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Dynamic Relationship between Information Dissemination by Local Governors and Mobility during the COVID-19 Pandemic

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Dynamic Relationship between Information Dissemination by Local Governors and Mobility during the COVID-19 Pandemic [*1]

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Abstract

The COVID-19 pandemic has prompted countries to implement a variety of containment measures, including non-pharmaceutical interventions such as stay-at-home orders. Japan has avoided legally enforcing strict measures such as complete or partial lockdowns, instead relying on voluntary restraint from going out during the state of emergency.

We evaluate the impact of information dissemination on people's mobility. First, we apply the latest findings in natural language processing research to precisely measure the information dissemination effect for each prefecture in Japan. Second, we analyse the dynamic relationship between information dissemination and mobility in each prefecture in Japan using econometric methods. Third, we divide the sample into an early and a later period when the Delta variant emerged in order to analyse the time-varying dynamics of the information effect.

Our investigation yields two major findings: First, the stay-at-home information dissemination significantly suppressed people's mobility. Second, we found a remarkable change in the magnitude of the information effect over time. The information effect weakens after the dominance of the Delta variant compared with the early stage of the pandemic.

Keywords: COVID-19, impulse response analysis, mobility control policy, sentiment analysis, BERT
JEL Classification: C23, C55, C61, H12, I18

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I. Introduction

The COVID-19 pandemic has prompted countries to implement a variety of containment measures, of which non-pharmaceutical interventions (NPIs), such as stay-at-home orders, have proven to be an effective tool. While China, the United States, and European countries have legally enforced strict measures such as complete or partial lockdowns, Japan has avoided such a strategy, instead relying on voluntary restraint from going out during the state of emergency. This study analyses the effectiveness of policies sans legal enforcement, as in the case of Japan. Of especial importance to us are Watanabe and Yabu's (2020, 2021)[1)] studies, which examine the mechanisms through which such policies induce behavioural changes in people. Watanabe and Yabu (2020, 2021) use mobility data as an indicator of the extent of people's stay-at-home behaviour and decompose the changes in these data into two channels: an intervention effect and an information effect. The former refers to changes in behaviour arising from government orders or requests, while the latter refers to voluntary changes in people's behaviour that arise when people update their risk perceptions based on information about the pandemic, such as government announcements and the number of new infections. Watanabe and Yabu (2020, p.1) find that the information effect is more significant than the intervention effect; that is, 'what is necessary to contain the spread of COVID-19 is not strong, legally binding measures but the provision of appropriate information that encourages people to change their behaviour'.

Our primary contribution to the exhaustive and growing corpus of literature on the effectiveness of COVID-19 policymaking is that we re-examine the information effects analysed by Watanabe and Yabu (2020, 2021), but this time, we account for the dynamic relationship between information dissemination by local governors and mobility in 18 prefectures that had relatively high numbers of infections in Japan during the pandemic.

First, we develop a more refined measure of government information dissemination. While Watanabe and Yabu (2020, 2021) measure information dissemination by using dummy variables for the issuance and lifting of specific policies (e.g. declaration of a state of emergency), we apply sentiment analysis, a natural language processing (NLP) technique. While the presence or absence of specific policies is one element that represents the "information" disseminated by a government, the government disseminates information in various forms on a daily basis. Watanabe and Yabu (2020, 2021) may have missed a significant portion of this information.

Sentiment analysis, our preferred technique, transforms text into quantitative data[2)]. It allows us to measure information not only in terms of specific policies but also on a daily basis, including daily alerts on the threat of a pandemic. We use bidirectional encoder representations from transformers (BERT[3)]), a deep learning-based sentiment analysis approach, to conduct sentiment analysis on text data from press conferences in order to precisely measure government information dissemination. BERT-based sentiment analysis is increasingly being used in economics literature for nowcasting economic trends, as exemplified by Seki et al.'s (2022) S-APIR Index. However, very few scholars use this approach to evaluate policy effects. By exploring the dynamic relationship between information dissemination and mobility in each prefecture in Japan using econometric methods, we evaluate the impact of government information dissemination on people's mobility.

Second, we also employ the local projection (LP) method in line with Inoue and Okimoto (2023), who also analyse the dynamic relationship between changes in mobility and the spread of COVID-19. The LP method helps us estimate the duration of the information effect after the information is disseminated, that is, as an impulse response function. Other factors and their impacts that concern our investigation include the information effect of factors other than government announcements (e.g. information on the infection status, including daily number

1) A similar study based on Watanabe and Yabu (2020) was conducted by the Cabinet Office, Government of Japan (2021).

2) Grimmer and Stewart (2013)

3) BERT is explained in detail in Section II.

of infected people and vaccination rate), intervention effect of the state of emergency declaration, and others (e.g. climatic factors).

Third, we analyse the time-varying dynamics of the information effect. We divide the sample period into the early stage of the pandemic and the later stage after the Delta variant outbreak in July 2021[4], primarily to determine whether the magnitude of the information effect differs between these two periods. We already know that the magnitude of an intervention effect changes over time[5], as evidenced by Watanabe and Yabu (2021), albeit in the context of the early stage of the pandemic. To the best of our knowledge, very few studies examine the time-varying effects of information during the later stages of the pandemic when vaccination was widespread and rapidly mutating strains, such as the Delta and Omicron variants, emerged. In summary, our analysis sheds light on the time-varying dynamics of the information effect over a longer period than most literature tackles.

Our investigation yields two major findings: First, the stay-at-home information dissemination significantly suppressed people's mobility. Second, we found a remarkable change in the magnitude of the information effect over time. The information effect weakens after the dominance of the Delta variant compared with the early stage of the pandemic.

The remaining article is organized as follows: In section II, we construct a model that quantifies the extent to which local governors aim to suppress mobility in their information dissemination. In section III, we analyse the dynamic relationship between information dissemination and mobility. In section IV, we examine the time-varying dynamics of the relationship between information dissemination and mobility. Section V concludes.

II. Measuring information dissemination

II.1. Model

We apply sentiment analysis, an NLP technique, to constructs a model that quantifies the extent to which local governors aim to suppress mobility in their information dissemination.

Al-Qablan et al. (2023) classify sentiment analysis techniques into three categories: lexicon-based, machine learning (ML) based, and deep learning (DL) based. Lexicon-based approaches utilize predefined sentiment dictionaries or rules to assign sentiment scores. This method has advantages such as simplicity and speed, but it is usually designed for specific domains. In this article, we require a COVID-19-specific Japanese dictionary, which has not yet been established in the literature. Using a dictionary unrelated to COVID-19 may have trouble with terms such as 'Three Cs' (known as 'sanmitsu' in Japanese), making it difficult to accurately measure sentiment.

The majority of ML-based approaches provide high accuracy by learning from labelled data. DL-based approaches have the potential to automatically learn complex patterns, capture contextual information, and demonstrate impressive performance. In this study, we utilize BERT, a DL-based model developed by Devlin et al. (2018). BERT has been applied in economics in various ways. For instance, Alaparthi and Mishra (2021) analysed movie review data from IMDb, while Seki et al. (2022) constructed the S-APIR Index. Alaparthi and Mishra (2021) compared BERT with lexicon-based and ML-based approaches and found that BERT outperformed the others. Based on these characteristics, we selected BERT for its strong performance in sentiment analysis, as demonstrated in the study by Al-Qablan et al. (2023), and its suitability for index creation, as proven in the study by Seki et al. (2022). We utilized the Japanese BERT tokenizer released by the NLP Group

4) National Institute of Infectious Diseases (2022) defines July 3 - August 15, 2021 as the Delta strain epidemic period.

5) Yeyati, and Sartorio (2020), Goldstein et al. (2021)

at Tohoku University[6] for our implementation. To assess the model's performance, we divided the data into three sets: 70% for training, 15% for validation, and 15% for testing. Stratified sampling is employed to maintain the same distribution of class labels in the divided data as in the original data.

II.2. Data

This study utilizes two sets of data: textual data on information dissemination regarding COVID-19 and indices of the stringency of the COVID-19 response measures. The textual data consists of daily announcements made by the Prime Minister and relevant ministers in Japan. The data on the information disseminated by the Prime Minister are obtained from the Prime Minister's Office website.

The data on information disseminated by ministers are collected from two sources on the website of the Japanese government. The first source is the Ministry of Health, Labour and Welfare (MHLW) website, which contains information disseminated by the former Minister before March 17, 2020. The second source is the website of the Cabinet Agency for Infectious Disease Crisis Management, which contains information disseminated by the minister in charge of the COVID-19 response. To assess the government's proactive information dissemination, we collect data based solely on the opening statements of press conferences, excluding question-and-answer sessions. For the purpose of this study, which aims to create an index of information dissemination at the prefectural level, the text classification model uses data on the dissemination of information by the central government, while data from local governments are only used when calculating the index based on the constructed model.

Regarding the second type of data, we utilize the COVID: Stringency Index[7] to label the textual data. A higher index value indicates a stricter government policy against COVID-19, while a lower value indicates a looser policy. The index is transformed into daily differenced data and labelled as follows: 'Strict' should be used if the difference is greater than 0, 'neutral' if the difference is 0, and 'lenient' if the difference is less than 0. It should be noted that policy changes may not occur on the same day as information dissemination. Thus, we align the dissemination of information with the policy change that triggered the index update. Mathieu et al. (2020) provide notes that form the basis for changes in the index. On this basis, the text data should be labelled as 'strict' when they provide information on policies that contributed to strict index changes, 'lenient' when they provide information on policies that contributed to lenient index changes, and 'neutral' in all other cases. To analyse the impact of information dissemination on human mobility, this study focuses on Japanese citizens, who are the primary recipients of this information. Therefore, we exclude any index changes based on border control measures and related text data from our analysis. Our model construction utilizes only the information provided by the central government. We exclude information related to local government measures as the index also takes them into account. Additionally, it is possible that the index may have missed some policy changes. If a policy change involves the issuance or expansion of a state of emergency (SOE) or quasi-state of emergency (QSOE), the labels will be adjusted to 'strict'. If a policy change involves lifting the SOE or QSOE, or reducing the target regions, the labels will be partially corrected to 'lenient'.

II.3. Prediction accuracy of the text classification model

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[6] Tohoku NLP Group. “cl-tohoku/bert-japanese: BERT models for Japanese text”. Retrieved from: ‘https://github.com/cl-tohoku/bert-Japanese’. (Accessed: November 17, 2023)

[7] Mathieu et al. (2020)

Table 1 presents the classification performance metrics for the developed model. The evaluation metrics comprise precision, recall, and F1 score. We focus on the F1 score, which provides a balance between precision and recall, and is an amalgamation of these two measures. Specifically, we focus on the macro F1 score, which is the average of the F1 scores calculated for each class. The data used in this study is unbalanced, with the neutral class having the most data and the remaining two classes having less data. To avoid overestimating the accuracy of the class with the most samples, a simple average is more suitable than a weighted average.

Table 1: Prediction accuracy of the text classification model

	Precision	**Recall**	**F1 score**
macro avg.	0.98	0.87	**0.92**
weighted avg.	0.95	0.95	0.95

As shown in Table 1, the macro F1 score of the model is measured at 0.92, indicating a high accuracy. This result is consistent with the results reported by Alaparthi and Mishra (2021), who constructed a text classification model for IMDb review data.

II.4. Calculation of information dissemination index based on the constructed model

The following describes the process of creating the local governor's information dissemination index ('local governor's index') using the constructed model. The 18 prefectures with the highest cumulative number of new cases at the end of the analysis period, October 13, 2022, were targeted, excluding two prefectures. As this study focuses on changes in mobility during the COVID-19 pandemic, the sample is limited by the number of cases, and it is assumed that regions with a high number of cases have more active NPIs. Regarding the two excluded prefectures, regular press conferences are published in text format on their websites, while press conferences related to COVID-19 are only published in video format. For the purpose of this study, which aims to analyse the dynamic changes in information dissemination and human mobility during the COVID-19 pandemic, it is deemed appropriate to exclude the data from these two prefectures. The textual data are obtained from the websites of the 18 prefectures[8] mentioned above.

To measure local governor's index, we define the index as:

$$lg\_info = P(strict) \cdot 1 + P(neutral) \cdot 0 + P(lenient) \cdot (-1) \qquad (1)$$

where $P(strict)$ denotes the probability that the given text encourages staying at home, $P(lenient)$ denotes the probability that the text encourages going out, and $P(neutral)$ denotes the probability that the text is neither strict nor lenient.

Note that the maximum token length is set to 512 when the model is created. To construct a model with high accuracy, it is sufficient to read the beginning and end of the document, as the main message is often concentrated in these sections[9]. For documents longer than 512 tokens, the local governor's index for each prefecture in this study is calculated using the average value estimated by the first 512 tokens and the value estimated by the last 512 tokens.

[8] These are Aichi, Chiba, Fukuoka, Gifu, Hiroshima, Hokkaido, Ibaraki, Kanagawa, Kumamoto, Kyoto, Mie, Miyagi, Okayama, Okinawa, Osaka, Saitama, Shizuoka, and Tokyo.
[9] Sun et al. (2019)

III. Dynamic relationship between information dissemination and mobility

III.1. Model

We apply the LP method[10)], following Inoue and Okimoto (2023), to investigate the responses of the level of change in the mobility h periods ahead to a change in causal variables at time t. The R package 'lpirfs', developed by Adämmer (2019), is used for implementation. The following assumptions are made for each of the variables.

We assume that the level of mobility factor from t to $t+h-1$ collectively consists of multiple factors identified in previous studies. Specifically, information effect, including the local governor's index, intervention effects, represented by the SOE declaration, and other factors such as weather and autocorrelation are considered. For the measure of mobility $m_{i,t}^{a}$, we use the Google COVID-19 Community Mobility Reports[11)] index as the dependent variable.

