strongly negative
4	Late May, 2020	No restrictions	
5	July 21, 2020	Domestic tourism promoted (without Tokyo)	Positive
6	October 1, 2020	Domestic tourism and consumption promoted (with Tokyo)	Positive
7	Late November, 2020	No restrictions or promotions	
8	Early January, 2021	Second state of emergency (11 prefectures)	Strongly negative
9	Late March, 2021	No restrictions	
10	Late April, 2021	Third state of emergency (10 prefectures)	Strongly negative
11	Late June, 2021	Weak enforcement policies in some areas	Negative
12	Early August, 2021	Fourth state of emergency (21 prefectures)	Strongly negative
13	Mid-September, 2021	Weak enforcement policies in some areas	Negative

Table 1. Phases of the COVID-19 pandemic and the corresponding policies in Japan
Note: This table shows the 13 phases of the analysis period (January 1, 2020, to September 30, 2021), which are defined according to each city's conditions. The start date for each phase is defined based on information published by the government and by each municipality.

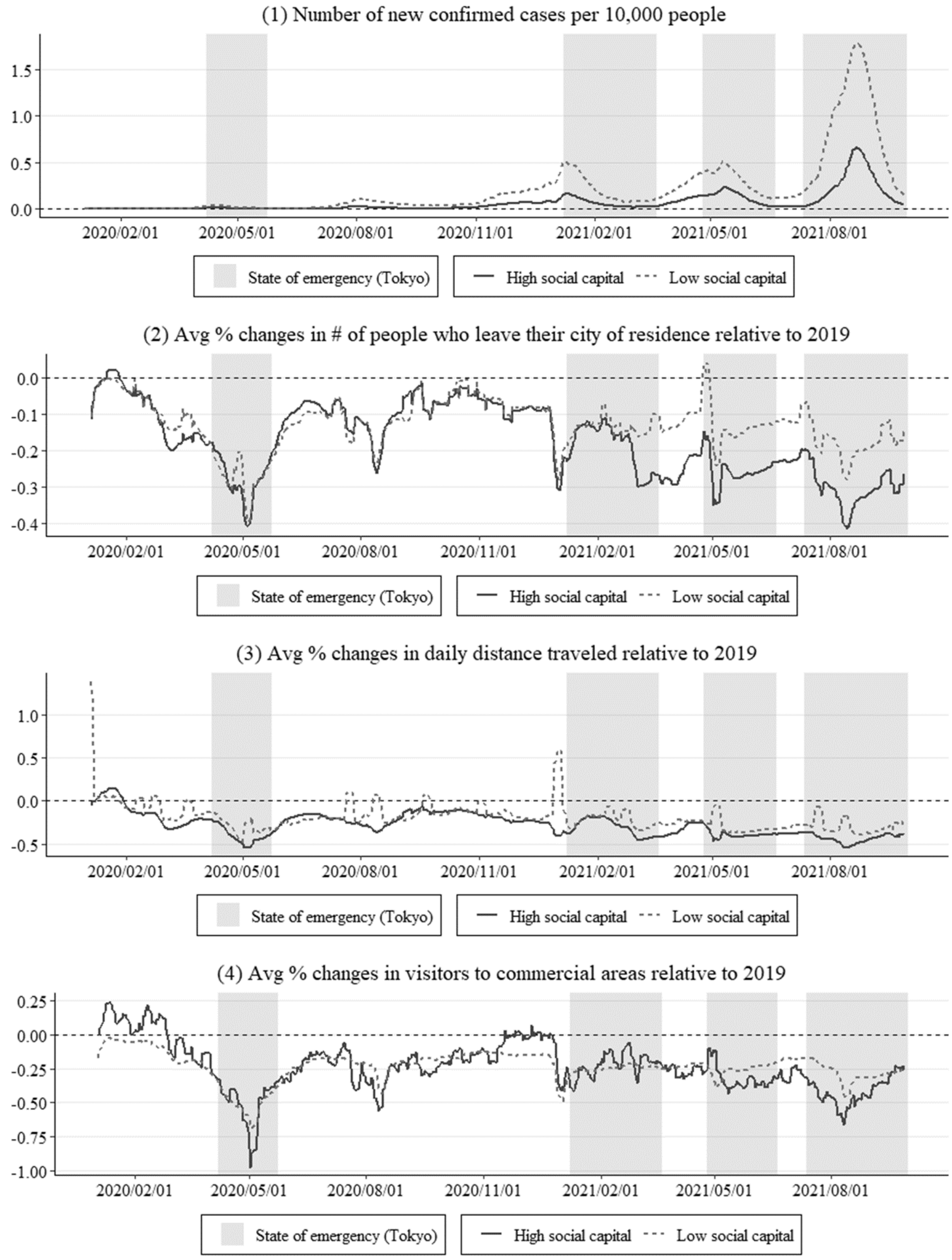


Figure 1. Changes in the number of confirmed cases per capita and various mobility measures plotted by social capital (7-day moving averages)

Note: This figure describes the changes over time in the number of COVID-19 cases and the mobility of people in Japan. Solid lines indicate cities with high levels of social capital, dotted lines indicate cities with low levels of social capital, and shaded areas indicate periods when states of emergency were declared in Tokyo.

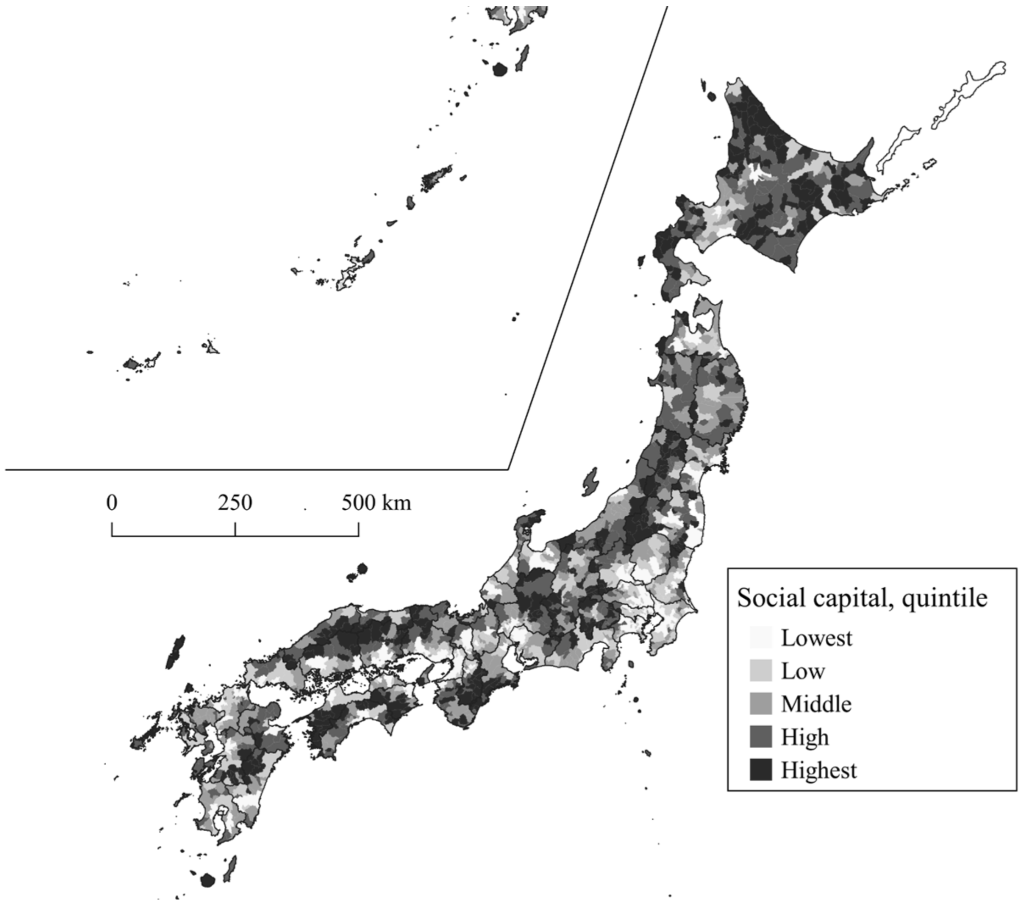


Figure 2. Geographic distribution of social capital in Japan

Note: This figure illustrates the geographic distribution of the quintiles of our main social capital measure. For visual ease, Okinawa Prefecture, a remote chain of islands at the southern tip of Japan, is shown in the area enclosed by the line in the upper left corner of the figure.

