# Exploring the dynamic relationship between mobility and the spread of COVID-19, and the role of vaccines

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# Motivation

This study aims to:

1. Analyze the dynamic relationship between mobility and the rate of change in the number of new infections (NNIs) in Japan.
2. Evaluate the effects of various policies, such as mobility control and vaccination, as well as the impact of climate factors on the NNIs.

Models are estimated based on 72 weekly panel data from July 5th, 2020 to November 14th, 2021 for 20 Japanese prefectures.

- Daily data are compiled for a period of one week from Sunday to Saturday prior to the model estimation.
- 20 Japanese prefectures: Hokkaido, Miyagi, Ibaraki, Tochigi, Saitama, Chiba, Tokyo, Kanagawa, Gifu, Shizuoka, Aichi, Mie, Shiga, Kyoto, Osaka, Hyogo, Nara, Hiroshima, Fukuoka, and Okinawa.

# Findings

The analysis reveals:

1. A strong positive relationship between the growth rate of the NNIs and mobility.
2. Governmental policy of regulating mobility shows a weaker effect on preventing the spread of infection, as the emergency declaration is repeatedly invoked.
3. By contrast, the recent increase in the infection rate seems to reduce the spread of infection by inducing voluntary restraint, and this phenomenon has become even stronger in the recent period.
4. Regarding the effect of vaccination, the results demonstrate little effect on attenuating the spread of infection by reducing the susceptible population. However, it has significantly weakened the mobility–spread relationship, suggesting that it may help in the implementation of economic revitalization policies.

# Literature Review

1. Studies on COVID-19's impact on the economy and mobility
   - Eichenbaum, Rebelo, and Trabandt (2021) combined the SIR model with a macroeconomic model to analyze the relationship between economic choices and infectious diseases
2. Examined the effects of mobility control policies
   - Allcott, Boxwell, Conway, Ferguson, Gentzkow, and Goldman (2020) suggested that although the mobility control policy suppressed the flow of people, the degree of suppression was smaller compared with voluntary suppression
   - Mendolia, Stavrunova, and Yerokhin (2021) reported that although the spread of infection tended to suppress mobility voluntarily, the effect of mobility suppression policies was more substantial

3. Examined the relationship between mobility and the NNIs
    - Based on the SIR model, Wilson (2021) examined the dynamic relationship between mobility and the rate of change in the NNIs. The results showed that a 1% increase in mobility at various locations may increase the NNIs by 0.5% to 2% and that an increase in the cumulative NNIs may significantly suppress the NNIs through the herd immunity effect.

# Model

1. The SIR model divides the population into three groups according to the stage of infection—susceptible, infected, and recovered—and models the change in the state of infection over time.
2. This study follows Wilson (2021) and considers a discrete SIR model for the evolution of the NNIs at time $t$, $I_t$, as shown in the following equation:

$$\Delta I_{t+1} = \left( \beta_t \frac{S_t}{N} - \gamma \right) I_t = (\beta_t s_t - \gamma) I_t \tag{1}$$

where $\beta_t$ is the infection rate per unit time, $S_t$ is the susceptible population, $N$ is the total population, and $\gamma$ is the removal rate by recovery or isolation per unit time.

3. For the unit time, a seven-day week from Sunday to Saturday is used, reflecting a significant weekly effect in the number of daily new positive cases.
4. Moreover, similar to Wilson (2021), we set $\gamma = 1$, which implies that the infection will be discovered and recovered or isolated within seven days of infection.
5. Under this assumption, Eq.(1) is rewritten as:

$$I_{t+1} = I_t \beta_t s_t. \tag{2}$$

6. By iteratively substituting Eq.(2) forward, the NNI at time $t + h$ is expressed as:

$$I_{t+h} = (\beta_{t+h-1} s_{t+h-1}) \cdots (\beta_{t+1} s_{t+1})(\beta_t s_t) I_t.$$

7. Taking the natural logarithm of both sides and collecting similar terms, we obtain:

$$\log I_{t+h} - \log I_t = \underbrace{\log \prod_{\tau=0}^{h-1} \beta_{t+\tau}}_{\text{infection rate factor}} + \underbrace{\sum_{\tau=0}^{h-1} \log s_{t+\tau}}_{\text{susceptible pop. factor}} . \tag{3}$$

8. Infection rate factor from $t$ to $t + h - 1$ collectively consists of multiple factors identified in previous studies.
    - We consider: (a) mobility $m_{it}$, (b) weather $w_{it}$, (c) governmental regulations, and (d) voluntary restraint.
    - Watanabe and Yabu (2021) calls factor (c) the "intervention effect" and factor (d) "fear effect."
    - Among other various (c), we focuses on the effect of a declaration of an SOE.
    - Assume that a rational individuals will take precautionary action based on the available information, even if the government does not restrict them.
    - The deterrent effect of an SOE with that of self-restraint are compared.
    - Also examine whether the deterrent effect diminishes as the situation becomes more protracted.

9. Susceptible population factor are formulated, as in Wilson (2021).
   - If no vaccine exists, the ratio of the susceptible population at $t+\tau$ is:

$$s_{t+\tau} \equiv 1 - \frac{\sum_{j=0}^{t+\tau} I_j}{N} = 1 - c_{t+\tau},$$

   where we assume that:

     1. An infected (tested positive) individual cannot be reinfected, and
     2. Total population of the region is fixed at $N$.