To measure the information effect at time t, we use the local governor's index constructed in section II. The data is aggregated into weekly totals in each prefecture.

The COVID-19 infection status is also included as a variable related to the information effect. The perception of infection risk among individuals may change based on the information they receive about the spread or containment of the infection, and their behaviour may adapt accordingly. This study focuses on the daily number of new cases and deaths and the vaccination rate. As the number of cases and deaths increases, people may be more likely to stay at home as they perceive a higher risk of infection. We denote the total number of daily cases or deaths per 1 million in the population at time t in prefecture i by x_{it}. Following Watanabe and Yabu (2020, 2021), we transform x_{it} using the inverse hyperbolic sine transformation. Specifically, we define $X_{it} = ln(x_{it} + \sqrt{x_{it} + 1})$. On the other hand, a higher vaccination rate is associated with a lower perceived risk of infection, which may lead to an increase in mobility.

It is important to note that the variables of the daily numbers of new cases and deaths are considered with a time lag, as it is assumed that people need time to recognize the number of cases and deaths and adjust their behaviour accordingly. Additionally, there is a delay in behavioural changes following vaccination, and recovery at home may be necessary due to side effects. Moreover, the relationship between the infection status and mobility variables is interdependent, and the potential issue of endogeneity is acknowledged. The objective of this study is to examine the dynamic relationship between various variables and mobility, rather than to draw strict causal inferences. However, the use of time lags can help to mitigate the problem of endogeneity to some extent.

To assess the impact of the intervention, we also construct a variable that counts the number of days that the declaration of a SOE was implemented in week t. Additionally, we include a variable for the number of days of a QSOE, which was introduced from April 2021 as an equivalent measure. Our analysis differs from that of Watanabe and Yabu (2020, 2021) in that we use weekly data instead of daily data.

As for the weather, in addition to the precipitation data used by Watanabe and Yabu (2020, 2021), we also incorporate maximum temperature data as a weather factor that affects the change in people's mobility used by Inoue and Okimoto (2023). However, while Inoue and Okimoto (2023) used temperature to capture the possibility that extreme temperature may lower immunity and make ventilation difficult due to room temperature control problems, we examine the relationship between the number of hot summer days and ice days per week

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[10)] Jordà (2005)

[11)] Google LLC. "Google COVID-19 Community Mobility Reports". Retrieved from: 'https://www.google.com/covid19/mobility/'. (Accessed: October 17, 2023) and mobility considering the possibility that extreme temperature may discourage people from going out, regardless of COVID-19 prevalence.

Furthermore, as the Google COVID-19 Community Mobility Reports indices used in this study are time series data, we consider the autocorrelation and use the mobility data of the previous period. The regression model that integrates the above is written as:

$$m_{i,t+h}^{a} - m_{i,t}^{a} = \beta^{ah} lg\_info_{it} + \sum_{\tau=1}^{P} \gamma^{ah\tau} X_{i,t-\tau} + \delta^{ah} Z_{it} + \varepsilon_{t}^{ah} + \varepsilon_{i}^{ah} + \epsilon_{it}^{ah} \quad (2)$$

where β, γ and δ are the regression coefficients. Variable $m_{i,t}^{a}$ denotes the mobility observed in the category of place a of prefecture i during week t.

Variable lg_info_{it} denotes the level of information dissemination by local governors, which is the main explanatory variable in this study. The control variables are represented by $X_{i,t-\tau}$ and Z_{it}. Among the control variables, $X_{i,t-\tau}$ is the lagged[12)] control variable and comprises three variables: the number of cases, the number of deaths, and vaccination rate; Z_{it} is the control variable that does not consider lags, which are variables other than $X_{i,t-\tau}$.

ε_{t}^{ah} is a time-fixed effect representing factors such as the nationwide changes in mobility due to the changes in the perception of the risk of infection or serious illness due to the appearance of mutant strains, the implementation or changes in policies, and the number of national holidays at different times of the year that are not explicitly considered in Eq. (2). ε_{i}^{ah} is a prefecture fixed effect representing the specificity and heterogeneity of each prefecture, including demographics, lifestyle (e.g. commuting modes, presence of downtown areas), external human mobility, average household size, and others. Lastly, ϵ_{it}^{ah} is an error term.

Note that the left side of Eq. (2) is the amount of change in mobility from t to $t+h$. In LP, the values of the regression coefficients vary across the forecast horizon h, necessitating the addition of h as a superscript to distinguish them.

III.2. Data

This study uses weekly panel data for 18 prefectures in Japan from April 17, 2020 to October 13, 2022. The data used in this analysis are described below.

The Google COVID-19 Community Mobility Reports indices are utilized to measure prefecture-level mobility on a daily basis. This index classifies the mobility of the categories of places into six categories: retail and recreation, grocery and pharmacy, parks, transit stations, workplaces, and residential. The index was created using the early stage of the COVID-19 pandemic (from January 3 to February 6, 2020) as the base period. The indices are calculated based on the percentage increase or decrease from the median of the corresponding day of the week during this period. In this study, we represent the weekly mobility level by averaging the daily values per week.

The analysis focuses on data up until October 15, 2022, the latest Thursday in the data release period for weekly aggregation. Figure 1 illustrates mobility trends by prefecture and category. Following Watanabe and Yabu (2020), we use level data instead of differenced data. Three types of unit root tests[13)] were conducted, each of which rejected the null hypothesis of non-stationarity.

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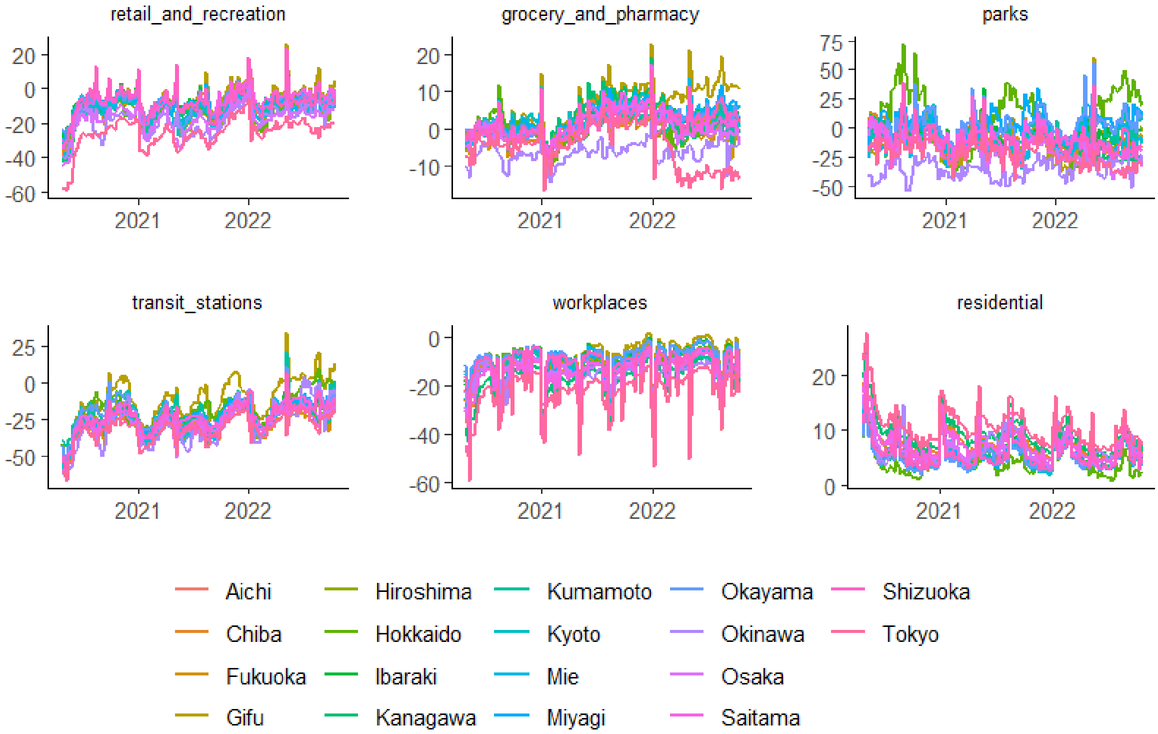
12) We treat the lag order of the variables as $P = 1$. To assess robustness, we also estimate the models with the case where the maximum lag order $P = 2,3$, and obtain qualitatively similar outcomes.

13) Levin et al. (2002), Im et al. (2003), and Maddala and Wu (1999)

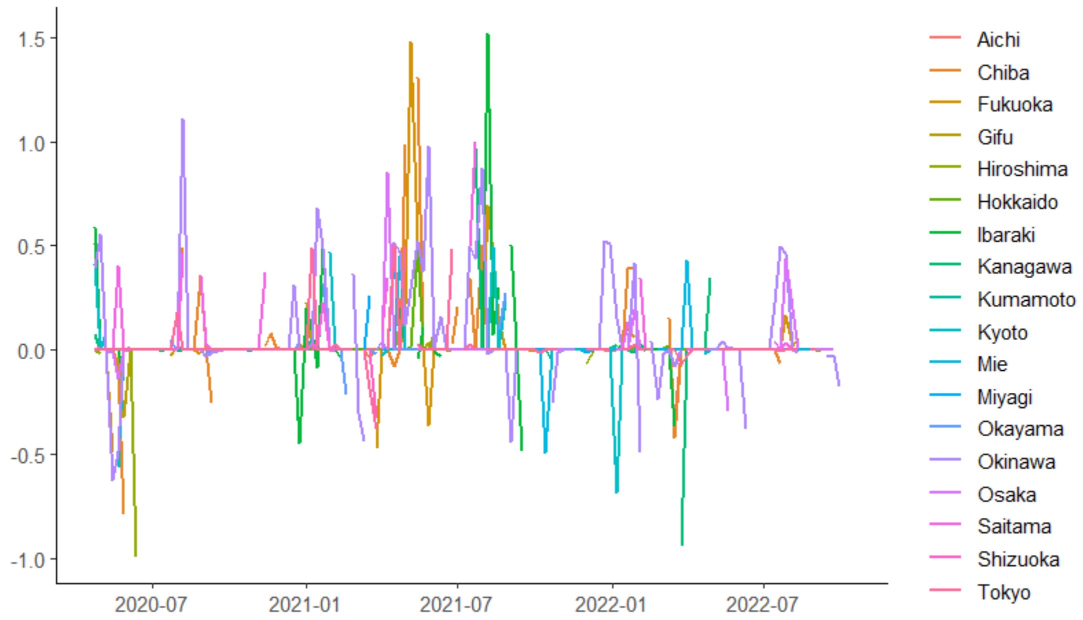
Figure 1: Trends in mobility by prefecture and category



This analysis focuses on the local governor's index, which is constructed in section II. The model construction method and the data used are detailed in the same section. We use the weekly aggregated data from this index, as explained in section III. If there were no press conferences during the week, we treat the data as an NA[14). Figure 2 shows the trends of the local governor's index for each prefecture.

14) To assess robustness, we also estimate the models with the index of NAs filled with 0, and obtain qualitatively similar outcomes.

Figure 2: Trends in local governor's index by prefecture

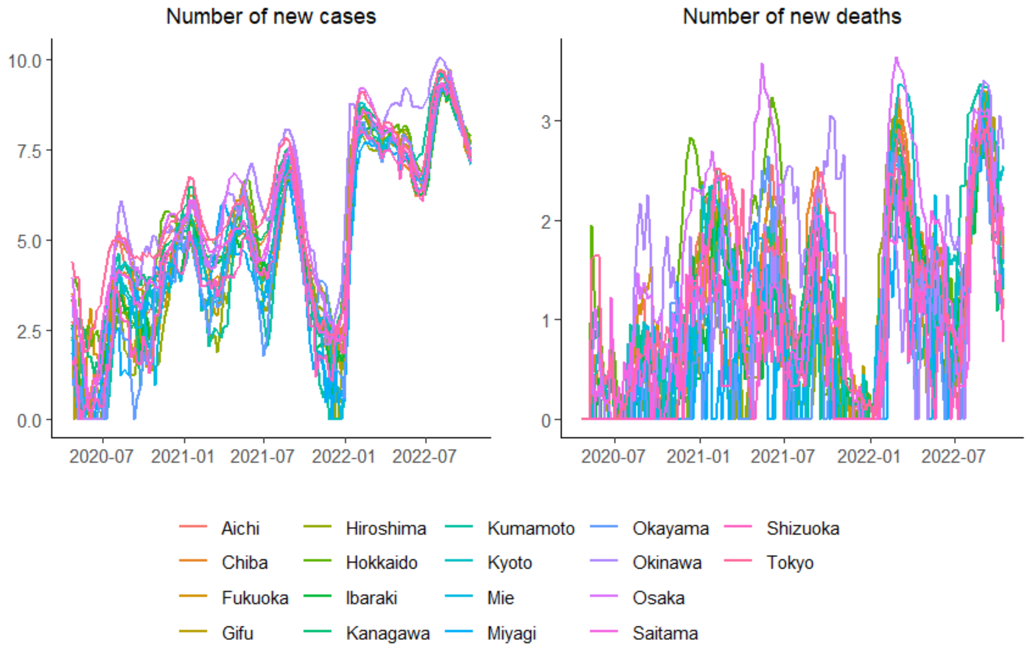


Data is collected from the 'Data Shows – COVID-19 Information' section of the MHLW website. Regarding the daily number of new cases, the 'Trend of New Positive Cases (Daily)' data is used, while for the number of deaths, the 'Trend of Deaths' data is referenced. Both datasets are available at the prefectural level. According to the website, the number of cases is aggregated based on HER-SYS data, except for the period between September 21, 2022, and September 25, 2022, when individual cases reported by each local government are used. The number of deaths is the aggregated value reported by each local government and excludes charter flights. To calculate rates per 1 million population, we divide the number of cases and deaths by the total population of each prefecture, and we also multiply the result by 100 million to enhance clarity.