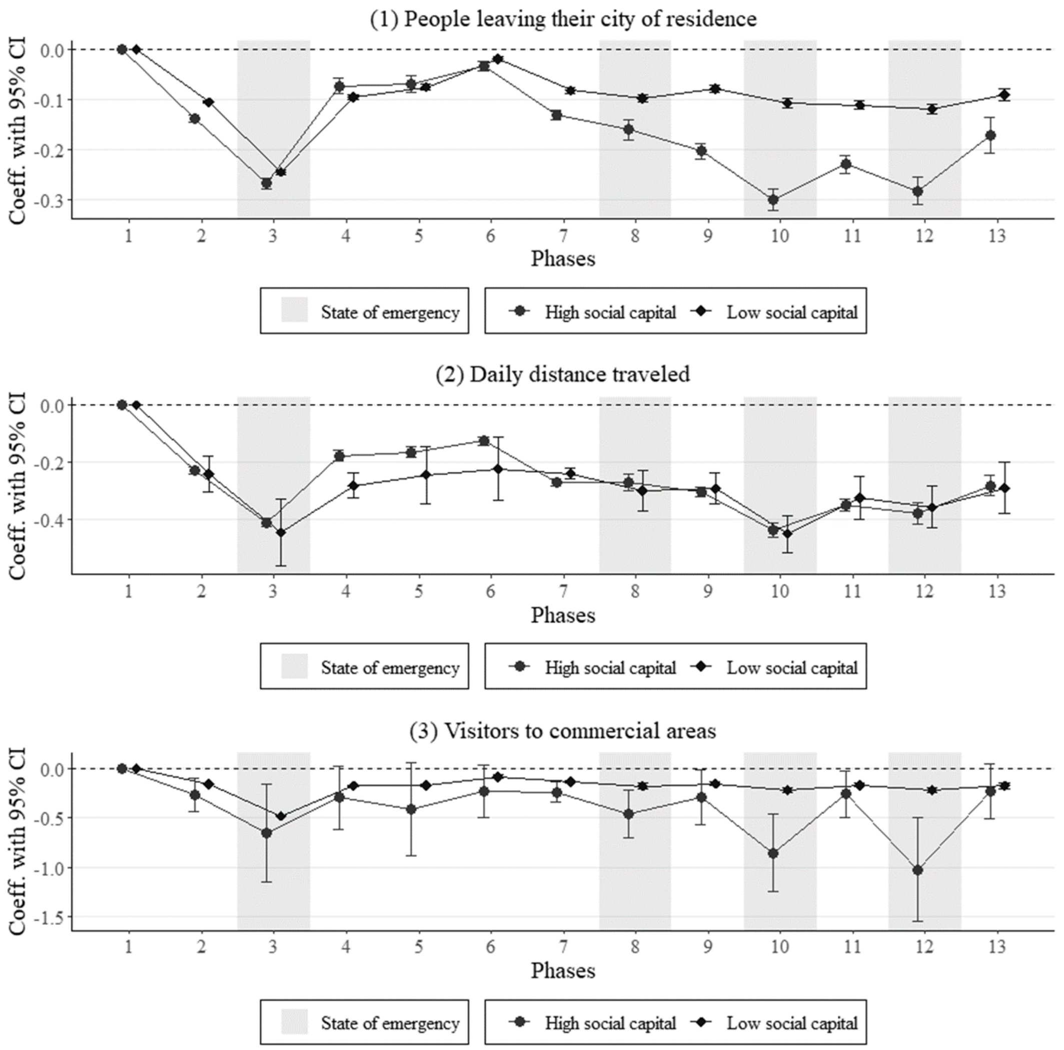


Figure 3. Changes in mobility among residents of cities with high and low social capital during the pandemic

Note: Using city-by-day level data, we plot the coefficients for each phase dummy from regressions that include weather variables, pre-emergency measure dummies (indicating normal vs. priority status), holiday dummy, day-of-week fixed effects, city fixed effects, and (the natural logarithm of) the previous day's COVID-19 cases and deaths as controls. Standard errors are clustered at the city level, and bars represent 95% confidence intervals. The round dots indicate the results of the estimation using a subsample that includes cities with social capital levels greater than the median, while the square dots indicate the results from using a subsample that includes cities with social capital levels below the median. The shaded areas indicate phases in which a state of emergency was declared. The explained variables are (1) the number of people who travel outside their city of residence, (2) the distance traveled, and (3) the number of visitors to commercial areas, each of which is measured as the percentage change from the corresponding values during normal times.

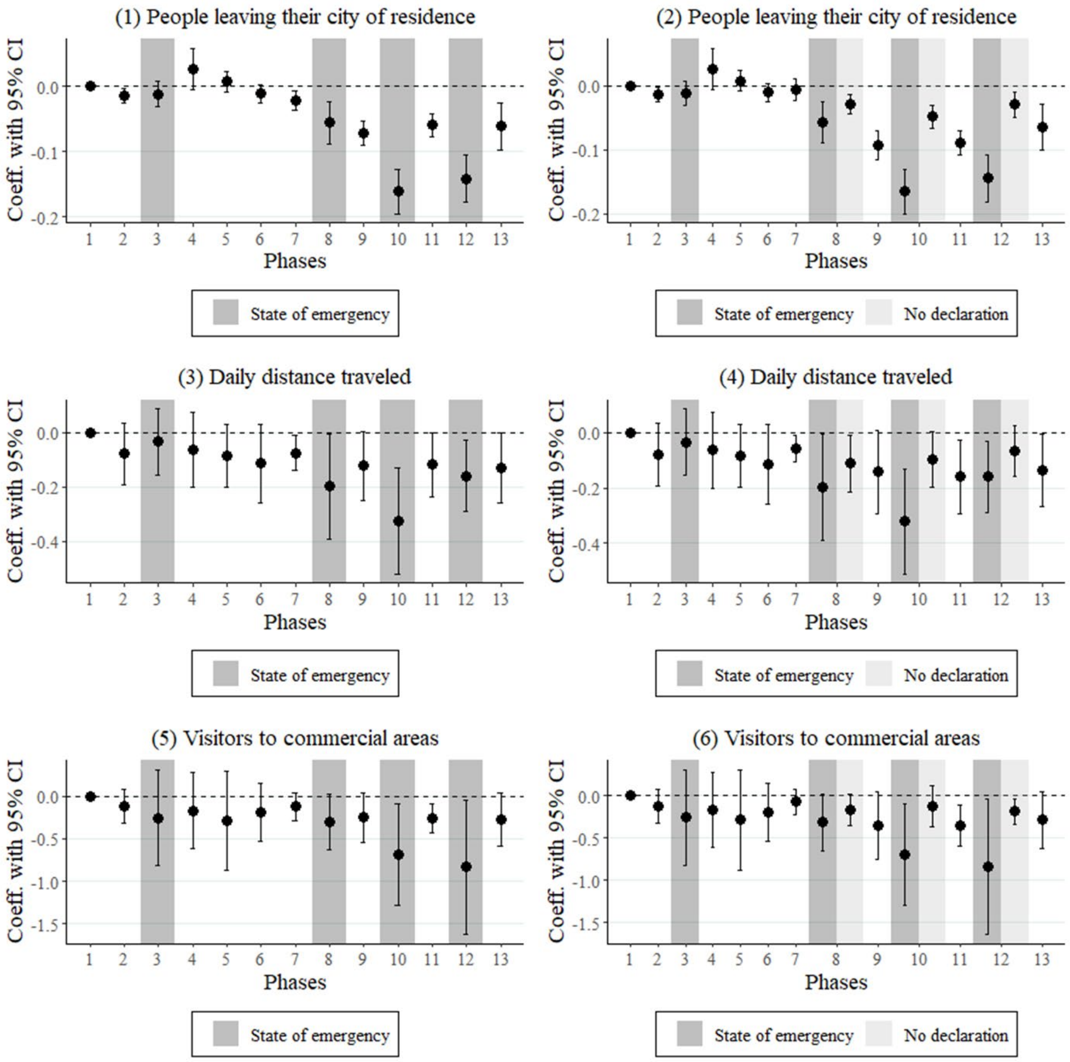


Figure 4. Differences in mobility changes between cities with high and low social capital

Note: Using city-by-day level data, we plot the coefficients on the cross terms between each phase dummy and the high-social capital city dummy (in graphs (2), (4), and (6), these terms are further multiplied by the declaration dummy) from regressions that include weather variables, pre-emergency measure dummies (indicating normal vs. priority status), holiday dummies, day-of-week fixed effects, city fixed effects, date fixed effects, the cross terms between the phase dummies and variables for local characteristics, and (the natural logarithm of) the previous day's COVID-19 cases and deaths as controls. Standard errors are clustered at the city level, and bars represent 95% confidence intervals. The darker shaded areas and lighter shaded areas indicate the differences in the percentage change in mobility due to social capital in cities where a state of emergency was declared and in those where a state of emergency was not declared, respectively. The explained variables are (1)-(2) the number of people who leave their city of residence, (3)-(4) the distance traveled, and (5)-(6) the number visitors to commercial areas, respectively, and each is measured as the percentage change from the corresponding value during normal times.