   - Once the vaccine is developed, the ratio is modified as:

$$s_{t+\tau} \equiv \left(1 - \frac{\sum_{j=0}^{t+\tau} I_j}{N}\right)\left(1 - \sigma \frac{\sum_{j=0}^{t+\tau-2} V_j}{N}\right) = (1 - c_{t+\tau})(1 - \sigma \nu_{t+\tau})$$

   where $V_t$ denotes the number of people who have completed two doses of vaccination at $t$.

9. Susceptible population factor (continued)
   - Following previous studies, we further assume:
     1. Vaccine efficacy rate $\sigma$ is 0.895.
     2. It takes two weeks after the second vaccination for the preventive effect to appear.
     3. Once antibodies are obtained, the effect lasts for the duration of the analysis.
     4. Vaccination targets uninfected individuals.
     5. $c_t = c_{t+\tau}, \nu_t = \nu_{t+\tau}$ for $\tau > 0$, as in Wilson (2021)
   - Susceptive population factor is rewritten as:

$$\sum_{\tau=0}^{h-1} \log s_{t+\tau} = \underbrace{h \log(1 - c_t)}_{\tilde{c}_t^h} + \underbrace{h \log(1 - \sigma \nu_t)}_{\tilde{\nu}_t^h} \qquad (4)$$

However, Eq.(4) is an approximation since in reality:

1. Target of vaccination includes those who have been previously infected,
2. Vaccine efficacy rates may change with the emergence of new variants, and
3. Antibodies may decrease and resistance may decline as time passes.

10. The regression model that integrates the above is written as:

$$\log I_{i,t+h} - \log I_{it} = \psi^h m_{i,t} + \delta^h w_{i,t} + \phi^h SOE_{it} + \rho^h \Delta \log I_{it} \\ + \rho^{*h} \Delta \log I^*_{it} + \theta^h \tilde{c}^h_{it} + \lambda^h \tilde{\nu}^h_{it} + \kappa^h m_{it} \tilde{\nu}^h_{it} + \alpha^h_t + \alpha^h_i + \epsilon_{i,t,t+h} \tag{5}$$

where $\psi$, $\delta$, $\phi$, $\rho$, $\theta$, $\lambda$, $\kappa$, and $\alpha$ are the regression coefficients.

11. Moreover, to examine if people's behaviors toward compulsory and voluntary suppressions may change over time, the coefficients of $SOE$, $\Delta \log I$, and $\Delta \log I^*$ are allowed to differ between the first and the second subperiods.
    - End of March 2021 is chosen as the point of separation since [1] the SOEs of all the prefectures, including the Tokyo metropolitan area, were once lifted by March 21st, 2021 and [2] it is in the middle of the sample period.

12. Note that Eq.(5) has various devices for causal inference.
    - By specifying the future variation of NNIs by variables at present, Eq.(5) mitigates the problem of simultaneity. Put differently, we can consider that we examine the Granger causality from the various factors to the future infection rate from Eq.(5).
    - Moreover, the presence of a third factor makes it challenging to identify the causal relationship. As a remedy, control variables are added if they are observable. Even if they are not directly observable, the inclusion of both prefecture and weekly time dummies will mitigate the problem of the omitted variable bias.

# Data

1. We estimate Eq.(5) based on 72 weekly panel data from July 5th, 2020 to November 14th, 2021 for 20 Japanese prefectures.
   - Hokkaido, Miyagi, Ibaraki, Tochigi, Saitama, Chiba, Tokyo, Kanagawa, Gifu, Shizuoka, Aichi, Mie, Shiga, Kyoto, Osaka, Hyogo, Nara, Hiroshima, Fukuoka, and Okinawa.
   - Daily data are compiled for a period of one week from Sunday to Saturday prior to the model estimation.

## ❶ Number of new infections $I_{it}$

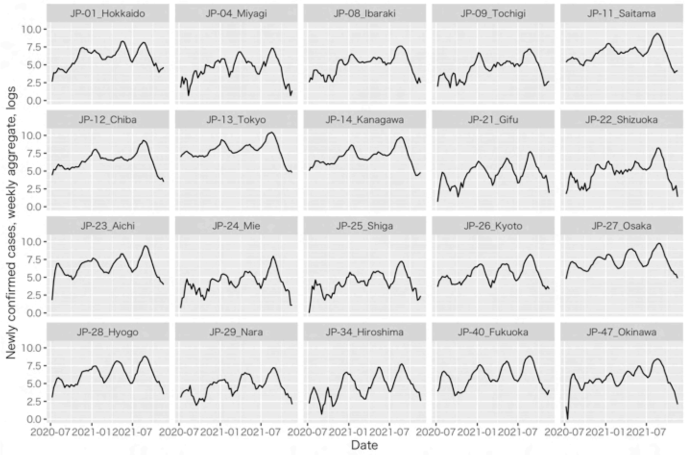



Figure: Number of new infections per week (in logarithm)

2. mobility $m_{it}$
   - To measure prefecture-level mobility, this study uses the indices of Google COVID-19 Community Mobility Reports.
   - This index classifies the places people visit into six categories: retail and recreation, grocery and pharmacy, parks, transit stations, workplaces, and residential.
   - Each of these indices is first converted to a weekly average rate and then logarithmically transformed as:

$$m = \log\left(1 + \frac{\text{average weekly rate of change}(\%)}{100}\right). \tag{6}$$