Data on the total population by prefecture is obtained from the 'Population by Age Group' section of the 'Basic Resident Register (2022) (City/Ward/Town/Village)' published on the website of the Ministry of Internal Affairs and Communications.

Following Inoue and Okimoto (2023), we use weekly aggregated values for the number of cases and deaths, as these tend to have a strong weekly effect. We follow Watanabe and Yabu (2020, 2021) by taking the inverse hyperbolic sine transformed values. The website reports the number of cases from January 16, 2020. However, for our analysis, we have limited the data from April 17, 2020, when the infection had spread nationwide and at least one weekly positive case was recorded in each of the 18 prefectures analysed. Our analysis accounts for approximately 75% of the total number of infected individuals and deaths nationwide as of October 13, 2022. Figure 3 illustrates the trend of the number of new cases and deaths per million population in 18 prefectures.

Figure 3: Trends in the number of new cases and deaths
(per million population, inverse hyperbolic sine transformed)



The vaccination rate is calculated based on the data obtained from two sources. The weekly number of vaccinations is collected from the 'Open Data – Prefectural Vaccination Number Details' published by the Vaccination Record System (VRS) of the Digital Agency, Japan. This data is used to determine the number of people who completed the second vaccination dose in each prefecture. To calculate the vaccination rate for each prefecture, 'the Basic Resident Register (2022) (City/Ward/Town/Village)' is used, following the same method as for the number of cases and deaths.

Regarding the SOE and QSOE, data are obtained from the website of the Cabinet Agency for Infectious Disease Crisis Management. The number of days on which SOE or QSOE declarations were implemented in week t is taken into consideration.

It is important to note that the local governor's index we constructed had almost no linear relationship with other variables related to the information effect and the variables related to the intervention effect. This outcome can be attributed to the delay between information dissemination and policy intervention, as well as the difference in information volume between raw data, such as the number of new cases, and processed data, such as the actual textual information disseminated by the government.

The maximum daily temperature and total daily precipitation data for each prefecture are obtained from the Japan Meteorological Agency website. The observation data of the prefectural capital are used as the representative weather condition of the prefecture. The number of days with extremely high and low temperatures per week is calculated from the daily maximum temperature. The weekly precipitation is calculated by aggregating the daily total precipitation for each week. Figure 4 shows the trends of the number of days with extremely high and low temperatures and precipitation.

Figure 4: Trends in climatic factors by prefecture

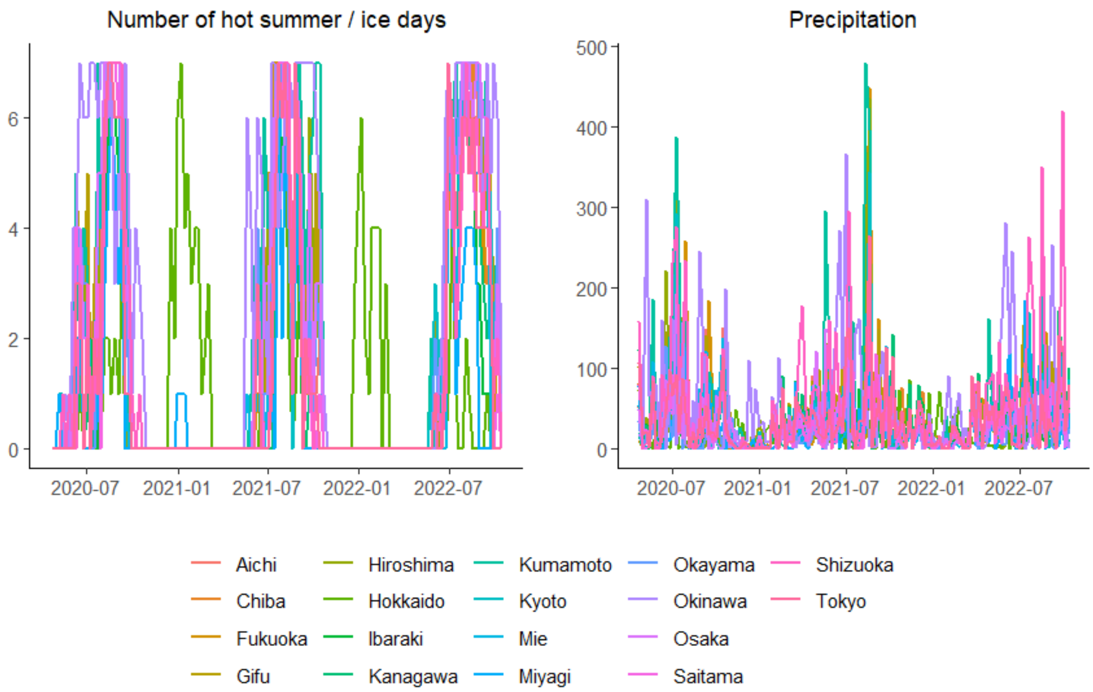


Table 2 displays the descriptive statistics for the aforementioned data.

Table 2: Descriptive statistics

Variable	Obs.	Mean	Std.Dev.	Min.	Max.
m1(retail_and_recreation)	2340	-11	9.2	-59	26
m2(grocery_and_pharmacy)	2340	1.2	5.1	-17	23
m3(parks)	2340	-9.4	16	-54	72
m4(transit_stations)	2340	-24	11	-66	34
m5(workplaces)	2340	-14	9.2	-59	1.3
m6(residential)	2340	6.7	3.4	0.86	28
lg_info	1228	0.019	0.18	-0.99	1.5
log(cases)	2340	5.1	2.5	0	10
log(deaths)	2340	1	0.92	0	3.6
vaccination	2340	0.35	0.35	0	0.81
SOE	2340	0.98	2.4	0	7
QSOE	2340	0.8	2.1	0	7
hot summer / ice days	2340	1.5	2.4	0	7
precipitation	2340	36	51	0	480

III.3. Estimation results

III.3.1. Estimation results for one-week ahead model

Table 3 presents the estimation results of Eq. (2) for the one-week-ahead model ($h = 1$). The R^2 values for all models, except for transit stations and workplaces mobility, are above 0.6, indicating that this specification has high explanatory power[15)].

The information effects of the local governor's index show a significant positive coefficient for residential mobility and significant negative coefficients for the mobility of other categories. This suggests that the mobility of residential category is increased while the mobility of other categories is decreased, indicating that the stay-at-home information dissemination significantly suppressed people's mobility of all categories of places. Note

15) The VIF values were calculated and were all below 1.5, so it is considered that there is little concern about multicollinearity.

that the local governor's index we constructed had almost no linear relationship with other variables related to the information effect and the variables related to the intervention effect (see Appendix D). This can be interpreted as confirming, to a certain extent, the unique effect of information dissemination. The confirmation of the information effect even after extracting the unique effects of information dissemination further strengthens prior findings.

Regarding the number of new cases, with the exception of the grocery and pharmacy mobility, a significant effect of discouraging people from going out was confirmed. Upon examination of the coefficients of the local governor's index and the number of cases in the residential mobility, it was found that the local governor's index was 0.345 and the number of cases was 0.328. This indicates that a suppression effect on people's going out behaviour can be achieved at the same level when the number of cases is $1.0 \times \frac{0.345}{0.328} = 1.052$, as when the local governor's index is 1.0. Although the units differ, a local governor's index of 1.0 indicates information dissemination equivalent to declaring a SOE, while an index of -1.0 indicates information dissemination equivalent to lifting such a declaration. Regarding the number of cases, a value of 1.052 means that 1.335 infected people per million population were observed in one week, which translates to 18,419 infected people in Tokyo. Conversely, no significant effect was confirmed for the number of deaths.

The vaccination rate had a significant impact on people's behaviour in different categories of places. In terms of the mobility of retail and recreation and residential categories, vaccination was found to reduce people's mobility, whereas vaccination increased the mobility of workplaces category. This finding regarding the workplaces and the residential mobility is consistent with the assumption that vaccination reduces the perceived risk of infection. However, there may be some kind of bias in retail and recreation mobility, where residents who are more willing to be vaccinated may be more likely to refrain from going out to prevent the spread of infection, and this altruistic behaviour may influence their vaccination behaviour.

While the intervention effects of the declaration of a SOE and QSOE may vary from category to category, they generally have a suppressive effect on people's mobility. Specifically, the declaration of a SOE has a significant negative effect on the mobility of retail and recreation, transit stations, and workplaces categories, while it has a positive effect on residential mobility. Similarly, a QSOE has a significant negative effect on mobility in transit stations category at the 10% level, while it has a positive effect on residential mobility. Although it may be difficult to compare the values of the coefficients directly with the local governor's index, the index is equal to 1.0 when the dissemination of information is equivalent to the declaration of a SOE. Analogously, when a SOE is declared, the value of the SOE variable is also 1.0, indicating that the units of both are similar. Based on Table 3, the coefficient for the local governor's index is consistently larger in magnitude than that for the declaration of a SOE in all categories. This suggests that the local governor's index is more significant in terms of the regression coefficient.

The weather factors of hot summer days and ice days had no significant effect, while an increase in precipitation had a suppressing effect on the mobility of all categories of places. For the lagged mobility, the coefficients were consistently positive for all mobility indices.

Table 3: Estimation results for one-week ahead model

	Google COVID-19 Community Mobility Reports					
	(1) retail_and_recreation	(2) grocery_and_pharmacy	(3) parks	(4) transit_stations	(5) workplaces	(6) residential
lg_info	-1.077***	-0.675**	-2.080***	-0.897**	-0.451***	0.345***
	(0.236)	(0.327)	(0.708)	(0.434)	(0.161)	(0.081)
log(cases)_lag1	-1.217***	-0.026	-0.484**	-1.341***	-0.445***	0.328***
	(0.221)	(0.083)	(0.22)	(0.169)	(0.155)	(0.076)
log(deaths)_lag1	0.003	-0.018	0.168	-0.038	-0.065	0.002
	(0.109)	(0.087)	(0.358)	(0.236)	(0.104)	(0.049)
vaccination_lag1	-12.271**	3.086	-7.579	-14.792	7.252**	-2.012***
	(6.081)	(2.84)	(13.316)	(11.859)	(3.332)	(0.404)
SOE	-0.200***	0.022	0.034	-0.081***	-0.130***	0.081***
	(0.054)	(0.016)	(0.102)	(0.029)	(0.03)	(0.018)
QSOE	-0.046	-0.007	0.006	-0.084*	-0.008	0.023**
	(0.036)	(0.022)	(0.065)	(0.048)	(0.023)	(0.01)
hot_ice_days	0.015	0.033	-0.503	-0.105	-0.054	0.003
	(0.116)	(0.054)	(0.485)	(0.125)	(0.036)	(0.027)
precipitation	-0.012***	-0.012***	-0.062***	-0.017***	-0.005**	0.005***
	(0.003)	(0.002)	(0.012)	(0.004)	(0.002)	(0.001)
mobility_lag1	0.558***	0.720***	0.682***	0.566***	0.497***	0.579***
	(0.051)	(0.049)	(0.029)	(0.04)	(0.077)	(0.069)
Observations	1212	1212	1212	1212	1212	1212
R^2	0.620	0.604	0.640	0.503	0.390	0.641

Note: Heteroscedasticity-consistent robust standard errors in parentheses. Asterisks denote statistical significance: *p<0.1;**p<0.05;***p<0.01.

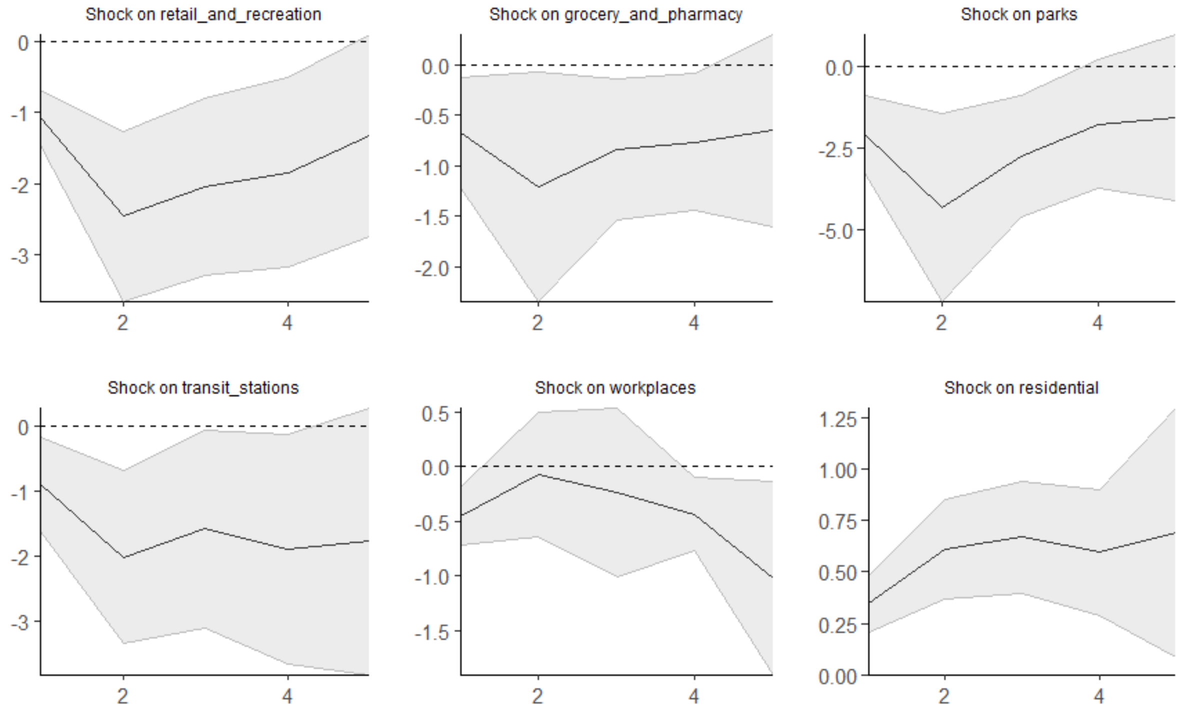
III.3.2. Impulse response analysis

This subsection conducts an impulse response analysis based on the LP method. Figure 5 shows the impulse response functions (IRFs) of the level of change in the mobility of each of the six categories of places when the local governor's index increases by 1.0. The impulse response and its confidence interval are calculated from the coefficient $\beta^{ah} (a = 1, 2, \ldots, 6; h = 1, 2, \ldots, 5)$ and its standard error, estimated by panel OLS based on Eq. (2), and show how much mobility changes when the local governor's index increases by one unit.