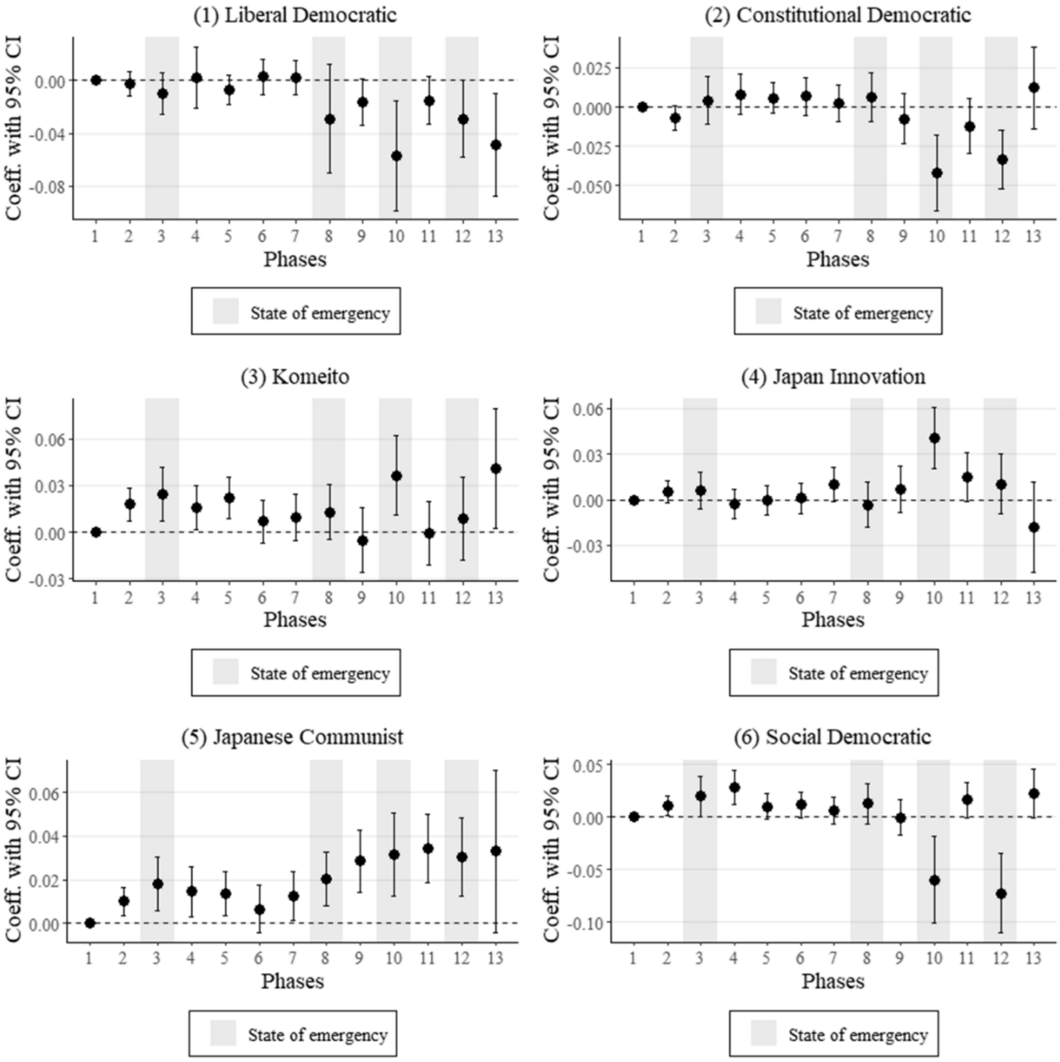


Figure 5. Differences in mobility change by political preferences

Note: Using city-by-day level data, we plot the coefficients of each phase dummy and dummy representing high approval ratings for each party from regressions that include weather variables, pre-emergency measure dummies (indicating normal vs. priority status), holiday dummies, day-of-week fixed effects, city fixed effects, date fixed effects, the cross terms between the phase dummies and variables for local characteristics, and (the natural logarithm of) the previous day's COVID-19 cases and deaths as controls. Standard errors are clustered at the city level, and bars represent 95% confidence intervals. The shaded areas indicate phases in which a state of emergency was declared. The explained variables are the percentage change in the number of people who travel outside their city of residence compared to the number who travel during normal times.

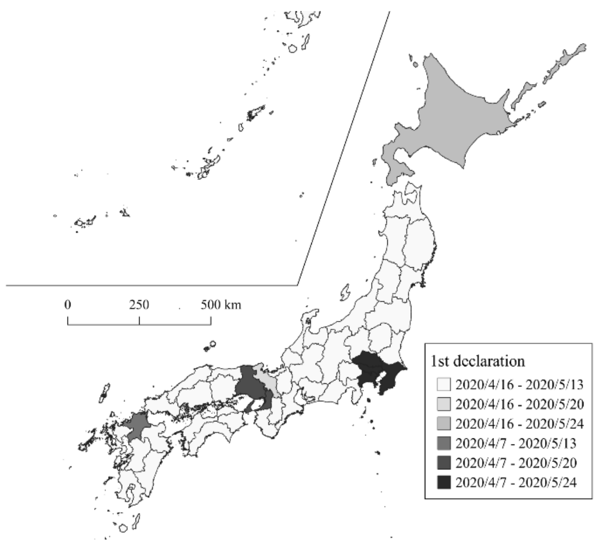
A. Additional Figures and Tables

Table A1. Summary statistics

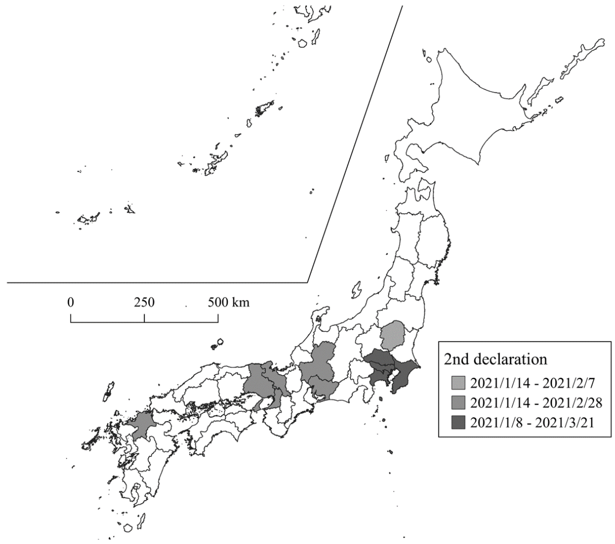
	N	Mean	Std. Dev.	Min.	Max.	Data source
Mobility index relative to 2019 value						
Leaving the city of residence	1,205,166	-0.162	0.238	-1.000	88.653	Mobile Spatial Statistics (NTT Docomo)
Daily distance traveled	1,199,667	-0.229	5.464	-1.000	4465.456	Mobile Spatial Statistics (NTT Docomo)
Visitors to commercial areas	1,205,182	-0.236	7.003	-716.979	1386.451	Mobile Spatial Statistics (NTT Docomo)
Leaving the prefecture of residence	1,205,166	-0.423	0.824	-1.000	223.133	Mobile Spatial Statistics (NTT Docomo)
People in hotspots	1,205,182	-0.108	0.534	-1.000	120.634	Mobile Spatial Statistics (NTT Docomo)
People around train stations	1,205,182	-0.142	0.630	-1.000	228.044	Mobile Spatial Statistics (NTT Docomo)
Policies other than the state of emergency						
Pre-emergency measures: normal	1,205,182	0.062	0.242	0.000	1.000	Public materials from each municipality
Pre-emergency measures: priority	1,205,182	0.019	0.138	0.000	1.000	Public materials from each municipality
Health						
Number of confirmed cases	1,205,182	1.279	6.649	0.000	465.000	Public materials from each municipality
Number of deaths caused by COVID-19	1,205,182	0.997	2.928	0.000	129.000	Public materials from each municipality
Weather						
Precipitation	1,205,182	5.190	14.971	0.000	490.000	Japan Meteorological Agency
Temperature	1,205,182	15.249	8.917	-22.900	34.000	Japan Meteorological Agency
Wind speed	1,204,985	2.376	1.456	0.000	26.100	Japan Meteorological Agency
Snowfall	1,205,182	0.168	1.631	0.000	117.000	Japan Meteorological Agency
City characteristics						
Share of people aged 65 or over	1,889	31.287	7.147	12.678	60.485	National Census 2015
Population density	1,889	1543.180	3210.951	1.600	22380.200	National Census 2015
Share of white-collar workers	1,889	0.309	0.065	0.094	0.562	National Census 2015
Unemployment rate	1,889	0.041	0.013	0.000	0.137	National Census 2015
Share of residents with a college degree or above	1,889	0.138	0.083	0.023	0.534	National Census 2010
Number of hospital beds per capita	1,889	57.423	58.815	0.000	630.562	Survey of Medical Institutions 2015
Average taxable income	1,889	2.886	0.505	2.042	9.799	Ministry of Internal Affairs and Communications
Social capital						
Composite civic capital index	1,889	0.000	1.508	-2.641	12.261	
Voter turnout in national elections	1,889	0.593	0.076	0.363	0.943	Ministry of Internal Affairs and Communications
Number of community centers per capita	1,889	3.056	5.820	0.000	98.280	Social Education Survey 2008
Number of public meeting places per capita	1,889	9.204	15.416	0.000	212.121	Social Education Survey 2008
Participation rate in volunteer fire brigade	1,889	0.023	0.026	0.000	0.310	Fire and Disaster Management Agency

Note: Since the number of visitors to a commercial area is calculated as the difference between the daytime population and the permanent nighttime population, it can take on a negative value if the daytime population is less than the nighttime population. Thus, the percentage change relative to the pre-pandemic ("normal") period can be less than -1.

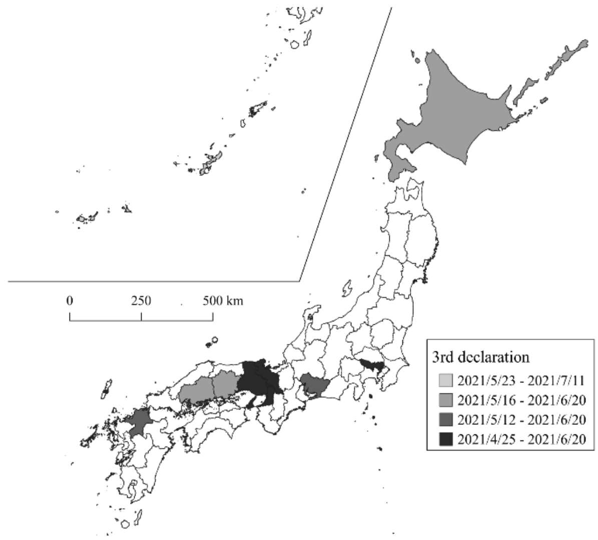
Figure A2. Timing of the state of emergency declarations



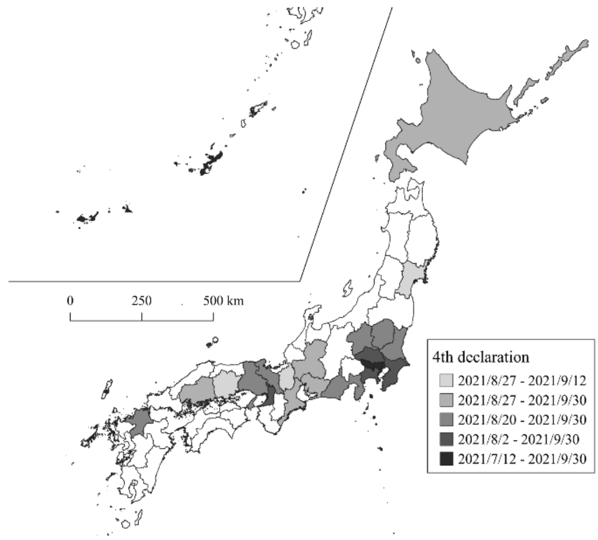
(1) First state of emergency declaration



(2) Second state of emergency declaration



(3) Third state of emergency declaration



(4) Fourth state of emergency declaration

Note: The color gradation indicates the duration of the state of emergency declaration; the darker the color, the longer the duration of the declaration. The third and fourth waves were defined according to the number of COVID-19 cases, but in Okinawa only (a remote island off the southern tip of Japan), the period covered by the third and fourth declarations was continuous (May 23, 2021, to September 30, 2021).