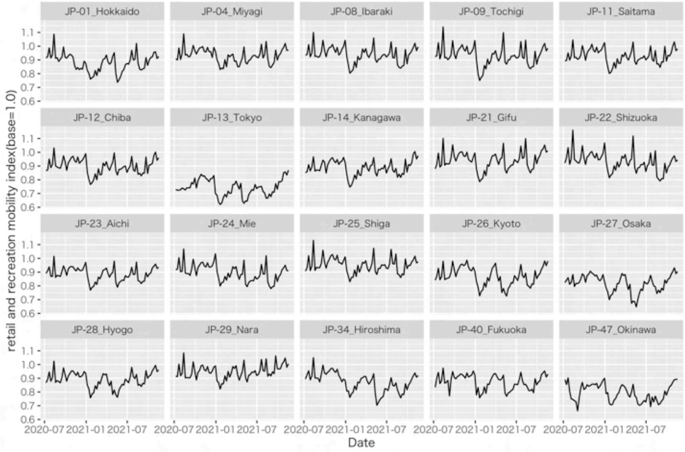



Figure: Retail and recreation mobility index

3. Two weather-related data $w_{it}$
    - Daily maximum temperature and total precipitation, are obtained from the Japan Meteorological Agency (JMA) website.
    - Number of hot summer days and ice days per week: According to the classification by the JMA, a *hot summer day* is defined as a day on which the temperature goes above 30 degree Celsius ($^\circ$C). In comparison, an *ice day* is defined as a day on which the temperature stays below 0 $^\circ$C.
    - Weekly precipitation: Weekly sum of the daily precipitation.

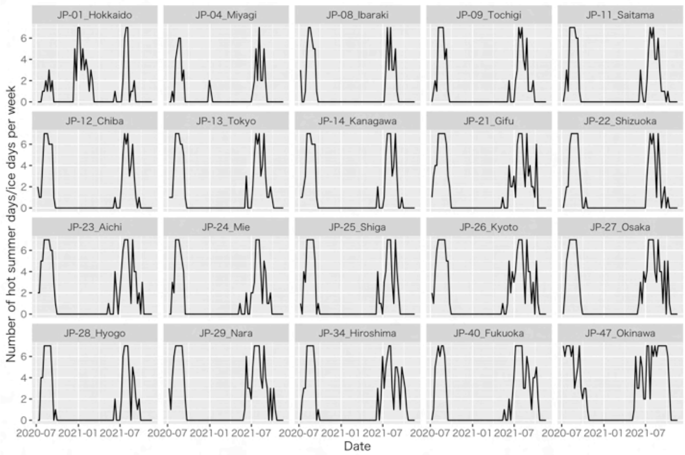



Figure: The number of hot summer days and ice days per week

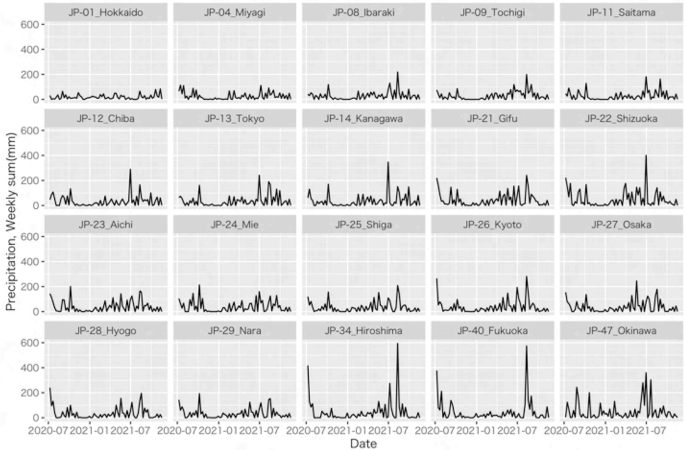



Figure: Weekly sum of the daily precipitation

4. The vaccination rate factor $\tilde{\nu}_t^h$
   - Calculated based on the number of vaccinees from the Government Chief Information Officer's Portal and the population data from the Ministry of Internal Affairs and Communications website.
   - Variables in the regression model is defined as:

$$\tilde{\nu}_{it}^h \equiv h \log(1 - \sigma \nu_{it})$$

where vaccine efficacy rate $\sigma$ is 0.895, and

$$\nu_{it} \equiv \frac{\sum_{j=0}^{t-2} V_{i,j}}{N}$$

and $V_{i,t}$ denotes the number of people who have completed two doses of vaccination at $t$ in Prefecture $i$.

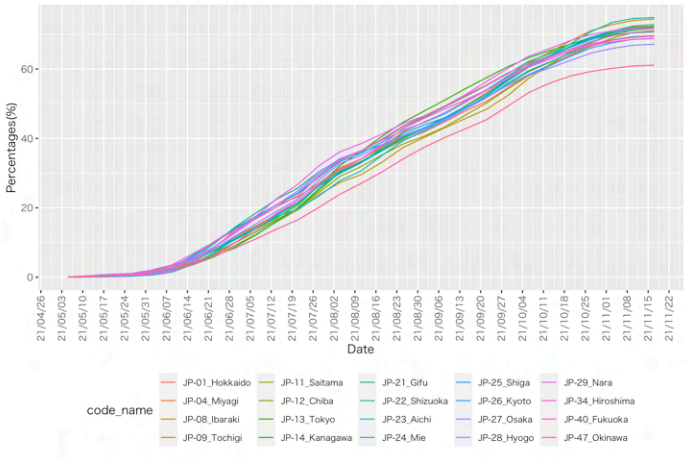



Figure: Percentages of people who completed two vaccination doses

5. The SOE declaration dummy
    - Takes one for weeks when an SOE is declared and zero for other weeks, is created based on the document by the Cabinet Secretariat.