Figure 5 displays that an increase in the local governor's index resulted in a statistically significant decrease in the mobility of categories other than residential and workplaces categories for at least three weeks after the increase. In the workplace category, mobility decreased significantly in the first, fourth, and fifth weeks after the index increase. By contrast, mobility in residential category increased significantly from the first week to at least the fifth week after the increase in the local governor's index.

In summary, the analysis of the impulse response indicates that an increase in the local governor's index significantly reduces mobility for at least one week ahead. Although the strength of the effect varies across categories of places, it persists afterwards.

Figure 5: IRFs of the rate of change in the level mobility to an increase in the local governor's index



Note: The solid lines correspond to the point estimate and the shaded areas correspond to the 90% confidence interval.

IV. The time-varying effects of information dissemination

Finally, we analyse the changes in the information effect over time by dividing the sample into the early phase of the pandemic and the period after the delta variant outbreak in July 2021. As explained in section I, previous studies have also suggested that the information effect changes over time. We estimate the one-week-ahead model for each period and perform an impulse response analysis using the LP method. The study period comprised 62 periods during the early pandemic and 68 periods after the delta variant outbreak. Tables 4 and 5 show the estimation results for each period and Figure 6 shows the results of the impulse response analysis.

The results of the one-week-ahead model's estimation are presented in Tables 4 and 5. We find a remarkable change in the magnitude of the information effect over time. However, the information effect weakens after the dominance of the Delta variant compared with the early stage of the pandemic.

Furthermore, Figure 6's impulse response analysis indicates that mobility was more suppressed during the early stages of the pandemic than after the Delta variant outbreak. Regarding residential mobility, the study found a significant decrease in mobility one to four weeks after the local governor's index increased during the early pandemic period. However, in the sample after the Delta variant outbreak, this significant decrease in mobility was no longer observed at one week or four weeks. Regarding mobility other than the residential category, the IRFs for the early pandemic period are generally lower and the period during which the IRFs are below 0 is longer. Previous studies have shown that the information effect varies over time, which is confirmed by this statement[16].

[16] To assess robustness, we also estimated the model the NAs filled with 0, and with the case where the maximum lag order $P = 2,3$. The outcomes obtained with these models were qualitatively similar.

Table 4: Estimation results for one-week ahead model in the early pandemic period

	Google COVID-19 Community Mobility Reports					
	(1)	(2)	(3)	(4)	(5)	(6)
	retail_and_recreation	grocery_and_pharmacy	parks	transit_stations	workplaces	residential
lg_info	-1.540***	-1.099***	-3.391***	-1.621**	-1.189***	0.576***
	(0.444)	(0.301)	(0.803)	(0.761)	(0.445)	(0.201)
log(cases)_lag1	-1.163***	-0.346***	-1.123***	-1.150***	-0.419***	0.301***
	(0.211)	(0.128)	(0.28)	(0.124)	(0.125)	(0.065)
log(deaths)_lag1	0.136	-0.077	0.675*	-0.045	-0.080	-0.067
	(0.178)	(0.113)	(0.349)	(0.244)	(0.234)	(0.08)
vaccination_lag1	-26.956	-14.394	-80.919	-72.434**	-48.576	23.721**
	(27.966)	(22.731)	(118.225)	(34.62)	(29.548)	(9.307)
SOE	-0.194***	0.036	-0.028	-0.093	-0.167***	0.089***
	(0.044)	(0.038)	(0.137)	(0.072)	(0.042)	(0.019)
QSOE	0.017	0.125***	0.084	0.076	0.035	0.019
	(0.042)	(0.028)	(0.129)	(0.072)	(0.037)	(0.015)
hot_ice_days	-0.040	-0.122	-1.041	-0.068	-0.065	0.011
	(0.129)	(0.15)	(0.862)	(0.174)	(0.055)	(0.04)
precipitation	-0.01***	-0.012***	-0.061***	-0.012***	-0.006***	0.005***
	(0.003)	(0.002)	(0.017)	(0.003)	(0.002)	(0.001)
mobility_lag1	0.585***	0.465***	0.601***	0.623***	0.538***	0.618***
	(0.043)	(0.078)	(0.033)	(0.049)	(0.06)	(0.055)
Observations	622	622	622	622	622	622
R^2	0.670	0.429	0.547	0.599	0.478	0.655

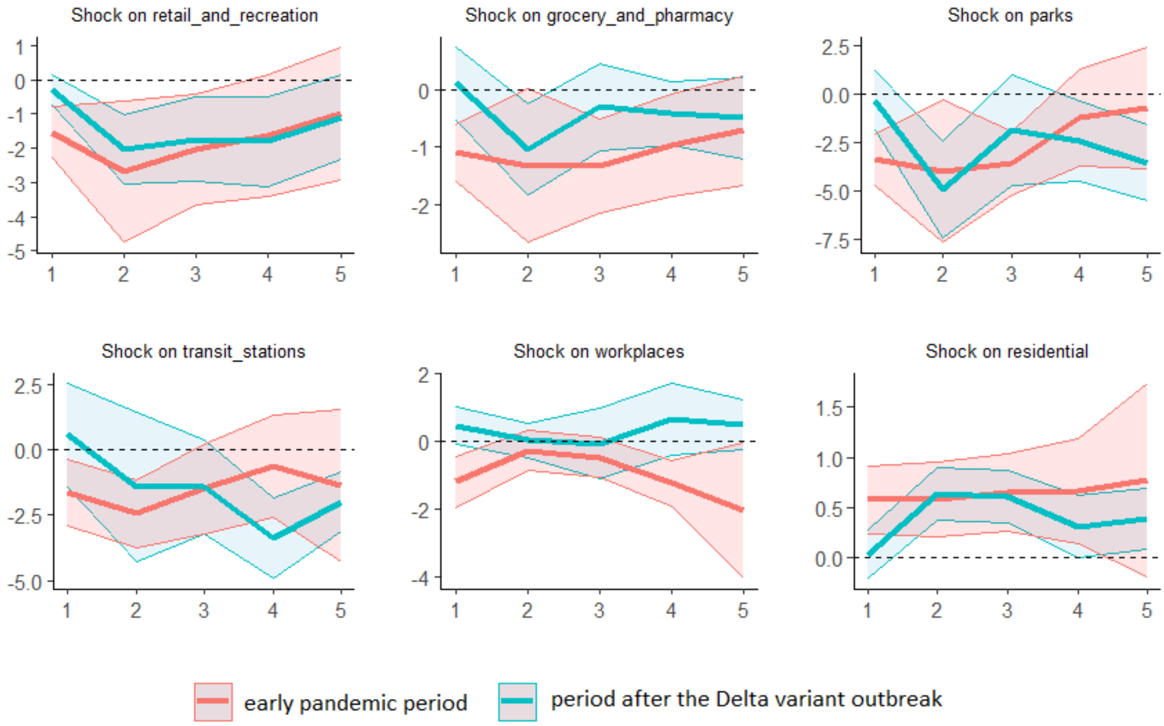
Note: Heteroscedasticity-consistent robust standard errors in parentheses. Asterisks denote statistical significance: *p<0.1;**p<0.05;***p<0.01.

Table 5: Estimation results for one-week ahead model in the period after the Delta variant outbreak

	Google COVID-19 Community Mobility Reports					
	(1)	(2)	(3)	(4)	(5)	(6)
	retail_and_recreation	grocery_and_pharmacy	parks	transit_stations	workplaces	residential
lg_info	-0.302	0.100	-0.355	0.553	0.471	0.031
	(0.274)	(0.381)	(0.923)	(1.187)	(0.334)	(0.145)
log(cases)_lag1	-1.089***	0.055	-0.144	-1.543***	-0.270	0.311***
	(0.144)	(0.139)	(0.383)	(0.453)	(0.196)	(0.074)
log(deaths)_lag1	-0.266*	-0.102	-0.522	-0.053	-0.148**	0.105***
	(0.151)	(0.163)	(0.54)	(0.232)	(0.067)	(0.023)
vaccination_lag1	-2.693	-0.383	-4.166	4.887	11.219***	-3.405*
	(10.056)	(7.97)	(17.215)	(12.139)	(3.987)	(1.936)
SOE	-0.390**	0.044	-0.089	-0.222	-0.069	0.099**
	(0.163)	(0.075)	(0.192)	(0.217)	(0.05)	(0.046)
QSOE	-0.160***	-0.035	-0.084	-0.203	-0.081	0.043
	(0.062)	(0.049)	(0.116)	(0.124)	(0.067)	(0.03)
hot_ice_days	-0.022	0.108***	-0.112	-0.096	-0.121**	0.022
	(0.153)	(0.032)	(0.217)	(0.155)	(0.06)	(0.023)
precipitation	-0.015***	-0.014***	-0.062***	-0.024***	-0.007*	0.006***
	(0.004)	(0.002)	(0.011)	(0.007)	(0.004)	(0.001)
mobility_lag1	0.401***	0.704***	0.712***	0.455***	0.239***	0.433***
	(0.072)	(0.058)	(0.049)	(0.048)	(0.067)	(0.091)
Observations	582	582	582	582	582	582
R^2	0.467	0.575	0.690	0.381	0.139	0.528

Note: Heteroscedasticity-consistent robust standard errors in parentheses. Asterisks denote statistical significance: *p<0.1;**p<0.05;***p<0.01.

Figure 6: IRFs in the early pandemic period and the period after the Delta variant outbreak



Note: The solid lines correspond to the point estimate and the shaded areas correspond to the 90% confidence interval.

Watanabe and Yabu (2021) put forward several hypotheses to explain the absence of the information effect after the delta variant outbreak, despite its presence in the early stages of the pandemic. These hypotheses included a possible decline in altruism[17)] over time and the emergence of a gap between people's perceptions of the severity of the infection and the actual situation.

Our investigation focuses on the impact of information dissemination on the information effect. Thus, we examine additional factors beyond those examined by Watanabe and Yabu (2021), who analysed the information effects of announcements of new cases and deaths. In the early stages of the pandemic, people struggled to make informed decisions based solely on announcements such as the number of cases. As a result, the dissemination of government information was critical. However, as people became better able to make decisions based on announcements of infection status, the importance of government information dissemination declined relative to its initial role.

Tables 4 and 5 show that the information effect of information dissemination was not observed after the Delta variant outbreak. However, information effect made by daily announcements of the number of cases continued to affect the majority of categories. Additionally, the impact of daily announcements of the number of deaths on mobility decreased significantly in more categories after the Delta variant outbreak compared to the early phase. This could be evidence of a decline in the relative importance of information dissemination.

V. Conclusion

In this article, we applied the latest findings in NLP research to precisely measure the information dissemination effect for each prefecture in Japan in the context of the COVID-19 pandemic. We then analysed

17) Alfaro et al. (2024) examine altruism as a potential motivator for changes in human behaviour. Altruism refers to the concern that one's own infection may endanger those around them.

the dynamic relationship between the index of information dissemination constructed based on the above and mobility, and followed through with an econometric analysis of the importance of the information effect presented in Watanabe and Yabu's (2020, 2021) study.

First, let us consider the proposed index of information dissemination for each prefecture. Unlike Watanabe and Yabu (2020, 2021), we did not simply use the presence or absence of certain policies as a dummy variable to create a new index, but applied the latest research in NLP to textual data. This method has gained popularity, especially for nowcasting economic trends. We built this model based on findings in extant literature on NLP. The accuracy of the model built for index construction was evaluated using the macro F1 score, which measured at 0.92, the same as Alaparthi and Mishra (2021), who constructed a text classification model for IMDb review data.

Second, econometric methods helped us study the dynamic relationship between the newly developed index representing information dissemination and mobility. We subsequently confirmed that the stay-at-home information dissemination done by local governors during the COVID-19 pandemic effectively suppressed people's mobility.

Our results are not unexpected. Watanabe and Yabu (2020, 2021) also impress upon the importance of the information effect through information dissemination. However, our approach is novel because it allowed us to precisely and quantitatively assess the impact of information dissemination on mobility based on existing data.

We also confirmed that the information effect of announcing the number of new cases and the intervention effect of declaring a SOE suppressed mobility, but the significance of this effect varied by the mobility of the categories of places. Moreover, an increase in precipitation had a suppressing effect on the mobility of all categories of places. These findings reaffirm Watanabe and Yabu's (2020, 2021) study through the use of our precise index representing information dissemination.

Significant results were obtained for the intervention of the declaration of a SOE only for some categories of places. However, the local governor's index significantly suppressed the mobility of all categories of places, further strengthening Watanabe and Yabu's (2020, 2021) claim that appropriate information encouraged behavioural change rather than legally binding countermeasures against COVID-19.