Table A3. Differences in mobility changes between high- and low-social capital areas (full results)

	(1)	(2)	(3)	(4)	(5)	(6)
1st interval without restrictions	-0.115***	-0.089***	-0.075**	-0.22	0.275	-0.045
	-0.003	-0.001	-0.028	-2796.9	-1221.9	-254.6
1st state of emergency declaration	-0.274***	-0.241***	-0.263***	-0.354	0.135	-0.185
	-0.005	-0.003	-0.045	-2796.9	-1221.9	-254.6
2nd interval without restrictions	-0.119***	-0.074***	0.021	-0.181	0.297	-0.023
	-0.007	-0.003	-0.043	-2796.9	-1221.9	-254.6
1st domestic travel promotion	-0.109***	-0.062***	0.015	-0.309	0.162	-0.156
	-0.008	-0.004	-0.041	-2796.9	-1221.8	-254.6
2nd domestic travel promotion	-0.057***	-0.024***	0.067	-0.162	2.4	0.597
	-0.005	-0.003	-0.036	-11776.9	-7133	-1100.8
3rd interval without restrictions	-0.098***	-0.081***	0.061	0.022	0.763	0.199
	-0.004	-0.003	-0.035	-6628.6	-2004.4	-383.7
2nd state of emergency declaration	-0.101***	-0.091***	0.009	-0.079	0.665	0.076
	-0.006	-0.004	-0.074	-6628.6	-2004.4	-383.7
Period of the 2nd state of emergency in prefectures without a declaration						0.193
						-383.7
4th interval without restrictions	-0.129***	-0.100***	0.170***	0.309	1.87	0.108
	-0.006	-0.004	-0.048	-6245.1	-3969.5	-151.2
3rd state of emergency declaration	-0.146***	-0.120***	-0.114	-0.016	1.52	-0.182
	-0.008	-0.005	-0.064	-6245.2	-3969.5	-151.2
Period of the 3rd state of emergency in prefectures without a declaration						0.214
						-151.2
5th interval without restrictions	-0.158***	-0.117***	0.152**	0.163	0.813	0.121
	-0.009	-0.005	-0.049	-8623.3	-1736.6	-151.2
4th state of emergency declaration	-0.172***	-0.133***	0.033	0.032	0.631	-0.028
	-0.009	-0.005	-0.063	-8623.3	-1736.6	-151.2
Period of the 4th state of emergency in prefectures without a declaration						0.179
						-151.2
6th interval without restrictions	-0.155***	-0.110***	-0.017	-0.003	0.674	0.028
	-0.013	-0.007	-0.097	-8623.3	-1736.6	-151.2
High social capital *						
1st interval without restrictions	0.020***	-0.025***	-0.016**	-0.015**	-0.014**	-0.014*
	-0.006	-0.003	-0.006	-0.006	-0.006	-0.006
1st state of emergency declaration	0.043***	0.001	-0.013	-0.012	-0.012	-0.012
	-0.008	-0.006	-0.01	-0.01	-0.01	-0.01
2nd interval without restrictions	0.065***	0.022***	0.029	0.026	0.026	0.026
	-0.007	-0.006	-0.018	-0.016	-0.016	-0.016
1st domestic travel promotion	0.046***	0.002	0.007	0.007	0.007	0.007
	-0.005	-0.005	-0.008	-0.008	-0.008	-0.008
2nd domestic travel promotion	0.018***	-0.025***	-0.011	-0.011	-0.011	-0.011
	-0.005	-0.005	-0.007	-0.007	-0.007	-0.007
3rd interval without restrictions	-0.007	-0.051***	-0.023**	-0.022**	-0.021**	-0.006
	-0.006	-0.005	-0.008	-0.008	-0.008	-0.009
2nd state of emergency declaration	-0.043*	-0.068***	-0.053**	-0.056***	-0.056***	-0.058***
	-0.018	-0.011	-0.018	-0.016	-0.016	-0.016
Period of the 2nd state of emergency in prefectures without a declaration						-0.029***
						-0.008
4th interval without restrictions	-0.127***	-0.171***	-0.074***	-0.072***	-0.072***	-0.092***
	-0.007	-0.007	-0.01	-0.01	-0.009	-0.011
3rd state of emergency declaration	-0.205***	-0.221***	-0.169***	-0.164***	-0.161***	-0.165***
	-0.013	-0.011	-0.018	-0.017	-0.017	-0.018
Period of the 3rd state of emergency in prefectures without a declaration						-0.048***
						-0.009
5th interval without restrictions	-0.128***	-0.168***	-0.067***	-0.062***	-0.059***	-0.089***
	-0.007	-0.008	-0.009	-0.009	-0.009	-0.01
4th state of emergency declaration	-0.170***	-0.200***	-0.140***	-0.141***	-0.141***	-0.144***
	-0.015	-0.012	-0.019	-0.019	-0.019	-0.019
Period of the 4th state of emergency in prefectures without a declaration						-0.029**
						-0.01
6th interval without restrictions	-0.113***	-0.148***	-0.057**	-0.056**	-0.061**	-0.065***
	-0.024	-0.016	-0.019	-0.019	-0.019	-0.019
Controls (health, policy, date, weather)	YES	YES	YES	YES	YES	YES
City characteristics	YES	NO	NO	NO	NO	NO
City FE	NO	YES	YES	YES	YES	YES
Day FE	NO	NO	NO	YES	YES	YES
Period * City characteristics	NO	NO	YES	YES	YES	YES
Day * Prefecture FE	NO	NO	NO	NO	YES	YES
Clustered SE	City	City	City	City	City	City
Observations	1204969	1204969	1204969	1204969	1204969	1204969
R-squared	0.18377	0.28993	0.30132	0.33553	0.33814	0.33942

Table A3.1. Changes in the number of residents traveling outside their city of residence relative to 2019 numbers

	(1)	(2)	(3)	(4)	(5)	(6)
1st interval without restrictions	-0.253***	-0.276***	-0.158	0.305	0.397	-0.08
	-0.024	-0.05	-0.114	-21225.9	-7314.2	-8510.4
1st state of emergency declaration	-0.441***	-0.452***	-0.577**	0.012	0.085	-0.391
	-0.043	-0.063	-0.183	-21225.9	-7314.2	-8510.3
2nd interval without restrictions	-0.293***	-0.328***	-0.047	0.549	0.662	0.186
	-0.015	-0.042	-0.117	-21226	-7314.2	-8510.5
1st domestic travel promotion	-0.330***	-0.262***	-0.065	-0.311	-0.229	-0.703
	-0.059	-0.058	-0.122	-21225.5	-7314.7	-8510
2nd domestic travel promotion	-0.252***	-0.253***	0.042	2.06	6.42	1.4
	-0.049	-0.072	-0.158	-77735	-80854.4	-77857.9
3rd interval without restrictions	-0.264***	-0.268***	-0.167	-0.101	0.317	-0.797
	-0.016	-0.019	-0.088	-47369.3	-15077.1	-12631.7
2nd state of emergency declaration	-0.333***	-0.352***	-0.27	-0.345	0.118	-0.904
	-0.059	-0.072	-0.276	-47369.2	-15077.3	-12631.5
Period of the 2nd state of emergency in prefectures without a declaration						-0.625
						-12631.7
4th interval without restrictions	-0.334***	-0.329***	0.002	0.584	1.14	-0.009
	-0.029	-0.049	-0.154	-37294.3	-18548.6	-4627.4
3rd state of emergency declaration	-0.552***	-0.505***	-0.071	0.503	1.05	-0.098
	-0.061	-0.067	-0.253	-37294.3	-18548.6	-4627.5
Period of the 3rd state of emergency in prefectures without a declaration						0.017
						-4627.5
5th interval without restrictions	-0.384***	-0.353***	-0.028	0.31	0.295	-0.048
	-0.027	-0.05	-0.14	-47327.7	-10163.9	-4627.4
4th state of emergency declaration	-0.460***	-0.399***	-0.211	0.167	0.112	-0.284
	-0.054	-0.058	-0.206	-47327.7	-10163.9	-4627.4
Period of the 4th state of emergency in prefectures without a declaration						-0.193
						-4627.4
6th interval without restrictions	-0.223***	-0.287***	-0.123	0.279	0.26	-0.186
	-0.043	-0.047	-0.142	-47327.8	-10163.7	-4627.5
High social capital *						
1st interval without restrictions	0.012	0.082	-0.078	-0.079	-0.078	-0.078
	-0.015	-0.067	-0.057	-0.058	-0.058	-0.058
1st state of emergency declaration	-0.038	0.034	-0.037	-0.032	-0.034	-0.034
	-0.035	-0.061	-0.06	-0.062	-0.061	-0.061
2nd interval without restrictions	0.081**	0.192**	-0.037	-0.062	-0.063	-0.063
	-0.025	-0.062	-0.061	-0.07	-0.071	-0.071
1st domestic travel promotion	0.091**	0.106	-0.08	-0.084	-0.085	-0.085
	-0.034	-0.06	-0.056	-0.058	-0.058	-0.058
2nd domestic travel promotion	0.096**	0.154	-0.113	-0.113	-0.113	-0.113
	-0.036	-0.086	-0.073	-0.074	-0.073	-0.073
3rd interval without restrictions	-0.011	0.029	-0.071*	-0.075*	-0.075*	-0.056*
	-0.023	-0.039	-0.031	-0.032	-0.032	-0.024
2nd state of emergency declaration	0.097	0.139	-0.201	-0.199*	-0.197*	-0.198*
	-0.097	-0.116	-0.105	-0.099	-0.099	-0.098
Period of the 2nd state of emergency in prefectures without a declaration						-0.111*
						-0.053
4th interval without restrictions	-0.006	0.056	-0.121	-0.122	-0.122	-0.142
	-0.022	-0.069	-0.063	-0.064	-0.065	-0.077
3rd state of emergency declaration	0.122	0.132	-0.337**	-0.330**	-0.324**	-0.322***
	-0.085	-0.116	-0.104	-0.101	-0.099	-0.097
Period of the 3rd state of emergency in prefectures without a declaration						-0.097
						-0.052
5th interval without restrictions	-0.037*	0.021	-0.122*	-0.118*	-0.118*	-0.159*
	-0.018	-0.06	-0.061	-0.06	-0.06	-0.068
4th state of emergency declaration	0.037	0.047	-0.162*	-0.158*	-0.159*	-0.159*
	-0.054	-0.075	-0.068	-0.068	-0.067	-0.066
Period of the 4th state of emergency in prefectures without a declaration						-0.067
						-0.047
6th interval without restrictions	-0.108*	0.014	-0.125*	-0.128*	-0.131*	-0.136*
	-0.052	-0.058	-0.062	-0.063	-0.066	-0.068
Controls (health, policy, date, weather)	YES	YES	YES	YES	YES	YES
City characteristics	YES	NO	NO	NO	NO	NO
City FE	NO	YES	YES	YES	YES	YES
Day FE	NO	NO	NO	YES	YES	YES
Period * City characteristics	NO	NO	YES	YES	YES	YES
Day * Prefecture FE	NO	NO	NO	NO	YES	YES
Clustered SE	City	City	City	City	City	City
Observations	1199470	1199470	1199470	1199470	1199470	1199470
R-squared	0.00234	0.02385	0.02424	0.02542	0.02584	0.02585