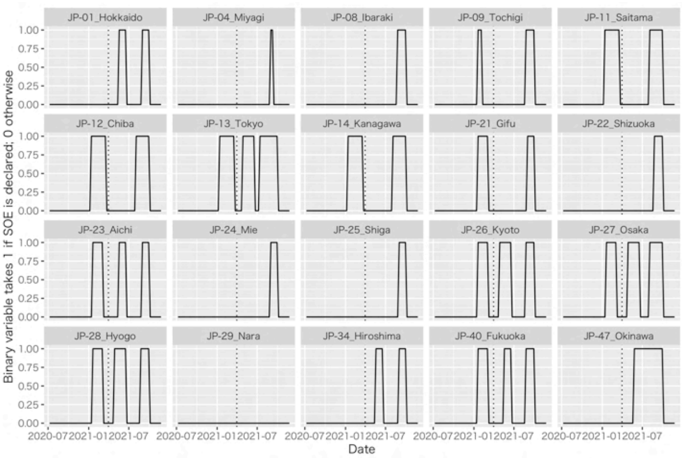

JP-01_Hokkaido
JP-04_Miyagi
JP-08_Ibaraki
JP-09_Tochigi
JP-11_Saitama
JP-12_Chiba
JP-13_Tokyo
JP-14_Kanagawa
JP-21_Gifu
JP-22_Shizuoka
JP-23_Aichi
JP-24_Mie
JP-25_Shiga
JP-26_Kyoto
JP-27_Osaka
JP-28_Hyogo
JP-29_Nara
JP-34_Hiroshima
JP-40_Fukuoka
JP-47_Okinawa
1.00
0.75
0.50
0.25
0.00
Binary variable takes 1 if SOE is declared; 0 otherwise
2020-07
2021-01
2021-07
Date

Figure: SOE

## Table: Descriptive statistics

| Names of the variables | Sample size | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|---|
| $\log I_{t+4} - \log I_t$ | 1,360 | −0.0338 | 1.3752 | −3.5205 | 6.3682 |
| m1 (retail & recreation) | 1,440 | −0.1197 | 0.0920 | −0.4780 | 0.1497 |
| m2 (grocery & pharmacy) | 1,440 | 0.0123 | 0.0481 | −0.1575 | 0.1422 |
| m3 (parks) | 1,368 | −0.1041 | 0.1798 | −0.9092 | 0.5686 |
| m4 (transit stations) | 1,440 | −0.2954 | 0.1190 | −0.7520 | 0.0862 |
| m5 (workplaces) | 1,440 | −0.1549 | 0.1212 | −0.8540 | −0.0101 |
| m6 (residential) | 1,440 | 0.0621 | 0.0282 | 0.0114 | 0.1906 |
| hot summer/ice days | 1,440 | 1.5111 | 2.4409 | 0 | 7 |
| precipitation | 1,440 | 35.8528 | 53.9215 | 0 | 594 |
| *SOE* dummy | 1,440 | 0.1889 | 0.3916 | 0 | 1 |
| $\Delta \log I_t$ | 1,420 | 0.0027 | 0.5202 | −2.1401 | 3.6109 |
| $\Delta \log I_t^*$ | 1,420 | −0.0096 | 0.3172 | −0.7226 | 0.8246 |
| $4 \log(1 - c)$ | 1,440 | −0.0197 | 0.0233 | −0.1375 | 0.0000 |
| $4 \log(1 - \sigma\nu)$ | 1,440 | −0.5542 | 1.0629 | −4.0000 | 0.0000 |

# Estimation

1. Local Projection (LP) method (Jordà, 2005), for $h = 1, \ldots, 5$

$$\log I_{i,t+h} - \log I_{it} = \psi^h m_{i,t} + \delta^h w_{i,t} + \phi^h SOE_{it} + \rho^h \Delta \log I_{it} + \rho^{*h} \Delta \log I^*_{it} + \theta^h \tilde{c}^h_{it} + \lambda^h \tilde{\nu}^h_{it} + \kappa^h m_{it} \tilde{\nu}^h_{it} + \alpha^h_t + \alpha^h_i + \epsilon_{i,t,t+h}$$

   where $\psi$, $\delta$, $\phi$, $\rho$, $\theta$, $\lambda$, $\kappa$, and $\alpha$ are the regression coefficients.
2. Estimated for 6 different mobility indices
3. Estimated by two-way fixed-effect estimator, with time-clustered heteroskedasticity-robust standard errors.

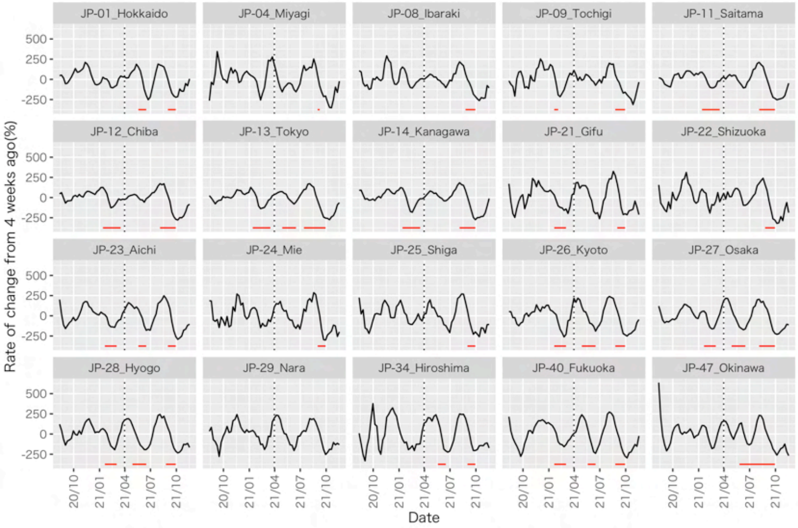



Figure: The rate of change in the NNIs over the previous four weeks (%): $100 \times (\log(I_t) - \log(I_{t-4}))$