The local governor's index we constructed had almost no linear relationship with other variables related to the information effect and the variables related to the intervention effect. This can be interpreted as confirming, to a certain extent, the unique effect of information dissemination. The confirmation of the information effect even after extracting the unique effects of information dissemination further strengthens prior findings.

Third, we split the sample into an early and a later period when the Delta variant emerged in order to analyse changes in the information effect over time. A comparison of the one-week-ahead models revealed a significant effect of suppressing mobility even after splitting the sample in the early pandemic period. No significant effect was confirmed in any area after the Delta variant outbreak. After including periods that have not been analysed in many previous studies, the finding holds that the information effect changes over time. Again, we strengthen the findings in extant literature.

Finally, we simultaneously analysed the changes over time of both the information effect caused by the announcement of the infection status and that caused by the dissemination of information. The weakening of the information effect caused by information dissemination over time is more significant than that caused by the announcement of the infection status. That is, both exploiting an information effect and knowing when and what kind of information to disseminate are equally important to maximize the overall effect. This finding has serious policy implications.

Our study is unique in applying findings of NLP research to create an index of information dissemination, and then using this index as a proxy for the information effect. We followed through with an econometric analysis to verify the information effect.

Nevertheless, it is essential to note the limitations of our methodology. Regarding the first analysis, we used a small number of samples for model construction. Although BERT can help construct highly accurate models even with a small number of samples, and we were indeed able to construct highly accurate prediction models, using more samples would be beneficial for constructing a more refined model.

The computer memory was also a limiting factor in model construction. We were unable to read text longer than 512 tokens. Following Sun et al. (2019), we compressed the input data for text data longer than a certain unit. If there were no such limitations, we could construct a model that is not dependent on the length of the text.

Regarding the second and third analyses, although we considered two fixed effects—time and prefecture—the time fixed effect may still differ by prefecture, which we did not examine.

Finally, we used impulse response analysis to analyse the impact of the local governor's index on mobility up to five weeks ahead. It may also be that information dissemination occurs in anticipation of the following week's mobility, so considering lead effects as well as lags would be interesting. Not all prefectures analysed are now governed by the same governor as when the study was undertaken. In such prefectures, we suggest including the effect of changes in information disseminators as an explanatory variable.

We hope that future research in this field will develop further once our limitations are considered when developing new methodologies for analysis.

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Appendix

Appendixes

A. Parameter settings

Table A.1 shows the values of the parameters used to construct the text classification model in Section II.

Table A.1: Parameter settings

Parameters	Settings
Transformer	Hugging Face
Batch size	32
Token length	512
Epochs	15
Learning rate	0.00005

B. Examples of estimated values of the text classification model

The model is applied to the actual statements of local governors announcing the issuance and lifting of a SOE. Examples of actual statements are as follows.

<u>Example 1: Statement by the Governor of Tokyo, April 23, 2021 (provisional translation)</u>

The government has just decided to declare a state of emergency under the Act on Special Measures against Novel Influenza for Tokyo, Osaka, Kyoto and Hyogo prefectures. The Tokyo Metropolitan Government has decided to implement emergency measures under the Act on Special Measures against Novel Influenza from Sunday, April 25 to Tuesday, May 11. In order to ensure that the people's mobility in Tokyo is controlled, we would like to request all citizens of Tokyo to stay at home during the period of this declaration.

<u>Example 2: Statement by the Governor of Okinawa, May 15, 2020 (provisional translation)</u>

On May 14, the government decided to change its basic policy on measures against COVID-19 and to remove 39 prefectures, including Okinawa Prefecture, from the area where emergency measures should be implemented based on the Act on Special Measures against Novel Influenza. This means that the emergency measures in Okinawa Prefecture will also be lifted, and daily life will gradually return to normal.

Example 1 is classified as 'strict' as it announces the implementation of a SOE in Tokyo, which requires individuals to stay indoors. In contrast, Example 2 is labelled as 'lenient' as it declares the lifting of the SOE in Okinawa.

Table B.1: Prediction results of the text classification model

	$P(strict)$	$P(neutral)$	$P(lenient)$
Example 1	**0.9955**	0.0002	0.0043
Example 2	0.0022	0.0015	**0.9963**

Table B.1 shows that the announcement of the application of the SOE in Example 1 has the highest probability of being classified as 'strict', while the announcement of the lifting of the SOE in Example 2 has the highest probability of being classified as 'lenient', which is in line with expectations. It was confirmed that the model construction was intuitively reasonable.

C. Panel unit root tests

As outlined in section III, we use level data instead of differenced data, following the approach of Watanabe and Yabu (2020). Table C.1 presents the results of the panel unit root tests. We conducted three types of unit root tests[18], each of which rejected the null hypothesis of non-stationarity.

Table C.1: The panel unit root test results

	Intercept & trend			**Intercept**		
	Levin-Lin-Chu	Im-Pesaran-Shin	Maddala-Wu	Levin-Lin-Chu	Im-Pesaran-Shin	Maddala-Wu
m1	-17.42	-16.389	349.41	-14.787	-16.298	376.5
retail and recreation	(< 2.2e-16)***	(< 2.2e-16)***	(< 2.2e-16)***	(< 2.2e-16)***	(< 2.2e-16)***	(< 2.2e-16)***
m2	-14.969	-14.525	351.17	-9.0733	-10.366	230.79
grocery and pharmacy	(< 2.2e-16)***	(< 2.2e-16)***	(< 2.2e-16)***	(< 2.2e-16)***	(< 2.2e-16)***	(< 2.2e-16)***
m3	-25.004	-25.723	667.79	-18.523	-21.388	583.47
parks	(< 2.2e-16)***	(< 2.2e-16)***	(< 2.2e-16)***	(< 2.2e-16)***	(< 2.2e-16)***	(< 2.2e-16)***
m4	-8.6732	-8.5914	157.39	-7.0808	-8.0056	147.91
transit stations	(< 2.2e-16)***	(< 2.2e-16)***	(7.573e-16)***	(7.167e-13)***	(5.942e-16)***	(2.717e-14)***
m5	-41.19	-35.196	989.18	-35.334	-33.389	1056.4
workplaces	(< 2.2e-16)***	(< 2.2e-16)***	(< 2.2e-16)***	(< 2.2e-16)***	(< 2.2e-16)***	(< 2.2e-16)***
m6	-21.356	-18.449	406.04	-18.71	-19.051	466.9
residential	(< 2.2e-16)***	(< 2.2e-16)***	(< 2.2e-16)***	(< 2.2e-16)***	(< 2.2e-16)***	(< 2.2e-16)***

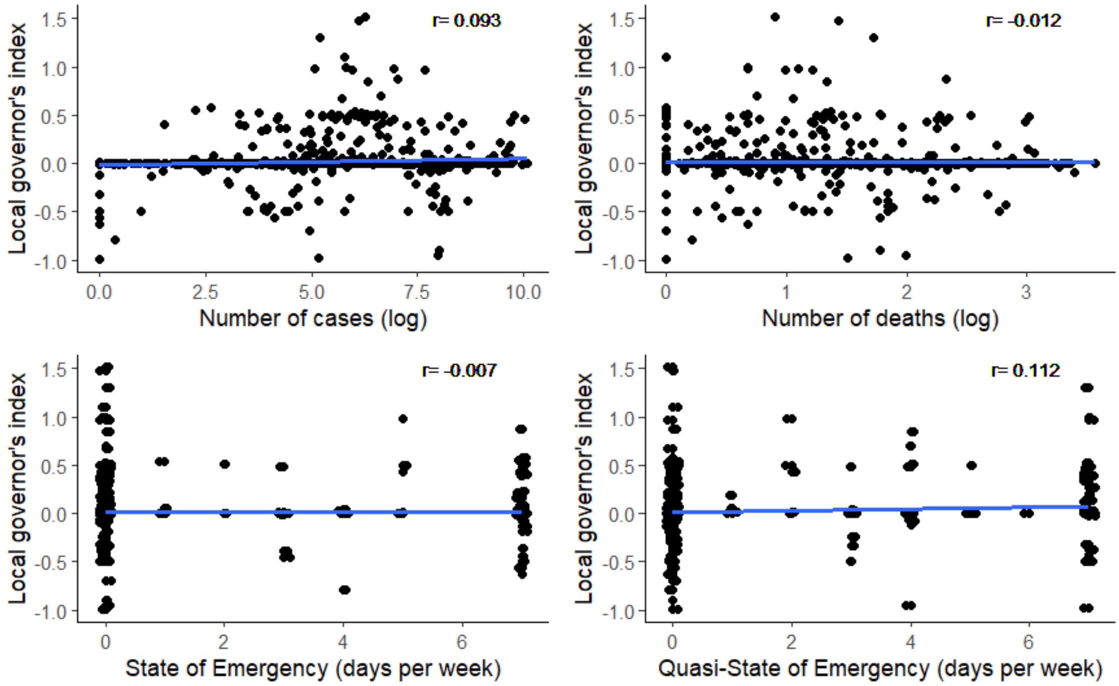
Note: Asterisks denote statistical significance: *p<0.1;**p<0.05;***p<0.01.

18) Levin et al. (2002), Im et al. (2003), and Maddala and Wu (1999)

D. Correlation analysis

The local governor's index we constructed had almost no linear relationship with other variables related to the information effect and the variables related to the intervention effect. The correlation coefficients between the variables have an absolute value of less than 0.2 in all cases. As explained in section II, the local governor's index is a numerical representation of the dissemination of information on various policies, including intervention measures. It is expected to reflect the intervention effect to an extent, as well as the information effect to some degree, given that intervention measures are based on infection status information. However, the correlation analysis results indicate that there is only a minimal linear relationship between the local governor's index and other variables associated with information and intervention effects. Scatter plots of the local governor's index and the four variables are shown in Fig. D.1.

Fig. D.1: The scatter plots of the local governor's index and the other variables



Note: Straight lines represent regression lines.

E. Robustness checks

This section evaluates the robustness of the estimation results of the one-week ahead model from two perspectives. First, the handling of NAs in the local governor's index is assessed. The second perspective is the robustness of the order of lags.

Robustness on handling of NAs

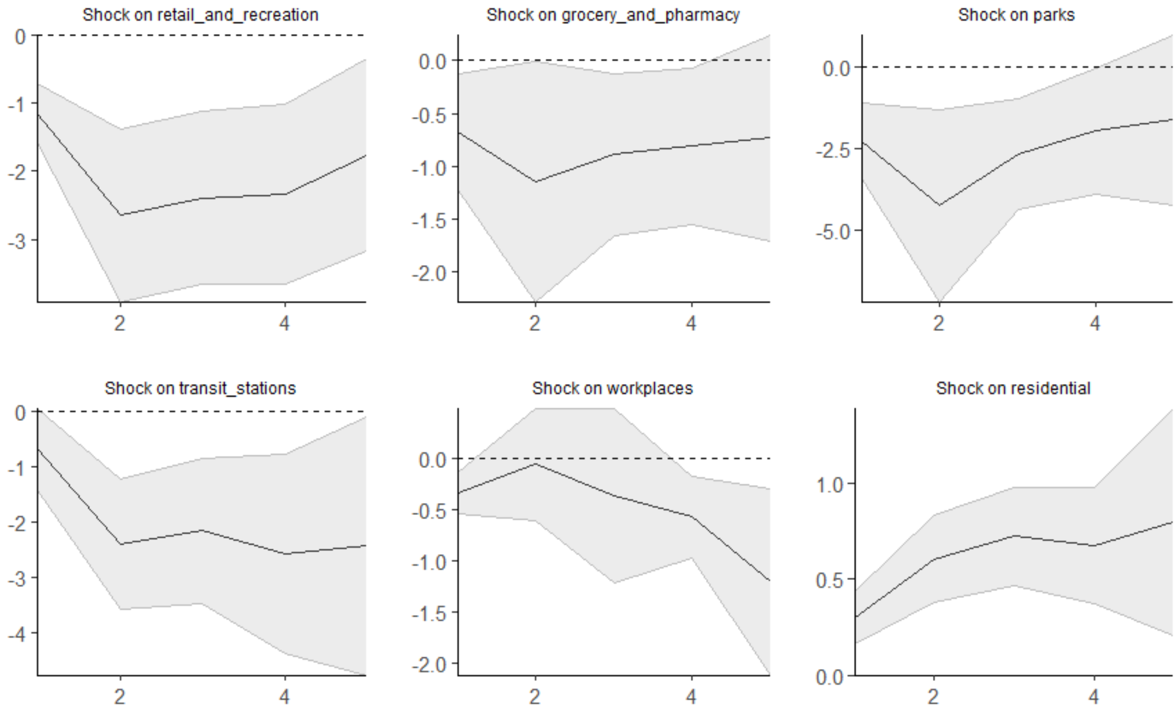
In section III, the local governor's index is treated as NAs if there was no information dissemination in that period to distinguish between no information dissemination and information dissemination equivalent to a value of 0. However, there is a possibility of introducing bias in the estimation results if the data for weeks with missing governor indices are not included in the analysis. Therefore, in this section, we reanalyse the data by filling in the NAs of the local governor's index with 0 and confirm the robustness of the analysis in section III.