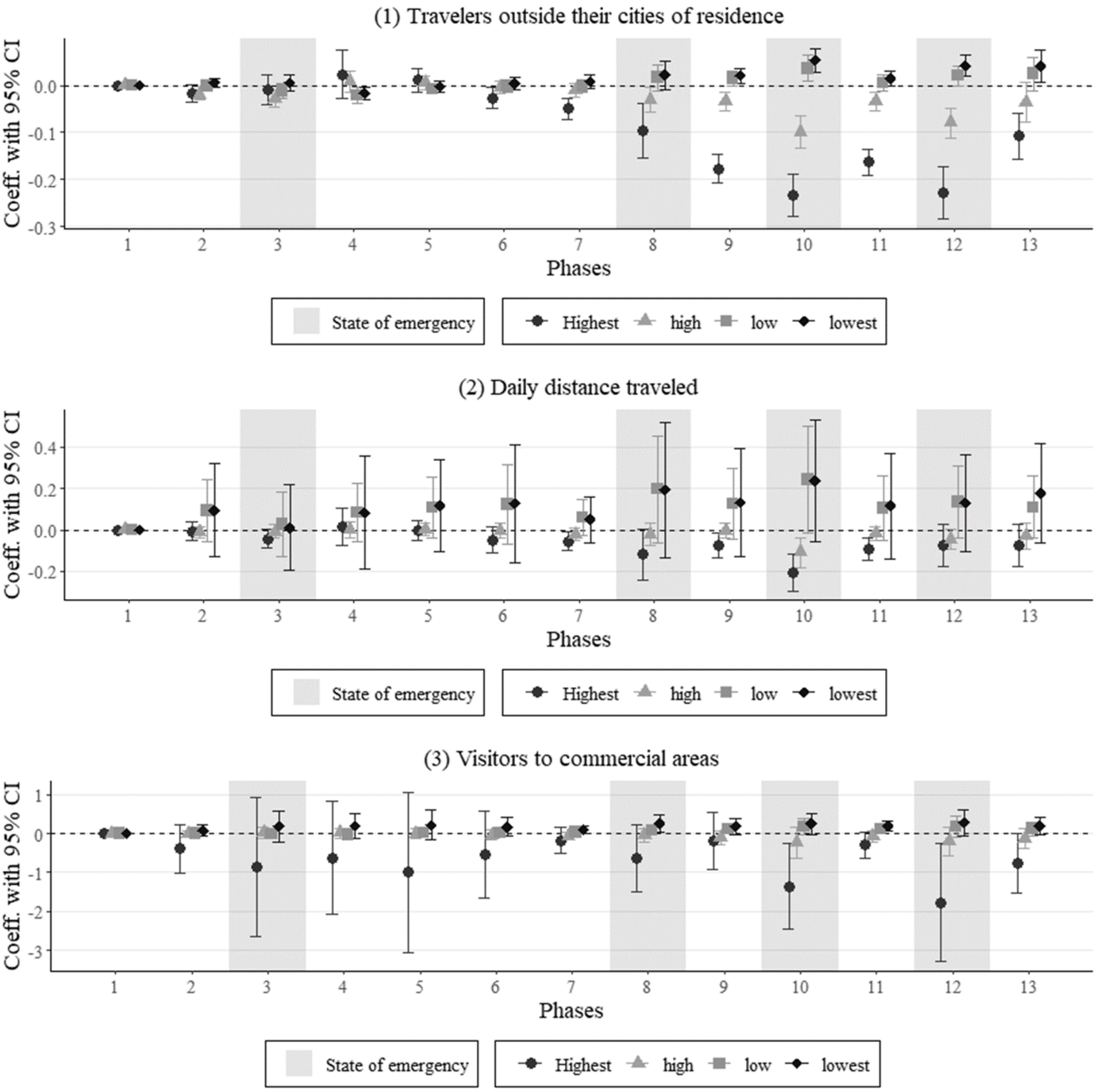
Table A3.2. Changes in daily distance traveled relative to 2019 values

	(1)	(2)	(3)	(4)	(5)	(6)
1st interval without restrictions	-0.188**	-0.160***	-1.23	2.02	0.758	2.07
	-0.06	-0.005	-1.3	-18483.7	-29060.5	-25082.9
1st state of emergency declaration	-0.438***	-0.480***	-3.99	-0.502	-1.83	-0.529
	-0.048	-0.014	-3.82	-18482	-29062.6	-25085.4
2nd interval without restrictions	-0.107	-0.172***	-3.1	0.123	-1.14	0.176
	-0.101	-0.028	-3.08	-18482.4	-29062	-25084.7
1st domestic travel promotion	-0.048	-0.158***	-4.4	-1.79	-3.04	-1.72
	-0.149	-0.036	-4.45	-18481.6	-29062.9	-25086
2nd domestic travel promotion	-0.05	-0.084***	-2.31	0.906	-9.7	-0.812
	-0.054	-0.022	-2.35	-99227.8	-148535.9	-53568
3rd interval without restrictions	-0.122***	-0.141***	-0.631	1.22	-0.911	0.333
	-0.033	-0.013	-0.435	-64925.2	-35100.9	-7778.1
2nd state of emergency declaration	-0.119*	-0.200***	-2.04	-0.196	-2.45	-1.3
	-0.052	-0.025	-1.61	-64924.1	-35101.6	-7779.1
Period of the 2nd state of emergency in prefectures without a declaration						0.334
						-7777.3
4th interval without restrictions	-0.019	-0.110**	-0.023	1.76	-2.43	0.477
	-0.104	-0.038	-1.43	-68035.9	-51297.6	-2190.2
3rd state of emergency declaration	-0.029	-0.228***	-2.35	-0.709	-4.95	-1.63
	-0.16	-0.04	-1.86	-68033.5	-51298	-2190.6
Period of the 3rd state of emergency in prefectures without a declaration						1.45
						-2190.1
5th interval without restrictions	0.051	-0.098	-0.98	0.385	-1.48	-0.964
	-0.202	-0.059	-0.827	-93631.9	-29066.8	-2190.4
4th state of emergency declaration	-0.089	-0.229***	-1.97	-0.843	-2.78	-1.45
	-0.158	-0.043	-1.79	-93630.2	-29067.9	-2190.6
Period of the 4th state of emergency in prefectures without a declaration						0.776
						-2190.4
6th interval without restrictions	0.172	-0.034	-1.1	-0.018	-2.13	-0.716
	-0.248	-0.085	-1.31	-93630.5	-29067.3	-2190.3
High social capital *						
1st interval without restrictions	-0.003	-0.107	-0.128	-0.122	-0.122	-0.122
	-0.09	-0.09	-0.102	-0.1	-0.101	-0.101
1st state of emergency declaration	-0.118	-0.178	-0.255	-0.25	-0.254	-0.256
	-0.136	-0.262	-0.286	-0.285	-0.288	-0.288
2nd interval without restrictions	-0.033	-0.135	-0.159	-0.173	-0.173	-0.173
	-0.071	-0.206	-0.231	-0.226	-0.227	-0.227
1st domestic travel promotion	-0.164	-0.269	-0.289	-0.289	-0.288	-0.288
	-0.163	-0.291	-0.301	-0.299	-0.3	-0.3
2nd domestic travel promotion	-0.059	-0.154	-0.195	-0.193	-0.192	-0.192
	-0.06	-0.163	-0.175	-0.174	-0.175	-0.175
3rd interval without restrictions	0.0006	-0.093	-0.132	-0.127	-0.124	-0.073
	-0.116	-0.058	-0.083	-0.082	-0.083	-0.075
2nd state of emergency declaration	-0.395	-0.237	-0.314	-0.304	-0.309	-0.312
	-0.207	-0.132	-0.169	-0.165	-0.167	-0.171
Period of the 2nd state of emergency in prefectures without a declaration						-0.163
						-0.095
4th interval without restrictions	-0.092	-0.207*	-0.26	-0.256	-0.253	-0.351
	-0.214	-0.1	-0.149	-0.15	-0.149	-0.207
3rd state of emergency declaration	-0.737**	-0.622**	-0.701*	-0.690*	-0.692*	-0.696*
	-0.25	-0.217	-0.3	-0.299	-0.304	-0.307
Period of the 3rd state of emergency in prefectures without a declaration						-0.125
						-0.121
5th interval without restrictions	-0.072	-0.219**	-0.256**	-0.267**	-0.263**	-0.352**
	-0.15	-0.074	-0.084	-0.087	-0.087	-0.124
4th state of emergency declaration	-0.979**	-0.785**	-0.839*	-0.827*	-0.832*	-0.839*
	-0.34	-0.258	-0.404	-0.401	-0.403	-0.408
Period of the 4th state of emergency in prefectures without a declaration						-0.188*
						-0.076
6th interval without restrictions	-0.526**	-0.388**	-0.299	-0.301	-0.275	-0.289
	-0.191	-0.123	-0.164	-0.166	-0.161	-0.17
Controls (health, policy, date, weather)	YES	YES	YES	YES	YES	YES
City characteristics	YES	NO	NO	NO	NO	NO
City FE	NO	YES	YES	YES	YES	YES
Day FE	NO	NO	NO	YES	YES	YES
Period * City characteristics	NO	NO	YES	YES	YES	YES
Day * Prefecture FE	NO	NO	NO	NO	YES	YES
Clustered SE	City	City	City	City	City	City
Observations	1204985	1204985	1204985	1204985	1204985	1204985
R-squared	0.00128	0.09776	0.09825	0.0987	0.09879	0.09886