## Table: Estimation results of four-week ahead prediction models ($h = 4$)

| | Google COVID-19 Community Mobility Reports | | | | | |
|---|---|---|---|---|---|---|
| | (1) retail & recreation | (2) grocery & pharmacy | (3) parks | (4) transit stations | (5) workplaces | (6) residential |
| mobility | 5.996*** | 4.767*** | 1.547*** | 3.473*** | 2.489 | −26.151*** |
| | (1.031) | (1.628) | (0.278) | (0.534) | (1.607) | (4.830) |
| hot summer/ice days | 0.038* | 0.029 | 0.053** | 0.039* | 0.027 | 0.049** |
| | (0.021) | (0.021) | (0.023) | (0.021) | (0.022) | (0.024) |
| precipitation | 0.001 | 0.00001 | 0.001 | 0.001 | −0.0004 | 0.001* |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| $4 \log(1 - c)$ | 9.511*** | 5.547* | 7.857*** | 6.667** | 3.685 | 2.100 |
| | (3.646) | (2.902) | (3.049) | (2.624) | (4.398) | (4.131) |
| $4 \log(1 - \sigma\nu)$ | −0.251 | −0.753*** | −0.643*** | −0.412 | −0.627 | −0.578 |
| | (0.309) | (0.267) | (0.236) | (0.285) | (0.398) | (0.465) |
| $4 \log(1 - \sigma\nu) \times$ mobility | 0.843* | 1.315* | 0.541** | 0.385 | 0.006 | 0.501 |
| | (0.442) | (0.720) | (0.241) | (0.330) | (1.096) | (2.933) |
| Observations | 1,340 | 1,340 | 1,273 | 1,340 | 1,340 | 1,340 |
| $R^2$ | 0.762 | 0.749 | 0.751 | 0.761 | 0.748 | 0.761 |

## Table: Estimation results of four-week ahead prediction models ($h = 4$)

| | Google COVID-19 Community Mobility Reports | | | | | |
|---|---|---|---|---|---|---|
| | (1) retail & recreation | (2) grocery & pharmacy | (3) parks | (4) transit stations | (5) workplaces | (6) residential |
| SOE(-2021/3) | $-0.143^{*}$ | $-0.508^{***}$ | $-0.541^{***}$ | $-0.362^{***}$ | $-0.448^{***}$ | $-0.190^{**}$ |
| | (0.081) | (0.067) | (0.069) | (0.065) | (0.089) | (0.086) |
| SOE(2021/4-) | 0.148 | $-0.069$ | $-0.048$ | 0.046 | $-0.104$ | 0.083 |
| | (0.099) | (0.089) | (0.087) | (0.098) | (0.098) | (0.114) |
| $\Delta \log I$(-2021/3) | $-0.304^{***}$ | $-0.297^{**}$ | $-0.296^{**}$ | $-0.317^{***}$ | $-0.299^{**}$ | $-0.315^{***}$ |
| | (0.109) | (0.116) | (0.134) | (0.109) | (0.119) | (0.110) |
| $\Delta \log I$(2021/4-) | $-0.342^{**}$ | $-0.345^{**}$ | $-0.447^{**}$ | $-0.309^{**}$ | $-0.356^{**}$ | $-0.343^{**}$ |
| | (0.133) | (0.143) | (0.177) | (0.132) | (0.148) | (0.135) |
| $\Delta \log I^*$(-2021/3) | $-0.041^{**}$ | $-0.056^{***}$ | $-0.051^{***}$ | $-0.044^{***}$ | $-0.056^{***}$ | $-0.045^{***}$ |
| | (0.017) | (0.016) | (0.017) | (0.016) | (0.017) | (0.016) |
| $\Delta \log I^*$(2021/4-) | $-0.056^{*}$ | $-0.070^{**}$ | $-0.075^{**}$ | $-0.063^{**}$ | $-0.068^{**}$ | $-0.066^{**}$ |
| | (0.033) | (0.033) | (0.032) | (0.032) | (0.028) | (0.031) |
| Observations | 1,340 | 1,340 | 1,273 | 1,340 | 1,340 | 1,340 |
| $R^2$ | 0.762 | 0.749 | 0.751 | 0.761 | 0.748 | 0.761 |

# Impulse Response Analysis

1. Impulse response analysis based on the LP method are conducted.

$$\log I_{i,t+h} - \log I_{it} = \psi^h m_{i,t} + \delta^h w_{i,t} + \phi^h SOE_{it} + \rho^h \Delta \log I_{it} + \rho^{*h} \Delta \log I^*_{it} + \theta^h \tilde{c}^h_{it} + \lambda^h \tilde{\nu}^h_{it} + \kappa^h m_{it} \tilde{\nu}^h_{it} + \alpha^h_t + \alpha^h_i + \epsilon_{i,t,t+h}$$

2. IR coefficients of mobility shock

$$\frac{\partial(\log I_{i,t+h} - \log I_{it})}{\partial m_{it}} = \psi^h + \kappa^h \tilde{\nu}^h_{it}$$

3. Size of shock is one standard deviation (1SD)
4. IRF shows the percentage change in the NNIs due to a 1SD increase in mobility over the initially expected level for five weeks after the shock.