Table E.1: Estimation results for one-week ahead model with NAs imputed with 0

	Google COVID-19 Community Mobility Reports					
	(1) retail_and_recreation	(2) grocery_and_pharmacy	(3) parks	(4) transit_stations	(5) workplaces	(6) residential
lg_info (filled)	-1.153***	-0.674**	-2.288***	-0.687	-0.335***	0.302***
	(0.26)	(0.327)	(0.693)	(0.441)	(0.12)	(0.083)
log(cases)_lag1	-6.278	3.797	-2.529	-4.717	4.267	-1.386**
	(4.626)	(2.413)	(10.159)	(12.148)	(3.458)	(0.588)
log(deaths)_lag1	-0.862***	0.055	-0.094	-0.854***	-0.307***	0.261***
	(0.129)	(0.056)	(0.215)	(0.161)	(0.103)	(0.048)
vaccination_lag1	0.032	-0.002	0.174	-0.103	-0.093	0.034
	(0.095)	(0.059)	(0.208)	(0.196)	(0.061)	(0.023)
SOE	-0.188***	0.033***	0.045	-0.086***	-0.132***	0.081***
	(0.05)	(0.013)	(0.06)	(0.031)	(0.021)	(0.015)
QSOE	-0.012	0.015	0.109*	-0.017	-0.016	0.019***
	(0.038)	(0.02)	(0.065)	(0.047)	(0.015)	(0.007)
hot_ice_days	-0.01	0.009	-0.388	-0.176	-0.049	0.007
	(0.103)	(0.057)	(0.383)	(0.128)	(0.034)	(0.027)
precipitation	-0.011***	-0.01***	-0.051***	-0.016***	-0.004*	0.004***
	(0.002)	(0.002)	(0.009)	(0.003)	(0.002)	(0.001)
mobility_lag1	0.615***	0.752***	0.718***	0.577***	0.501***	0.569***
	(0.036)	(0.047)	(0.042)	(0.041)	(0.076)	(0.057)
Observations	2322	2322	2322	2322	2322	2322
R^2	0.563	0.601	0.608	0.410	0.372	0.605

Note: Heteroscedasticity-consistent robust standard errors in parentheses. Asterisks denote statistical significance: *p<0.1;**p<0.05;***p<0.01.

Figure E.1: IRFs of the rate of change in the level mobility to an increase in the local governor's index



Note: The solid lines correspond to the point estimate and the shaded areas correspond to the 90% confidence interval.

The results of the one-week-ahead model indicated that the local governor's index, with NAs filled in, significantly suppressed the mobility of categories other than the transit station category. The results for the other variables are similar to those in section III. The difference between the estimation results in section III and Table E.1 is that the number of deaths was found to significantly suppress the mobility of four categories of places when NAs were filled: retail and recreation, transit transportation, workplaces, and residential. The impulse response analysis in Figure E.1 also confirmed the effect of suppressing mobility, even when using the local governor's index with imputed NAs, similar to the results in section III.

Robustness on lag order

In Section III, the lag order of the two variables related to infection status (number of new cases and number of deaths) considered as part of the information effect was treated as $P = 1$. On the other hand, there is little theoretical basis for how many lag periods should be included for these variables related to infection status, and it is necessary to make an empirical judgement. Therefore, we reanalyse the case in which the maximum lag order is $P = 2, 3$. We assume that the period for which the number of new cases and deaths can be recognized and used as a reference for behavioural change is at most three weeks, and we check the robustness of the analysis in Section III. Note that the lag order of the vaccination rate is fixed at $P = 1$ because the variable is cumulative and likely to be autocorrelated.

Table E.2: Estimation results for one-week ahead model ($P = 2$)

	Google COVID-19 Community Mobility Reports					
	(1) retail_and_recreation	(2) grocery_and_pharmacy	(3) parks	(4) transit_stations	(5) workplaces	(6) residential
lg_info	-1.047***	-0.633**	-1.969***	-0.872**	-0.490***	0.346***
	(0.228)	(0.298)	(0.641)	(0.441)	(0.188)	(0.085)
log(cases)_lag1	-1.400***	-0.206	-0.618	-1.415***	-0.094	0.260***
	(0.272)	(0.153)	(0.454)	(0.238)	(0.173)	(0.099)
log(cases)_lag2	0.227	0.247	0.175	0.070	-0.459***	0.098
	(0.265)	(0.153)	(0.508)	(0.274)	(0.172)	(0.06)
log(deaths)_lag1	0.063	0.078	0.770*	0.072	0.003	-0.037
	(0.14)	(0.097)	(0.449)	(0.275)	(0.096)	(0.029)
log(deaths)_lag2	-0.155	-0.222	-1.049*	-0.181	-0.021	0.054
	(0.124)	(0.146)	(0.582)	(0.139)	(0.115)	(0.046)
vaccination_lag1	-12.137**	3.852	-6.771	-14.731	6.783**	-1.986***
	(5.827)	(2.868)	(12.285)	(11.653)	(3.169)	(0.434)
SOE	-0.207***	0.018	0.051	-0.077***	-0.123***	0.081***
	(0.056)	(0.016)	(0.103)	(0.029)	(0.032)	(0.019)
QSOE	-0.052	-0.012	0.007	-0.084	-0.002	0.023**
	(0.036)	(0.023)	(0.068)	(0.051)	(0.023)	(0.011)
hot_ice_days	0.016	0.035	-0.515	-0.105	-0.059*	0.005
	(0.118)	(0.053)	(0.475)	(0.124)	(0.035)	(0.028)
precipitation	-0.012***	-0.012***	-0.062***	-0.017***	-0.005**	0.005***
	(0.003)	(0.002)	(0.012)	(0.004)	(0.002)	(0.001)
mobility_lag1	0.554***	0.720***	0.677***	0.565***	0.478***	0.558***
	(0.054)	(0.05)	(0.029)	(0.042)	(0.083)	(0.072)
Observations	1198	1198	1198	1198	1198	1198
R^2	0.617	0.605	0.643	0.502	0.374	0.631

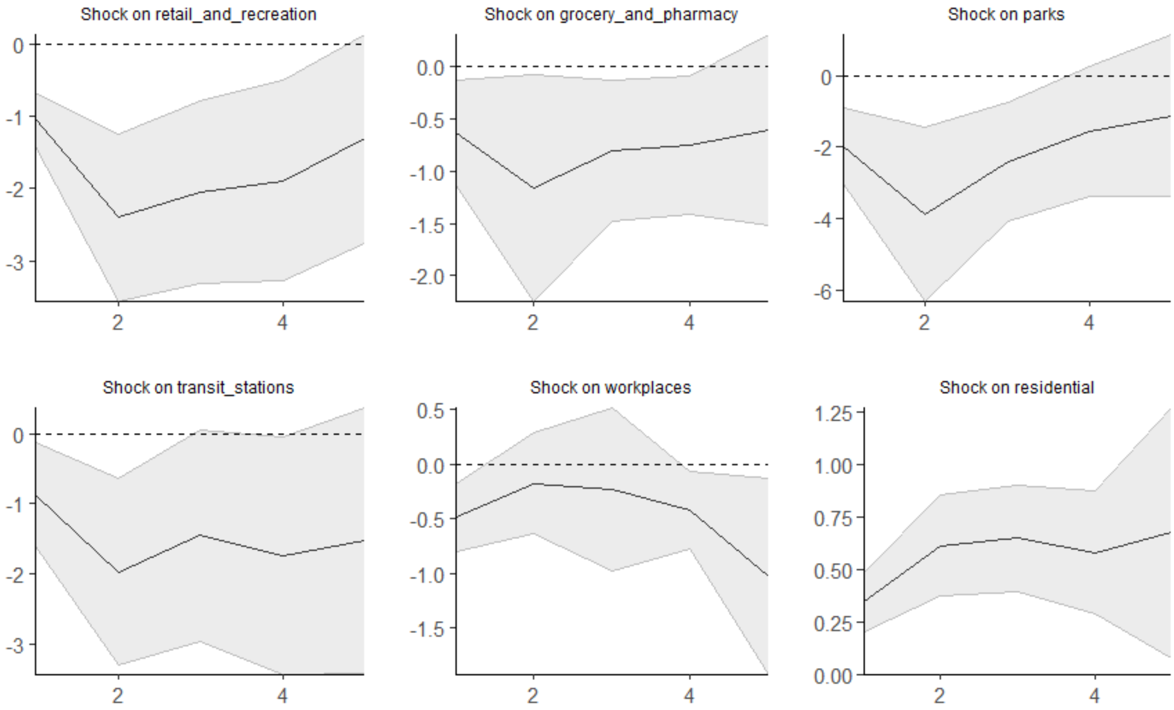
Note: Heteroscedasticity-consistent robust standard errors in parentheses. Asterisks denote statistical significance: *p<0.1;**p<0.05;***p<0.01.

Table E.3: Estimation results for one-week ahead model ($P = 3$)

	Google COVID-19 Community Mobility Reports					
	(1) retail_and_recreation	(2) grocery_and_pharmacy	(3) parks	(4) transit_stations	(5) workplaces	(6) residential
lg_info	-1.011***	-0.616**	-1.850***	-0.816*	-0.467**	0.332***
	(0.211)	(0.295)	(0.606)	(0.439)	(0.182)	(0.078)
log(cases)_lag1	-1.337***	-0.164	-0.632	-1.444***	-0.172	0.291***
	(0.257)	(0.165)	(0.441)	(0.239)	(0.139)	(0.081)
log(cases)_lag2	-0.129	0.088	-0.475	-0.308	-0.264	0.106
	(0.227)	(0.239)	(0.615)	(0.377)	(0.169)	(0.076)
log(cases)_lag3	0.395**	0.166	0.844*	0.499*	-0.163	-0.039
	(0.198)	(0.13)	(0.492)	(0.266)	(0.21)	(0.073)
log(deaths)_lag1	-0.011	0.064	0.559	0.012	-0.015	-0.026
	(0.142)	(0.104)	(0.412)	(0.275)	(0.099)	(0.025)
log(deaths)_lag2	-0.266**	-0.229**	-1.472**	-0.287	-0.09	0.081**
	(0.111)	(0.107)	(0.65)	(0.177)	(0.121)	(0.039)
log(deaths)_lag3	0.145	-0.005	0.739*	0.132	0.174**	-0.051
	(0.139)	(0.134)	(0.428)	(0.168)	(0.085)	(0.032)
vaccination_lag1	-11.973**	3.847	-5.797	-14.753	6.089**	-1.801***
	(5.821)	(2.832)	(11.784)	(11.381)	(2.986)	(0.453)
SOE	-0.216***	0.017	0.047	-0.074**	-0.121***	0.080***
	(0.058)	(0.016)	(0.104)	(0.029)	(0.03)	(0.02)
QSOE	-0.053	-0.012	0.013	-0.081	0.000	0.022*
	(0.036)	(0.023)	(0.067)	(0.052)	(0.024)	(0.011)
hot_ice_days	0.018	0.036	-0.504	-0.097	-0.058*	0.004
	(0.122)	(0.053)	(0.473)	(0.123)	(0.033)	(0.027)
precipitation	-0.012***	-0.013***	-0.062***	-0.017***	-0.006*	0.005***
	(0.003)	(0.002)	(0.012)	(0.004)	(0.003)	(0.001)
mobility_lag1	0.547***	0.719***	0.678***	0.564***	0.477***	0.557***
	(0.058)	(0.05)	(0.031)	(0.042)	(0.092)	(0.074)
Observations	1190	1190	1190	1190	1190	1190
R^2	0.619	0.607	0.643	0.505	0.380	0.638

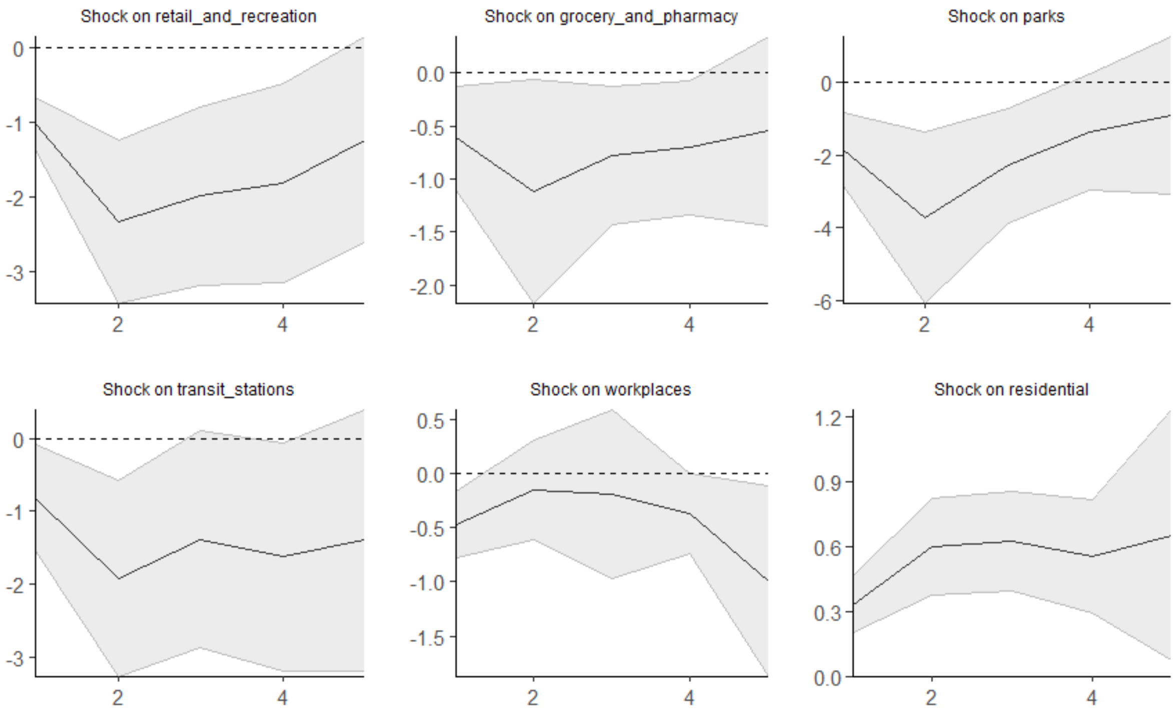
Note: Heteroscedasticity-consistent robust standard errors in parentheses. Asterisks denote statistical significance: *p<0.1;**p<0.05;***p<0.01.