Table A3.3. Changes in the number of visitors to commercial areas relative to 2019 numbers

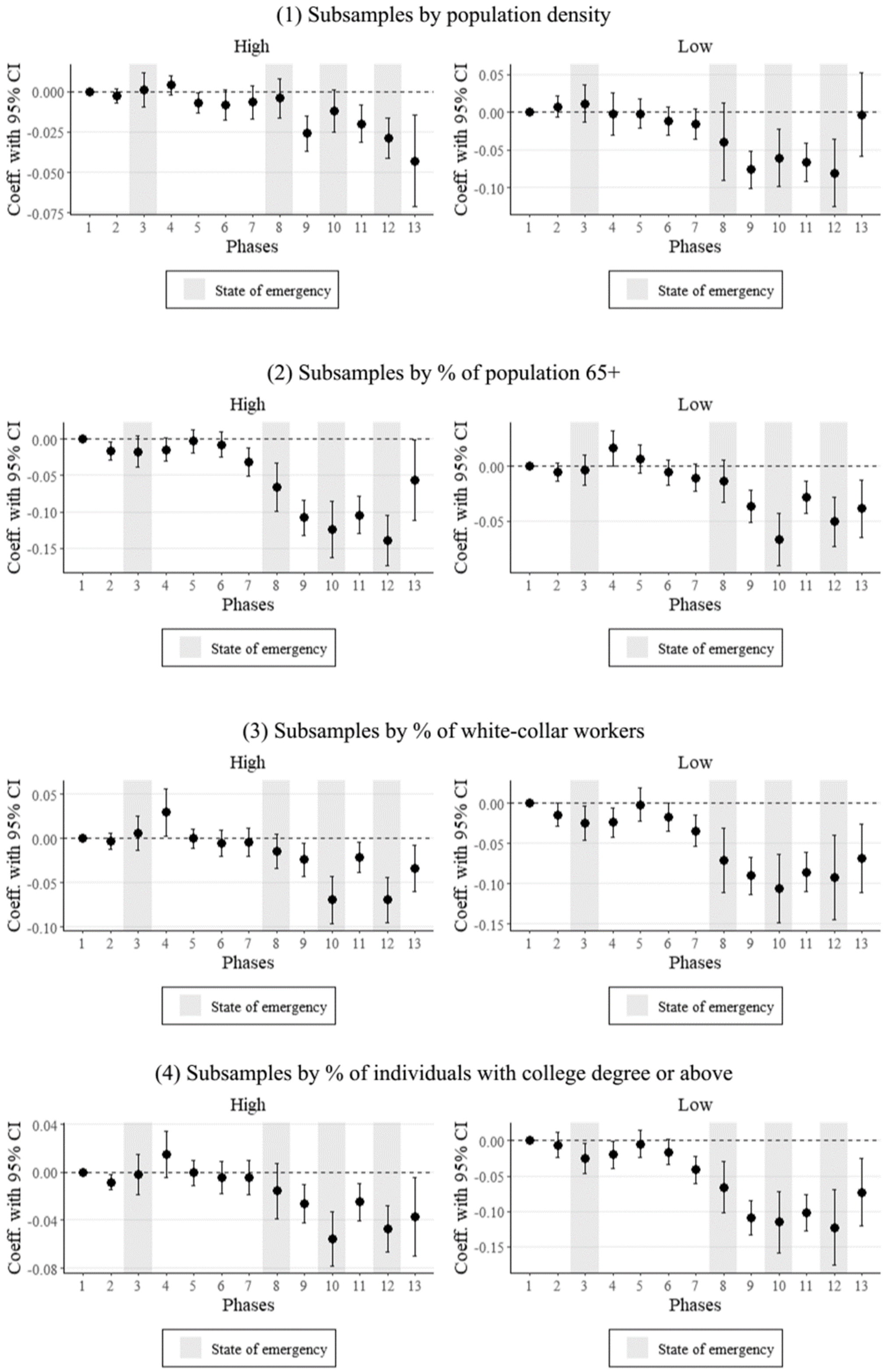
Note: Columns (5)-(6) in Tables A3.1, A3.2, and A3.3 correspond to plots (1)-(2), (3)-(4), and (5)-(6) in Figure 4, respectively. Robust standard errors clustered at the city level are in parentheses. *, **, and *** indicate statistical significance at the 5%, 1%, and 0.1% levels, respectively.

Figure A4. Nonlinear impact of social capital on changes in mobility



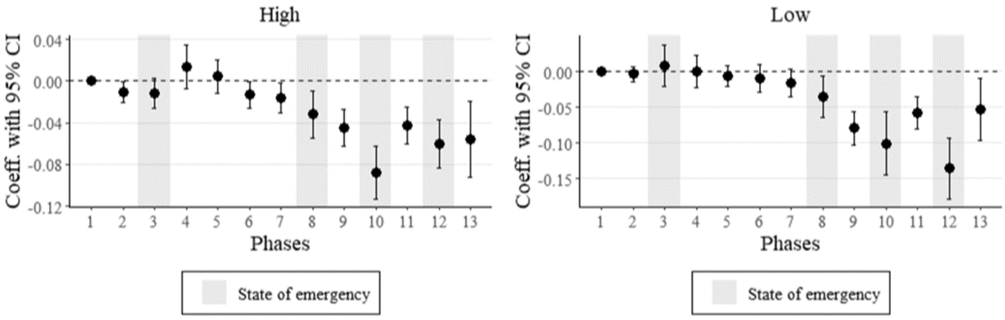
Note: Using city-by-day level data, we plot the coefficients on each phase dummy and the social capital quintile dummy obtained from regressions that include weather variables, preemergency measure dummies (indicating normal vs. priority status), holiday dummies, day-of-week fixed effects, city fixed effects, date fixed effects, cross terms between the phase dummies and local characteristic variables, and (the natural logarithm of) the previous day's COVID-19 cases and deaths as controls. Standard errors are clustered at the city level, and bars represent 95% confidence intervals. The estimates for cities in the first quintile of the social capital distribution (0%-20%) are represented by circles, those in the second quintile (20%-40%) by triangles, those in the fourth quintile (60-80%) by squares, and those in the fifth quintile (80-100%) by rhombuses. The coefficients indicate differences from the baseline of cities in the third quintile (40-60%). The shaded areas indicate phases in which a state of emergency was declared. The explained variables are (1) the number of people who leave their city of residence, (2) the distance traveled, and (3) the number of visitors to commercial areas, all measured as the percentage change relative to their values during normal times.