# Result-1: Effect of mobility, $\psi^h$ for $h = 1, \ldots, 5$

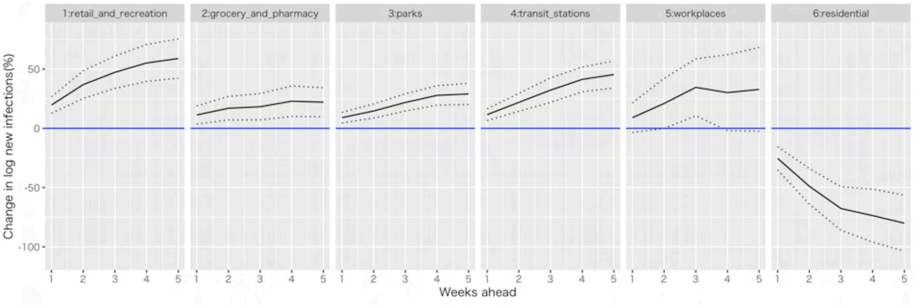



Figure: IRFs of the rate of change in the NNIs to a 1SD increase in mobility without vaccination

Note: The solid lines correspond to the point estimate and the dotted lines correspond to 90% CI.

# Result-2: Effect of hot summer/ice days, $\delta^h$ for $h = 1, \ldots, 5$

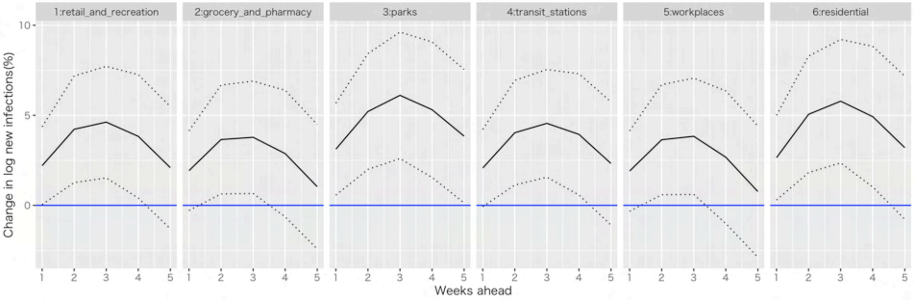



Figure: In response to a one-day increase in the number of hot summer and ice days

# Result-3: Effect of an SOE, $\phi^h$ for $h = 1, \ldots, 5$

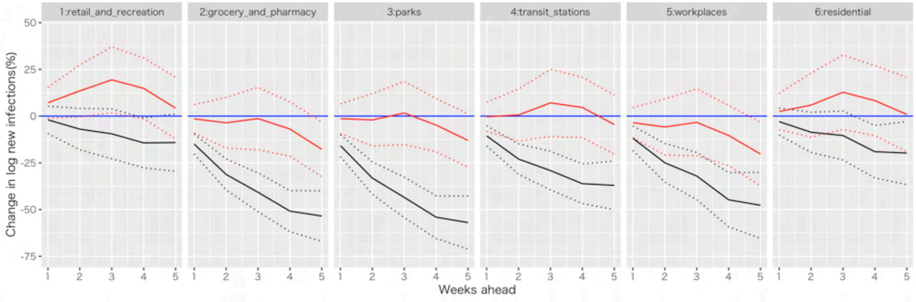



Figure: Declaration of an SOE

Note: Black: 1st subperiod (-2021/3), Red: 2nd subperiod (2021/4-).
Dotted lines correspond to 90% CI.

# Result-4: Effect of self-restraint, $\rho^h$ for $h = 1, \ldots, 5$

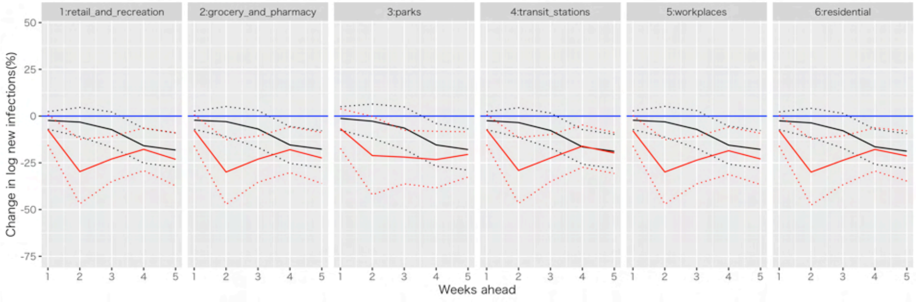



Figure: Self-restraint

Note: Black: 1st subperiod (-2021/3), Red: 2nd subperiod (2021/4-).
Dotted lines correspond to 90% CI.