Figure E.2: IRFs of the rate of change in the level mobility to an increase in the local governor's index ($P = 2$)



Note: The solid lines correspond to the point estimate and the shaded areas correspond to the 90% confidence interval.

Figure E.3: IRFs of the rate of change in the level mobility to an increase in the local governor's index ($P = 3$)



Note: The solid lines correspond to the point estimate and the shaded areas correspond to the 90% confidence interval.

The results of the one-week-ahead model, as presented in Tables E.2 and E.3, are consistent with those in section III, even when the lag order is set to $P = 2, 3$. In both cases, the local governor's index had a significant effect on mobility suppression. The results for the other variables are similar to those in section III.

The coefficient of the number of new cases with a lag order of P=3, as shown in Table E.3, was contrary to the results in section III in three areas: retail and recreation, parks, and transit stations. The analysis indicated that an increase in the number of new cases with a lag order of $P = 1$ significantly suppressed mobility. However, an increase in the number of new cases three weeks ago may have created the impression that the number of new cases was relatively low compared to three weeks ago, even if the number of new cases in the subsequent two weeks was high. Therefore, it is possible that the increase in the number of new cases three weeks prior appears to increase mobility.

The impulse response analysis shown in Figures E.2 and E.3 confirms the impact of mobility suppression, even when the maximum lag order is $P = 2,3$, which is consistent with the findings in section III.

F. Robustness on the analysis of the time-varying effects of information dissemination

As in the robustness checks conducted for the benchmark model in section III, we examine the robustness of the analysis of time-varying effects of information dissemination in section IV from two perspectives.

Robustness checks on handling of NAs

Examining the estimation results of the one-week-ahead models, it was found that in the model for the early pandemic period, the local governor's index, with NAs filled in, had a significant effect on suppressing mobility in almost all categories of places. However, in the period after the Delta-variant outbreak, no significant effects were observed. The main results for the other variables are similar to the estimation results in section IV. In addition, the impulse response analysis presented in Figure F.1 adheres to a conventional structure and suggests that mobility was suppressed more in the early stages of the pandemic. In summary, the primary conclusions drawn from these analyses were nearly identical to those outlined in section IV.

Table F.1: Estimation results for one-week ahead model with NAs imputed with 0 in the early pandemic period

	Google COVID-19 Community Mobility Reports					
	(1) retail_and_recreation	(2) grocery_and_pharmacy	(3) parks	(4) transit_stations	(5) workplaces	(6) residential
lg_info (filled)	-1.571***	-1.08***	-3.52***	-0.921	-0.788***	0.435***
	(0.433)	(0.346)	(0.794)	(0.702)	(0.288)	(0.166)
log(cases)_lag1	-0.949***	-0.245***	-0.992***	-0.987***	-0.323***	0.264***
	(0.131)	(0.091)	(0.131)	(0.164)	(0.082)	(0.044)
log(deaths)_lag1	0.153	-0.051	0.455*	-0.172	-0.039	-0.019
	(0.152)	(0.1)	(0.236)	(0.235)	(0.14)	(0.045)
vaccination_lag1	-0.636	-18.59	-6.499	-72.988***	-27.731	7.816*
	(14.975)	(15.667)	(45.242)	(18.817)	(17.896)	(4.236)
SOE	-0.194***	0.037	-0.053	-0.133***	-0.157***	0.088***
	(0.037)	(0.024)	(0.115)	(0.037)	(0.021)	(0.014)
QSOE	0.047	0.111***	0.153	0.028	0	0.021*
	(0.033)	(0.029)	(0.098)	(0.062)	(0.03)	(0.011)
hot_ice_days	0.024	-0.055	-0.604	-0.039	-0.032	-0.001
	(0.11)	(0.125)	(0.593)	(0.129)	(0.046)	(0.04)
precipitation	-0.009***	-0.01***	-0.054***	-0.013***	-0.004**	0.004***
	(0.002)	(0.002)	(0.013)	(0.002)	(0.002)	(0.001)
mobility_lag1	0.629***	0.486***	0.631***	0.596***	0.525***	0.584***
	(0.035)	(0.069)	(0.045)	(0.044)	(0.056)	(0.046)
Observations	1116	1116	1116	1116	1116	1116
R^2	0.616	0.387	0.535	0.495	0.431	0.609

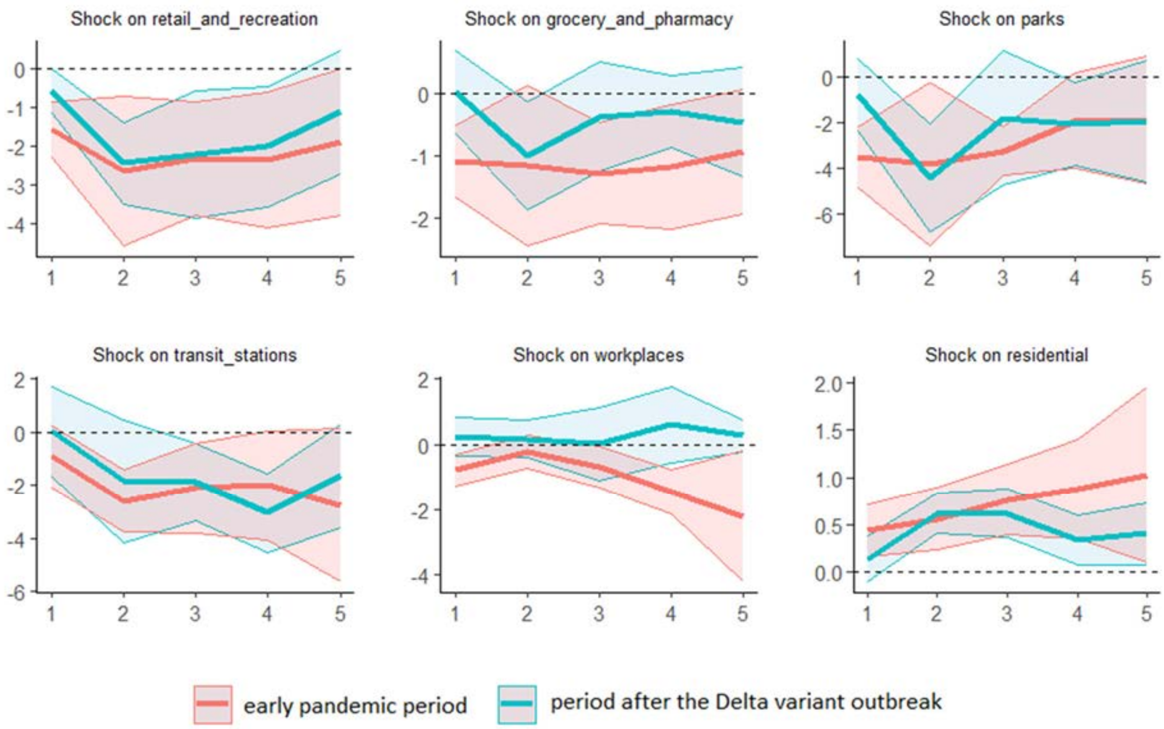
Note: Heteroscedasticity-consistent robust standard errors in parentheses. Asterisks denote statistical significance: *p<0.1;**p<0.05;***p<0.01.

Table F.2: Estimation results for one-week ahead model with NAs imputed with 0 in the period after the Delta variant outbreak

	Google COVID-19 Community Mobility Reports					
	(1) retail_and_recreation	(2) grocery_and_pharmacy	(3) parks	(4) transit_stations	(5) workplaces	(6) residential
lg_info (filled)	-0.554	0.018	-0.83	0.021	0.236	0.138
	(0.341)	(0.401)	(0.946)	(1.011)	(0.356)	(0.146)
log(cases)_lag1	-0.615***	0.126*	0.496	-0.644***	-0.238***	0.231***
	(0.114)	(0.068)	(0.339)	(0.19)	(0.079)	(0.05)
log(deaths)_lag1	-0.097	-0.032	-0.241	-0.009	-0.152***	0.091***
	(0.139)	(0.108)	(0.387)	(0.232)	(0.057)	(0.021)
vaccination_lag1	3.757	2.552	-1.896	13.405	9.602***	-2.911***
	(7.335)	(5.247)	(14.86)	(8.83)	(2.921)	(1.018)
SOE	-0.304**	0.07	0.083	-0.132	-0.08*	0.086**
	(0.136)	(0.055)	(0.172)	(0.167)	(0.042)	(0.034)
QSOE	-0.132**	-0.011	0.033	-0.102	-0.058	0.028
	(0.058)	(0.034)	(0.123)	(0.093)	(0.038)	(0.019)
hot_ice_days	-0.107	0.008	-0.446*	-0.268	-0.091	0.026
	(0.15)	(0.054)	(0.268)	(0.187)	(0.058)	(0.025)
precipitation	-0.013***	-0.01***	-0.051***	-0.019***	-0.005	0.005***
	(0.003)	(0.002)	(0.008)	(0.005)	(0.003)	(0.001)
mobility_lag1	0.444***	0.73***	0.727***	0.477***	0.234***	0.458***
	(0.049)	(0.054)	(0.063)	(0.047)	(0.062)	(0.08)
Observations	1188	1188	1188	1188	1188	1188
R^2	0.355	0.569	0.621	0.282	0.129	0.490

Note: Heteroscedasticity-consistent robust standard errors in parentheses. Asterisks denote statistical significance: *p<0.1;**p<0.05;***p<0.01.

Figure F.1: IRFs of the rate of change in the level mobility to an increase in the local governor's index with NAs imputed with 0



Note: The solid lines correspond to the point estimate and the shaded areas correspond to the 90% confidence interval.

Robustness on lag order

Examining the estimation results of the one-week-ahead models with maximum lag order $P = 2,3$, a significant effect of the local governor's index in suppressing mobility was confirmed in the model for the early pandemic period in all categories of places. However, no significant effect was observed in the period after the Delta-variant outbreak. The main results for the other variables are similar to the estimation results in section IV. Furthermore, the impulse response analysis depicted in Figures E.2 and E.3 indicated that mobility was significantly suppressed during the early pandemic period. In summary, the primary findings of these analyses are nearly identical to those presented in section IV.

Table F.3: Estimation results for one-week ahead model $(P = 2)$ in the early pandemic period

	Google COVID-19 Community Mobility Reports					
	(1) retail_and_recreation	(2) grocery_and_pharmacy	(3) parks	(4) transit_stations	(5) workplaces	(6) residential
lg_info	-1.499***	-1.041***	-3.201***	-1.619**	-1.224**	0.57***
	(0.443)	(0.289)	(0.724)	(0.786)	(0.49)	(0.201)
log(cases)_lag1	-1.328***	-0.396**	-0.887	-1.353***	-0.22	0.271***
	(0.314)	(0.194)	(0.79)	(0.199)	(0.14)	(0.102)
log(cases)_lag2	0.202	0.075	-0.379	0.237	-0.274*	0.05
	(0.279)	(0.182)	(0.901)	(0.356)	(0.156)	(0.062)
log(deaths)_lag1	0.124	0.112	1.359**	0.261	-0.036	-0.086
	(0.204)	(0.147)	(0.637)	(0.253)	(0.152)	(0.059)
log(deaths)_lag2	-0.055	-0.365**	-1.138	-0.57***	0.019	0.024
	(0.172)	(0.147)	(0.822)	(0.184)	(0.221)	(0.081)
vaccination_lag1	-29.845	-15.917	-80.376	-74.112**	-45.961	23.426**
	(27.564)	(22.357)	(118.228)	(36.748)	(29.543)	(9.925)
SOE	-0.2***	0.042	0.023	-0.081	-0.167***	0.09***
	(0.044)	(0.038)	(0.14)	(0.071)	(0.045)	(0.021)
QSOE	0.008	0.126***	0.101	0.076	0.042	0.019
	(0.037)	(0.026)	(0.134)	(0.071)	(0.042)	(0.016)
hot_ice_days	-0.035	-0.12	-1.09	-0.055	-0.071	0.013
	(0.134)	(0.146)	(0.86)	(0.177)	(0.054)	(0.043)
precipitation	-0.01***	-0.011***	-0.061***	-0.011***	-0.006***	0.005***
	(0.003)	(0.002)	(0.016)	(0.003)	(0.002)	(0.001)
mobility_lag1	0.581***	0.457***	0.591***	0.622***	0.527***	0.603***
	(0.047)	(0.08)	(0.035)	(0.052)	(0.069)	(0.058)
Observations	608	608	608	608	608	608
R^2	0.667	0.431	0.553	0.602	0.456	0.642

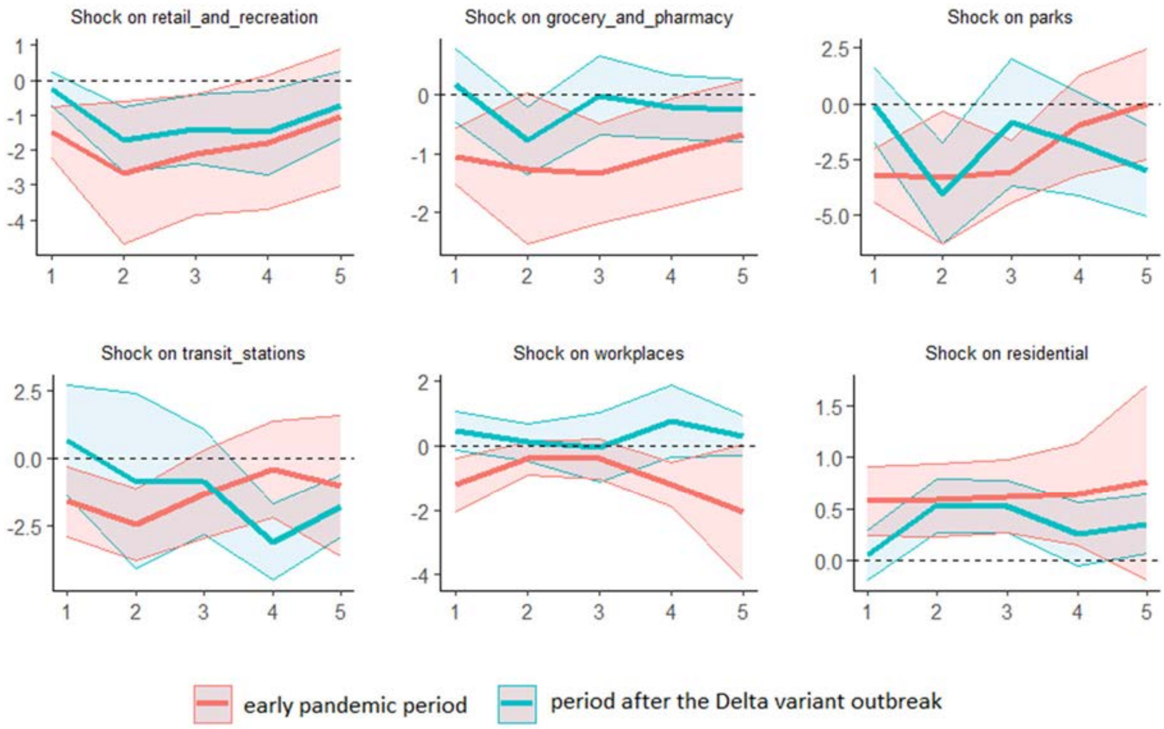
Note: Heteroscedasticity-consistent robust standard errors in parentheses. Asterisks denote statistical significance: *p<0.1;**p<0.05;***p<0.01.