Figure A5. Subsamples defined by being above or below the median for each characteristic

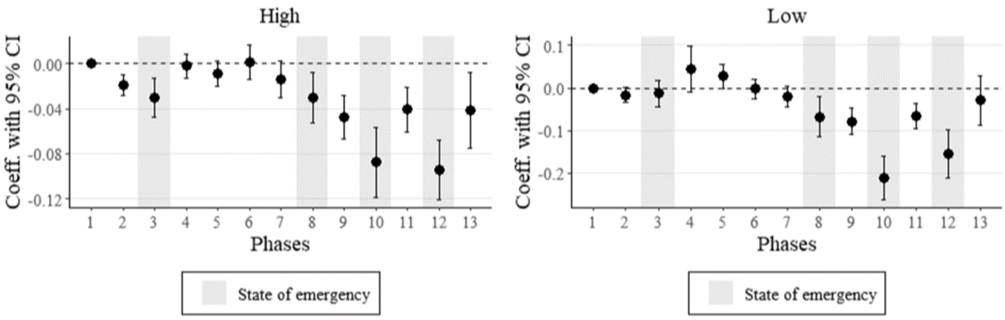


(continued)

(5) Subsamples by taxable income

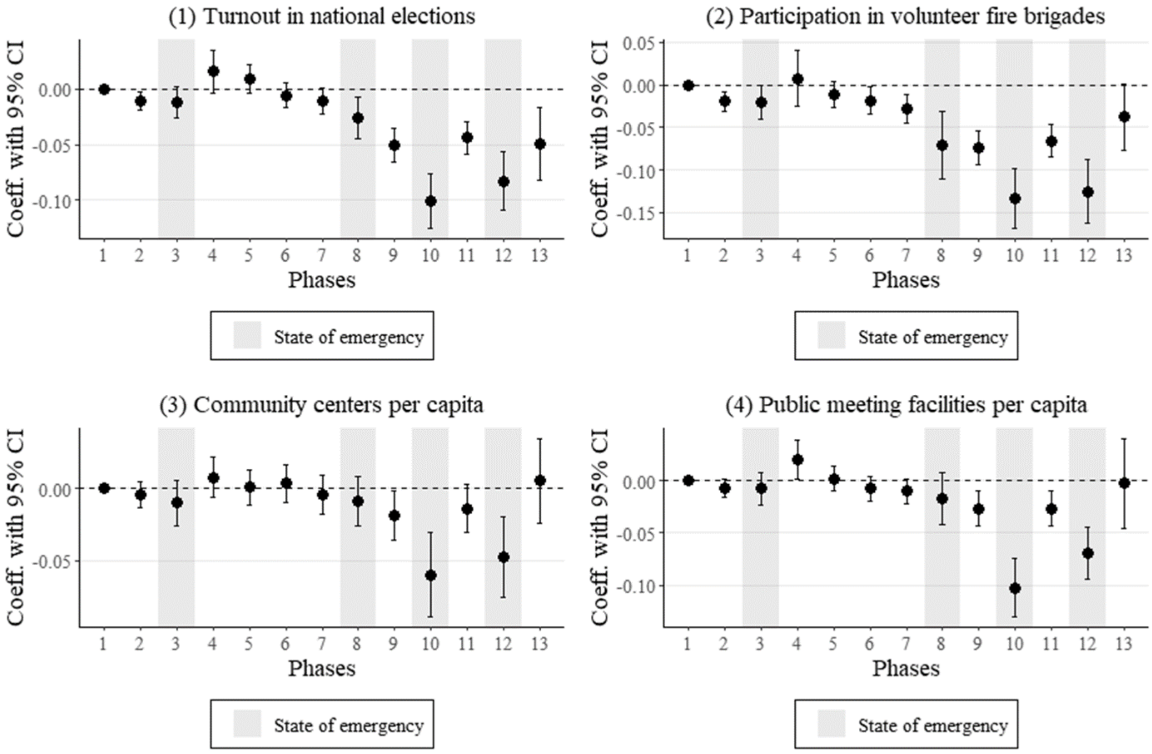


(6) Subsamples by # of hospital beds per capita



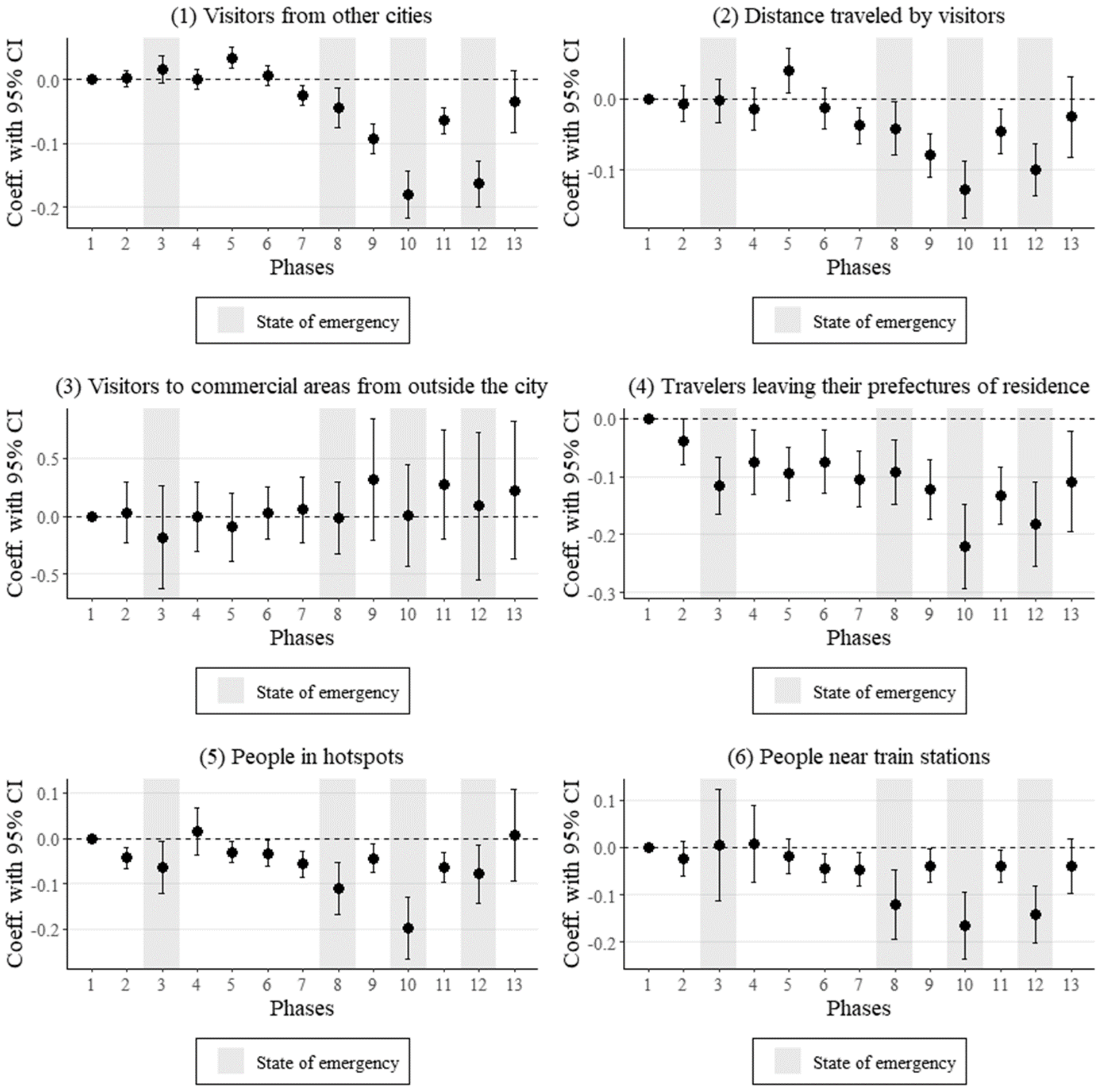
Note: Using city-by-day level data, we plot the coefficients on the cross terms of the phase dummies and the high social capital city dummy from regressions that include weather variables, preemergency measure dummies (indicating normal vs. priority status), holiday dummies, day-of-week fixed effects, city fixed effects, date fixed effects, cross terms between the phase dummies and local characteristic variables, and (the natural logarithm of) the previous day's COVID-19 cases and deaths as controls. Standard errors are clustered at the city level, and bars represent 95% confidence intervals. The shaded areas indicate phases in which a state of emergency was declared. The explained variables are the percentage change in the number of people who leave their city of residence compared to the same number during normal times. The left side plots the results of the estimation using the above-median subsample for each variable, and the right-side plots the results of the below-median subsample.

Figure A6. Results using alternative measures of social capital



Note: Using city-by-day level data, we plot the coefficients on the cross terms of the phase dummy and dummies for high social capital areas based on alternative social capital measures from regressions that include weather variables, preemergency measure dummies (indicating normal vs. priority status), holiday dummies, day-of-week fixed effects, city fixed effects, date fixed effects, cross terms between the phase dummies and local characteristic variables, and (the natural logarithm of) the previous day's COVID-19 cases and deaths as controls. Standard errors are clustered at the city level, and bars represent 95% confidence intervals. The shaded areas indicate phases in which a state of emergency was declared. The explained variables are the percentage change in the number of people who leave their city of residence relative to the same number during normal times. The proxy variables for social capital are (1) voter turnout in national elections, (2) participation in volunteer fire brigades, (3) the number of community centers per capita, and (4) the number of meeting facilities per capita.

Figure A7. Results using alternative measures of mobility



Note: Using city-by-day level data, we plot the coefficients on the cross terms of the phase dummies and the high social capital city dummy from regressions that include weather variables, preemergency measure dummies (indicating normal vs. priority status), holiday dummies, day-of-week fixed effects, city fixed effects, date fixed effects, cross terms between the phase dummies and local characteristic variables, and (the natural logarithm of) the previous day's COVID-19 cases and deaths as controls. Standard errors are clustered at the city level, and bars represent 95% confidence intervals. The shaded areas indicate phases in which a state of emergency was declared. The explained variables are the percentage change in (1) the number of people visiting from other cities, (2) the distance traveled by people visiting from other cities, (3) the number of people visiting commercial areas from other cities, (4) the number of people leaving the prefecture where they live, (5) the number of people in hot spots, and (6) the number of people near train stations relative to their values during normal times.

Table A8. Major political parties in Japan

Party	Average turnout	Share of seats in the House of Councillors (2012)	(2014)	(2017)	Ideology	Position
Liberal Democratic Party	0.336	0.613	0.613	0.611	Conservatism Japanese nationalism	Right
Democratic Party of Japan (The Democratic Party)	0.178	0.119	0.154	0.118	Liberalism Social Liberalism	Center-left
Komeito	0.136	0.065	0.074	0.062	Buddhist democracy Social conservatism	Center-right
Japan Innovation Party	0.119	0.113	0.086	0.024	Conservatism Neoliberalism Populism	Right
Japanese Communist Party	0.075	0.017	0.044	0.026	Communism Social democracy	Left
Social Democratic Party	0.025	0.004	0.004	0.004	Social democracy	Center-left

Note: Each party's share of the vote and number of seats are determined based on the results of national elections (held in 2012, 2014, and 2017) as reported by the Ministry of Internal Affairs and Communications. Descriptions of each party's ideology and standing are based on information obtained from each party's website, election-related materials, and Taniguchi and Winkler (2020).