# Result-5: Effect of vaccination on IRF of mobility

1. Date of evaluation
   - August 1st, 2021 (21.28%)
   - September 12th, 2021 (43.32%)
   - October 24th, 2021 (62.33%)
2. IR coefficients

$$\frac{\partial(\log I_{i,t+h} - \log I_{it})}{\partial m_{it}} = \psi^h + \kappa^h \tilde{\nu}_{it}^h$$

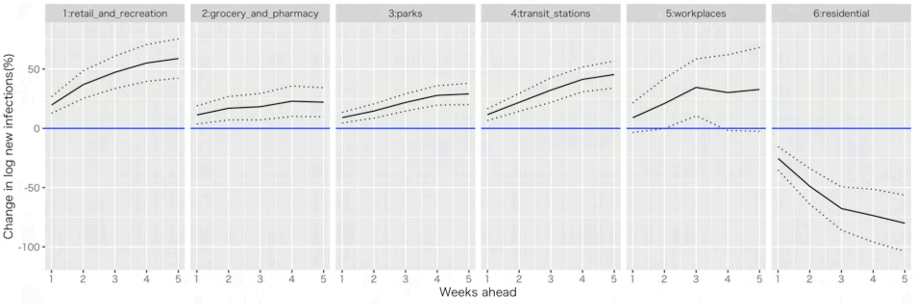



Figure: No vaccination

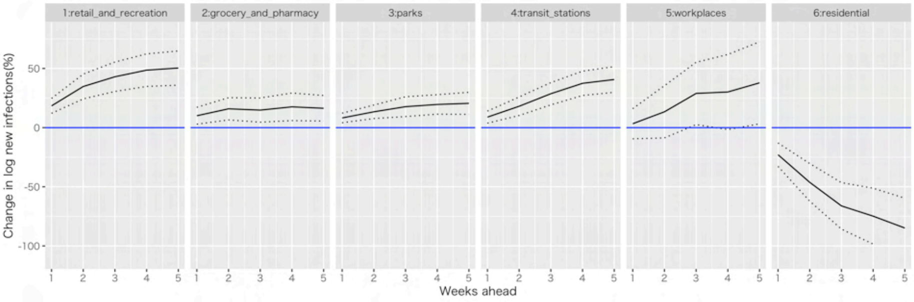



Figure: Week of 2021/8/1, 21.28%

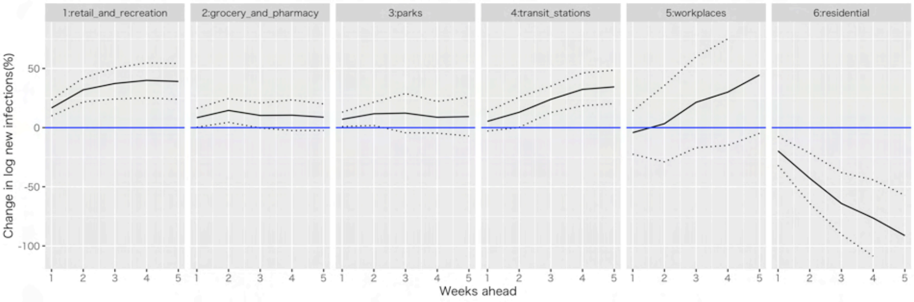



Figure: Week of 2021/9/12, 43.32%

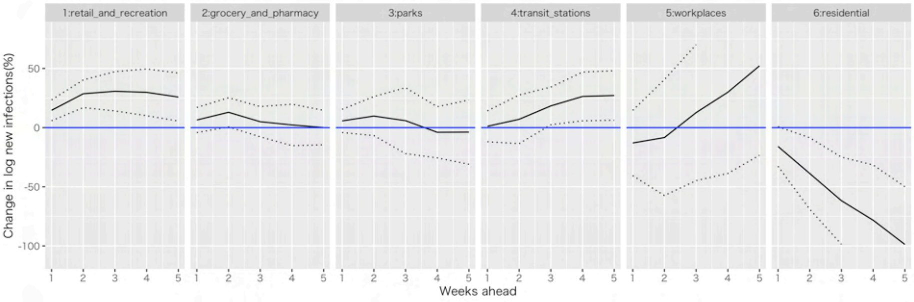
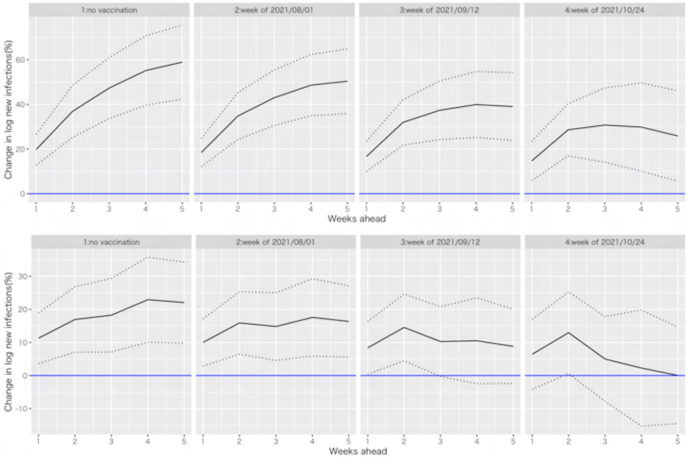
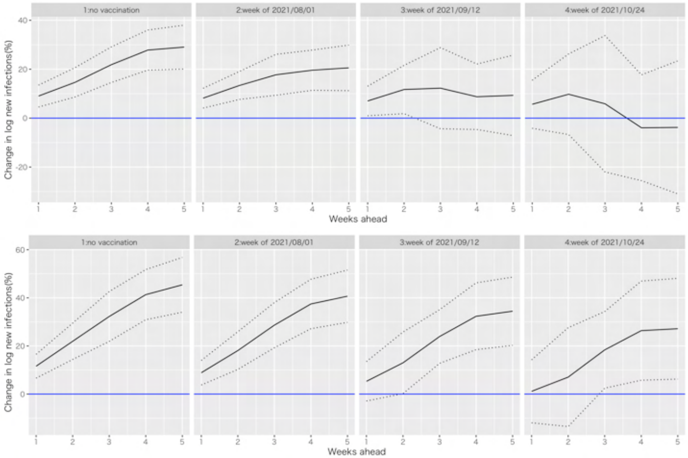