Table F.4: Estimation results for one-week ahead model $(P = 2)$in the period after the Delta variant outbreak

	Google COVID-19 Community Mobility Reports					
	(1) retail_and_recreation	(2) grocery_and_pharmacy	(3) parks	(4) transit_stations	(5) workplaces	(6) residential
lg_info	-0.253	0.167	-0.079	0.644	0.443	0.048
	(0.274)	(0.375)	(1.005)	(1.234)	(0.363)	(0.149)
log(cases)_lag1	-1.22***	-0.156	-0.477	-1.493***	0.451	0.133
	(0.29)	(0.212)	(0.73)	(0.576)	(0.325)	(0.135)
log(cases)_lag2	0.175	0.258	0.438	-0.072	-0.937***	0.229
	(0.3)	(0.281)	(0.548)	(0.41)	(0.311)	(0.141)
log(deaths)_lag1	-0.045	-0.053	0.209	-0.096	-0.1	0.047
	(0.147)	(0.136)	(0.376)	(0.36)	(0.065)	(0.032)
log(deaths)_lag2	-0.353**	-0.068	-1.119**	0.136	0.038	0.083**
	(0.175)	(0.202)	(0.523)	(0.29)	(0.096)	(0.041)
vaccination_lag1	-0.618	1.056	4.197	6.243	10.305**	-3.174
	(9.769)	(8.004)	(15.433)	(12.425)	(4.151)	(2.206)
SOE	-0.399**	0.037	-0.061	-0.209	-0.022	0.092**
	(0.165)	(0.071)	(0.162)	(0.219)	(0.049)	(0.045)
QSOE	-0.173***	-0.051	-0.134	-0.206	-0.058	0.038
	(0.06)	(0.053)	(0.119)	(0.13)	(0.061)	(0.028)
hot_ice_days	-0.029	0.108***	-0.126	-0.119	-0.128*	0.027
	(0.157)	(0.033)	(0.213)	(0.173)	(0.071)	(0.025)
precipitation	-0.015***	-0.014***	-0.064***	-0.024***	-0.008*	0.006***
	(0.004)	(0.002)	(0.012)	(0.007)	(0.004)	(0.001)
mobility_lag1	0.4***	0.703***	0.711***	0.452***	0.216***	0.411***
	(0.072)	(0.058)	(0.05)	(0.048)	(0.076)	(0.098)
Observations	574	574	574	574	574	574
R^2	0.467	0.571	0.693	0.382	0.164	0.533

Note: Heteroscedasticity-consistent robust standard errors in parentheses. Asterisks denote statistical significance: *p<0.1;**p<0.05;***p<0.01.

Fig. F.2: IRFs of the rate of change in the level mobility to an increase in the local governor's index ($P = 2$)



Note: The solid lines correspond to the point estimate and the shaded areas correspond to the 90% confidence interval.

Table F.5: Estimation results for one-week ahead model ($P = 3$) in the early pandemic period

	Google COVID-19 Community Mobility Reports					
	(1) retail_and_recreation	(2) grocery_and_pharmacy	(3) parks	(4) transit_stations	(5) workplaces	(6) residential
lg_info	-1.505***	-1.04***	-3.07***	-1.587**	-1.224**	0.556***
	(0.425)	(0.291)	(0.628)	(0.74)	(0.504)	(0.192)
log(cases)_lag1	-1.265***	-0.377*	-1.032	-1.409***	-0.308***	0.32***
	(0.313)	(0.199)	(0.864)	(0.247)	(0.113)	(0.086)
log(cases)_lag2	-0.1	0.041	-0.962	0.141	0.023	0.027
	(0.281)	(0.256)	(1.13)	(0.483)	(0.197)	(0.094)
log(cases)_lag3	0.365	0.033	0.943	0.279	-0.235	-0.034
	(0.288)	(0.165)	(0.852)	(0.349)	(0.265)	(0.076)
log(deaths)_lag1	-0.037	0.115	1.126**	0.054	-0.092	-0.057
	(0.222)	(0.161)	(0.568)	(0.235)	(0.176)	(0.061)
log(deaths)_lag2	-0.273*	-0.339***	-1.625*	-0.987***	-0.124	0.096
	(0.149)	(0.115)	(0.91)	(0.281)	(0.213)	(0.068)
log(deaths)_lag3	0.345	-0.045	0.802	0.817**	0.405***	-0.151***
	(0.242)	(0.14)	(0.674)	(0.349)	(0.156)	(0.038)
vaccination_lag1	-31.717	-18.242	-79.527	-69.861*	-47.251	23.877**
	(29.569)	(23.203)	(119.516)	(36.337)	(33.241)	(10.987)
SOE	-0.211***	0.041	0.023	-0.08	-0.166***	0.089***
	(0.046)	(0.039)	(0.139)	(0.07)	(0.04)	(0.02)
QSOE	0.001	0.125***	0.09	0.069	0.038	0.021
	(0.034)	(0.026)	(0.129)	(0.072)	(0.042)	(0.015)
hot_ice_days	-0.029	-0.116	-1.06	-0.053	-0.077	0.011
	(0.142)	(0.144)	(0.855)	(0.178)	(0.05)	(0.042)
precipitation	-0.011***	-0.012***	-0.06***	-0.012***	-0.008***	0.006***
	(0.003)	(0.002)	(0.017)	(0.003)	(0.003)	(0.001)
mobility_lag1	0.567***	0.454***	0.593***	0.628***	0.537***	0.606***
	(0.05)	(0.079)	(0.036)	(0.056)	(0.078)	(0.056)
Observations	600	600	600	600	600	600
R^2	0.674	0.432	0.554	0.612	0.479	0.658

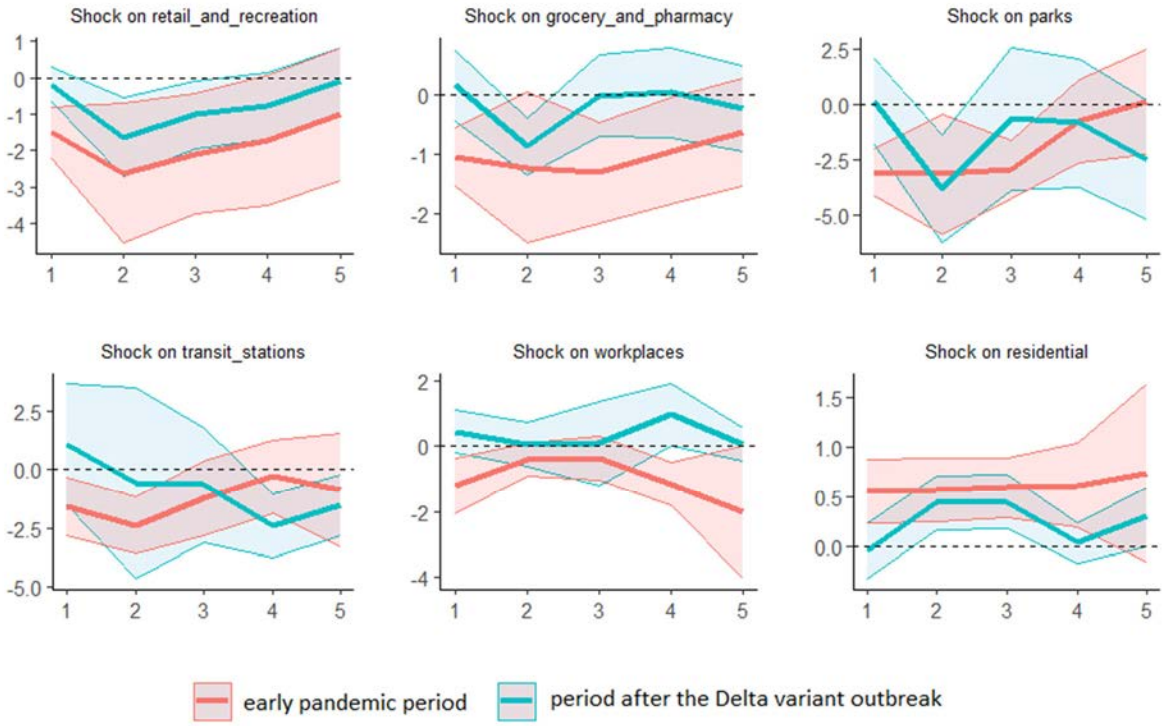
Note: Heteroscedasticity-consistent robust standard errors in parentheses. Asterisks denote statistical significance: *p<0.1;**p<0.05;***p<0.01.

Table F.6: Estimation results for one-week ahead model $(P = 3)$ in the period after the Delta variant outbreak

	Google COVID-19 Community Mobility Reports					
	(1) retail_and_recreation	(2) grocery_and_pharmacy	(3) parks	(4) transit_stations	(5) workplaces	(6) residential
lg_info	-0.186	0.153	0.132	1.092	0.448	-0.046
	(0.281)	(0.356)	(1.173)	(1.547)	(0.396)	(0.17)
log(cases)_lag1	-1.217***	-0.154	-0.491	-1.38***	0.386	0.159
	(0.28)	(0.207)	(0.736)	(0.506)	(0.303)	(0.131)
log(cases)_lag2	-0.338	-0.075	0.174	-0.928*	-0.662**	0.26**
	(0.339)	(0.32)	(0.89)	(0.558)	(0.278)	(0.131)
log(cases)_lag3	0.561**	0.349*	0.279	0.997**	-0.303*	-0.045
	(0.257)	(0.199)	(0.681)	(0.429)	(0.177)	(0.081)
log(deaths)_lag1	0.01	0.031	0.357	0.143	-0.087	0.008
	(0.14)	(0.138)	(0.377)	(0.414)	(0.066)	(0.046)
log(deaths)_lag2	-0.302*	0.015	-1.256**	0.535	0.018	0.043
	(0.164)	(0.168)	(0.635)	(0.364)	(0.104)	(0.042)
log(deaths)_lag3	0.002	-0.114	0.298	-0.687**	0.074	0.047
	(0.177)	(0.171)	(0.54)	(0.329)	(0.09)	(0.04)
vaccination_lag1	2.849	5.628	10.355	7.941	11.693**	-4.145*
	(8.561)	(7.268)	(13.674)	(11.01)	(4.687)	(2.187)
SOE	-0.324**	0.08	0.077	-0.091	0.003	0.059**
	(0.143)	(0.054)	(0.141)	(0.164)	(0.051)	(0.03)
QSOE	-0.173***	-0.06	-0.116	-0.16	-0.058	0.029
	(0.059)	(0.053)	(0.118)	(0.127)	(0.063)	(0.027)
hot_ice_days	-0.094	0.044	-0.266	-0.211	-0.147**	0.048**
	(0.133)	(0.031)	(0.229)	(0.154)	(0.067)	(0.019)
precipitation	-0.014***	-0.013***	-0.062***	-0.023***	-0.007**	0.006***
	(0.004)	(0.002)	(0.012)	(0.006)	(0.004)	(0.001)
mobility_lag1	0.405***	0.693***	0.706***	0.457***	0.206***	0.427***
	(0.073)	(0.055)	(0.049)	(0.05)	(0.076)	(0.087)
Observations	560	560	560	560	560	560
R^2	0.461	0.573	0.693	0.386	0.164	0.532

Note: Heteroscedasticity-consistent robust standard errors in parentheses. Asterisks denote statistical significance: *p<0.1;**p<0.05;***p<0.01.

Figure F.3: IRFs of the rate of change in the level mobility to an increase in the local governor's index $(P = 3)$



Note: The solid lines correspond to the point estimate and the shaded areas correspond to the 90% confidence interval.

G. Source of text data for each prefecture used to calculate the local governor's index[19)]

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[19)] All sources are in Japanese (Accessed: January 31, 2024).