Table A9. Differences in vaccination coverage by social capital level

	High social capital levels				Low social capital levels				t value
	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.	
Panel A: First round of vaccination									
Vaccination coverage 30 days after start date	0.019	0.007	0.008	0.040	0.011	0.005	0.004	0.022	4.240
Vaccination coverage 60 days after start date	0.160	0.024	0.112	0.208	0.133	0.026	0.097	0.186	3.635
Vaccination coverage 90 days after start date	0.366	0.024	0.317	0.420	0.331	0.027	0.261	0.410	4.038
Vaccination coverage on September 30	0.759	0.024	0.716	0.792	0.742	0.035	0.696	0.787	2.631
Vaccination coverage on September 30 (Total across all prefectures)	0.759				0.739				
Panel B: Second round of vaccination									
Vaccination coverage 30 days after start date	0.020	0.007	0.008	0.036	0.011	0.006	0.005	0.024	4.521
Vaccination coverage 60 days after start date	0.163	0.025	0.122	0.203	0.133	0.036	0.089	0.185	4.051
Vaccination coverage 90 days after start date	0.361	0.018	0.301	0.401	0.318	0.025	0.249	0.397	4.744
Vaccination coverage on September 30	0.655	0.027	0.595	0.707	0.633	0.039	0.568	0.714	2.260
Vaccination coverage on September 30 (Total across all prefectures)	0.652				0.629				

Note: This table provides information on vaccination coverage by subsample, with subsamples defined according to whether the prefecture's social capital level is above or below the median prefectural level of social capital. Panel A shows the coverage rate for the first round of vaccination, and Panel B shows the coverage rate for the second round of vaccination for each period after the vaccination start date. The bottom row in each panel represents the number of vaccinations for an entire given subgroup divided by that subgroup's population.

B. Detailed information on Mobile Spatial Statistics and the process for creating city-level data

B1. Mobile Spatial Statistics overview

Mobile Spatial Statistics are demographic data collected and published by NTT DOCOMO, Inc., Japan's largest wireless operator with over 80 million subscribers.[1 2] NTT DOCOMO, Inc. can determine the number of subscribers located in 500 square meter units (also known as mesh units) on an hourly basis (24 hours a day, 365 days a year) through the location information from subscribers' devices, which is continuously and automatically aggregated from the cellular phone operating network. Based on the number of subscribers in each region, a mesh-level estimated population is produced. There are approximately 2 million meshes throughout Japan, and of these, approximately 500,000 to 600,000 include areas with human activity, so population estimates at very fine geographical scales can be obtained.

The coverage area is the whole of Japan, and if one person stays in one mesh for 30 minutes, he or she is counted as 0.5 people in the hourly level data. Population estimates include information on gender and age or place of residence, with age reported from 15 to 79 years in 10-year increments (15-19 for teenagers) and place of residence reported at the city or prefectural level. To prevent the identification of specific individuals, data containing both gender and age and place of residence are not available. For example, if the estimated population of a given mesh at a given time is 100, we can see that there are 60 men in their 20s and 40 women in their 30s or that there are 30 people who live in Osaka city and 70 people who live in Yokohama city. However, we cannot observe the number of men in their 20s living in Osaka city in that mesh. Additionally, if there are fewer than 10 people in a certain gender and age cell in a given mesh, it is reported as a missing value (confidential processing)

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[1] For the official website (Japanese only), see https://mobaku.jp/

[2] For a complete methodological description, see https://www.docomo.ne.jp/english/corporate/technology/rd/technical_journal/bn/vol14_3/

to avoid the identification of individuals. Thus, gender and age data are available for urban areas but likely to be missing for rural areas. Our study focuses on the social capital level of places of residence, and therefore, to minimize the amount of missing data, we use only the information for place of residence.

The advantage of Mobile Spatial Statistics is the continuity of the data because it uses information from the mobile phone operating network. GPS data can provide more detailed location information, but if the device's GPS service is disabled, information cannot be retrieved, and the data are discontinuous. However, Mobile Spatial Statistics have very little missing data because all mobile phones that are turned on are included in the sample. While smartphone ownership is lower among elderly individuals, Mobile Spatial Statistics also cover traditional cell phones, so the elderly population can also be estimated with a high degree of accuracy. The information, including the individual's place of residence, is highly credible because it is based on subscriber information. Because the data are so representative and reliable, they are frequently used in Japan for policy-making and research, notably for measuring people's mobility during the COVID-19 pandemic.

B2. Generating mobility measures from Mobile Spatial Statistics

Raw data for Mobile Spatial Statistics are generated hourly in four files (population by gender and age, by city of residence, by prefecture of residence, and fully aggregated), with each file containing mesh-level information for all of Japan. We use the fully aggregated population data to create the mesh definitions and use the population by city of residence data to create the primary dataset used in the analysis. Each file contains information on the date, time, mesh ID, residential city code (for the city of residence data), and estimated population, giving us the mesh-level (by city of residence) population. To construct the city-level dataset used in our analysis from these raw data, we proceed as follows.

B2.1. Creating mesh definitions

Using 2019 data, we define commercial area meshes (meshes with high day/night population ratios) and hotspot meshes (meshes that attract people from a wide area).

Commercial areas

(a) The fully aggregated population data are used. For a given day for each mesh, the average nighttime and daytime populations are calculated for the 4 hours from 00:00 to 04:00 and the 8 hours from 09:00 to 17:00, respectively, to create daily mesh-level cross-sectional data.

(b) All data created by repeating step (a) for all 365 days in 2019 are merged to create the mesh-by-day-level panel data.

(c) From the data created in (b), we calculate the average daytime and nighttime populations for each mesh in 2019 to create mesh-level cross-section data.

(d) Based on the data generated in (c), we define a mesh as a commercial area if that mesh's 2019 average day/night population ratio is greater than 1.5 and its nighttime population is greater than 0.1 (because the day/night population ratio is overestimated for uninhabited meshes).

Hotspots

(a) In preparation, a correspondence table between meshes and cities is created using GIS software. If a mesh contains more than one city, the mesh is defined as belonging to the city that covers the largest share.

(b) The data on population by city of residence are used. For a given hour on a given day, the cities are connected with meshes based on the correspondence table created in (a).

(c) From the data created in (b), mesh-level cross-sectional data are created for a given hour by calculating the following for each mesh: (1) the percentage of people coming from other cities (i.e., those whose city of residence does not match the city they are currently in) and (2) the unique number of cities of residence for people currently in that mesh.

(d) We repeat step (c) 8 times for 09:00 to 17:00 to produce daily averages for (1) and (2), respectively. The step is repeated for all 365 days in 2019, merging all the created data to produce the mesh-by-day-level panel data.

(e) From the data produced in (d), the 2019 averages for (1) and (2) are calculated for each mesh to produce mesh-level cross-section data.

(f) Based on the data generated in (e), a mesh is defined as a hotspot if (1) is greater than 0.2 and (2) is greater than 2.

B2.2. Creating city-level mobility data

The population data by place of residence for 2019 to September 2021 are used to create the daily and city-level mobility variables. We use the mesh definitions described in B2.1 as appropriate.

(a) In preparation, a correspondence table between the meshes and the cities is created using GIS software. If a mesh contains more than one city, the area for each city is prorated by the ratio of the areas. This allows the mesh-level population to be converted to the city level. A distance matrix for distances between the centers of gravity for each city is also created using GIS software. Based on the station data published by the Ministry of Land, Infrastructure, Transport, and Tourism, a buffer of 150 meters around train stations is also created, and the share of the area in each mesh that is near a station is calculated.

(b) For a given time on a given day, the cities are linked to the meshes with the correspondence table created in (a), and the populations are prorated by the ratio of areas. The following process is then used to create each city-level variable for a given hour. In (1) through (3), by setting the aggregation criterion to the city where one is currently located rather than the city of residence, variables that measure incoming visitors rather than outgoing residents can be created.

(1). The percentage of individuals leaving their city of residence is created based on whether the city of residence and the current city are the same.

(2). The distance matrix created in (a) is used to calculate the distance between the city of residence and the current city, and the average distance traveled is computed.

(3). Using the definition of commercial areas for each mesh created in B2.1, only the number of people in commercial areas are counted.

(4). The percentage of individuals leaving their prefecture of residence is calculated based on whether the prefecture of residence and the current prefecture are the same.

(5). Using the station coverage rates for each mesh created in (a), the number of people in the station area is calculated by prorating the population based on the share of the area included in the station area.

(6). Using the definition of hotspots for each mesh created in B2.1, only the number of people in hotspots are counted.

(c) Process (b) is repeated for each hour from 09:00 to 17:00 to produce daily averages for (1) through (6). The process is repeated for 2019 through September 2021, and all data created are merged to produce daily and city-level panel data. For commercial areas, nighttime (00:00-04:00) data are also created.

(d) For the number of people in commercial areas at night, calculated in (c), the average for 2019 is calculated, which gives the number of people originally living in commercial areas. The number of people originally living in the commercial areas is subtracted from the number of people in the commercial area during the day, which is used to define the number of people visiting commercial areas during the daytime and is used in place of the total number of people in commercial areas.

(e) For each variable created in (c) (or in the case of commercial areas, the variable created in (d)), averages for each weekday and holiday in 2019 are calculated to provide a measure of mobility during normal times.

(f) The data from 2020 to September 2021 are merged with the data from 2019 ("normal times") created in (e), and the mobility measures divided by the average mobility measures during normal times – 1 are calculated. These measures of the change in mobility relative to that in normal times are used in the analysis.