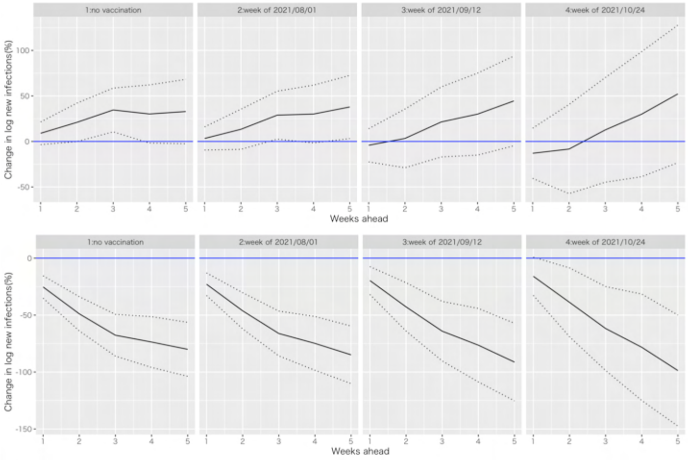

Figure: Week of 2021/10/24, 62.33%




Note: 1SD of the mobility index is 9.20% for retail and recreation, 4.81% for grocery and pharmacies.




Note: 1SD of the mobility index is 17.98% for parks, 11.9% for transit stations.




Note: 1SD of the mobility index is 12.12% for workplaces, and 2.82% for residential.

# Conclusion

1. Based on the SIR model, this study analyzes the dynamic relationship between mobility and the rate of change in the NNIs, the impact of vaccines on this relationship, to examine the effectiveness of the SOE and vaccination in controlling the transmission of COVID-19.
2. Declaration of an SOE had a significant effect in reducing the rate of change in the NNIs only in the early period, and almost disappeared in the recent period. On the other hand, the effect of self-restraint in reducing the spread of infection was observed in both periods. $\rightarrow$ Providing information to rational individual is more effective.
3. Mobility in all locations other than residential significantly increased the rate of change in the NNIs, and residential mobility significantly reduced it, underscoring that staying at home can reduce infection. $\rightarrow$ Effectiveness of promoting remote work and regulating restaurants and businesses.

4. One-day increase in hot summer and ice days per week increases infection by 3%-6% after three weeks. → Proper ventilation and countermeasures to maintain resistance may be effective.
5. Results did not show a significant infection control effect through the reduction of the susceptible population; however, there was a significant reduction in the positive relationship between mobility and the rate of change in the NNIs. In particular, the reduction effect was more significant in retail stores and recreation facilities, grocery stores, pharmacies, and parks. → These results provided a specific basis for economic revitalization policies as the number of vaccinated people increased.

9. Some limitations.
   1. Appropriateness of Google COVID-19 Community Mobility Reports index—as a measure of mobility in each prefecture—is a matter of debate. The index does not distinguish between inter-prefectural travel, and the model does not explicitly consider the possibility of virus transmission from neighboring prefectures.
   2. There is a considerable variation in the time fixed effects that cannot be explained by mobility, weather, or vaccines. This indicates that the emergence of mutant strains and the changes in the nature of the virus play a major role in the increase or decrease of NNIs, suggesting that even if the relationship between mobility and the spread of infection is weakened by the increase in vaccination rates, careful attention must be paid to the emergence of mutant strains.
   3. Data analyzed in this study comprise NNIs. A commonly held view is that mitigating the number of severe illnesses and deaths is more critical when enforcing policies. It is instructive to analyze the relationship between mobility and vaccination rates and the number of severe illnesses and deaths from actual data.

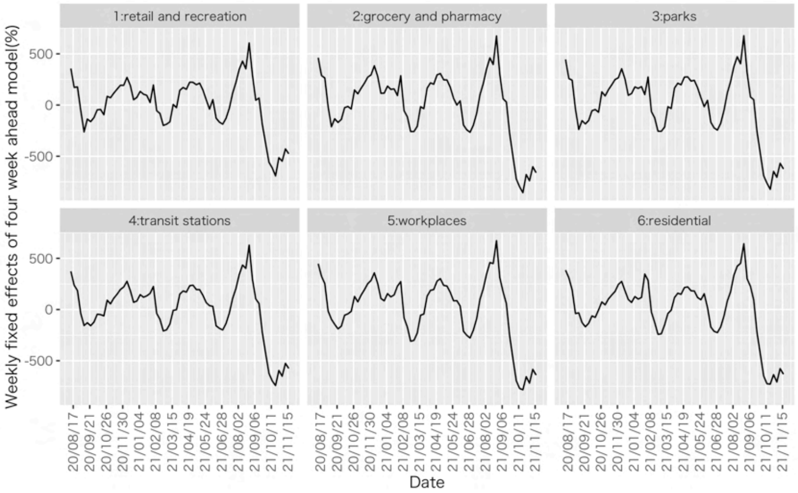



Figure: Estimates of weekly time fixed effect, $\hat{\alpha}_t^4$

Thank you very much for your kind attention.