Refereed Original Paper

Pandemic Fatigue in Japan: A panel data analysis of factors that affect human mobility during the seven waves of the COVID-19 pandemic

Keywords:
Mobility changes, COVID-19 pandemic, mobility restriction policies,vaccination rate

Zhaoyuan LIU, Beijing Center for Japanese Studies, Beijing Foreign Studies University

Abstract

This study aims to elucidate factors that affect mobility change throughout the seven waves of the COVID-19 pandemic in Japan. Specifically, it examines the impact of policy interventions and COVID-19 case numbers on mobility patterns. The study focuses on the effects of the Emergency State Declaration (ESD), the "Pre-emergency measures", and the "Go To Travel" campaign as significant policy factors. Additionally, it explores how vaccination rates influence mobility changes. The author utilized daily data spanning from March 18, 2020, to October 15, 2022, across 47 Japanese prefectures and employed a Feasible Generalized Least Squares (FGLS) model to analyze the panel data for each wave of the pandemic. Three principal findings emerge from this analysis: First, the positive COVID-19 cases negatively influences mobility, and this effect diminishes as the pandemic persists. Second, both the ESD and the "Pre-emergency measures" effectively reduced mobility, whereas the "Go To Travel" campaign significantly promoted mobility. Third, increases in the vaccination rate correlates positively with mobility increases. With previous studies emphasize the importance of restricting mobility to mitigate the pandemic spread, this study presents a contrasting perspective, highlighting that people's behaviors are inherently influenced by the pandemic situation. This interplay between the pandemic and human mobility should be conceptualized as a dynamic, interactive process.

1 Introduction

1.1 Background

The global outbreak of a novel coronavirus, the COVID-19 pandemic, marked 2020. Due to its highly infectious nature, by the end of 2020, over 90 million cases had been confirmed worldwide (Johns Hopkins University, 2020). Since the main transmission route is through person-to-person contact, staying at home and maintaining social distance are important ways to lower the risk of infection. To control the spread of the COVID-19 pandemic, governments in many countries have launched formal (legally imposed) restrictions on personal movements, such as closing borders, publishing “stay at home” orders, banning crowd gathering, and closing non-essential retail units and schools.

In Japan, the first COVID-19 case was confirmed on 16 January 2020. At the initial stage, Prime Minister Shinzo Abe called for a national response to the COVID-19 pandemic on 26 February 2020, suggesting that the nation should re-engage in “jishuku”. The Japanese word “jishuku” is defined as voluntary restraint from fun, luxury, and celebration activities (Ida et al. 2015). Up to 7 April 2020, there were 4478 cumulative positive and 98 death cases. The Japanese government announced an ESD (Emergency State Declaration) on 7 April in seven prefectures (Tokyo, Kanagawa, Saitama, Chiba, Osaka, Hyogo, and Fukuoka) to control the pandemic. On 16 April, the ESD was expanded to all 47 prefectures. On 25 May, the Japanese government lifted the ESD because it seemed the pandemic was under control. Due to subsequent waves of the pandemic, the Japanese government has issued three additional ESD. Furthermore, since April 2021, the Japanese government has also implemented “Pre-emergency measures (まん延防止等重点措置)” to curb the spread of the pandemic. Specific measures include shortened operating hours for dining establishments and voluntary refraining from outings to crowed locations to reduce infection risks. These measures were implemented just before issuing an ESD, defined as a stage requiring responses to prevent a rapid increase in infections and significant disruption to medical services.

The spread of the COVID-19 pandemic has caused severe damage to various industrial and social sectors. Tourism-related industries are among the most notably affected ones. Both the inbound and domestic tourism demand has decreased dramatically. According to the Overnight Travel Statistics Survey conducted by the Japan Tourism Agency (2021), the relative number of hotel guests staying in business hotels, resort hotels, city hotels, and ryokan (a classical Japanese style lodging) from March to June 2020 decreased by 48.9-84.9% compared with the same period in 2019. Meanwhile, inbound tourists to Japan were 32 million in 2019, but the cumulative count by October 2020 was only 4 million (JNTO 2021).

In order to promote the recovery of tourism demand, the Japan Tourism Agency initiated the “Go To Travel” campaign on 22 July 2020. This campaign offered 35% discounts on hotel charges and consumption coupons. By doing so, it aimed to increase tourism and consumer demand, thereby stimulating economic recovery. However, the campaign did not apply to Tokyo residents. Travel to Tokyo was also not included until October 2020 due to the severe pandemic.

1.2 Human mobility

To visualize human mobility changes during the pandemic, Google released "Community Mobility Reports" (CMR) (Google 2020). The data was collected from pceople who access Google's applications using mobile phones or other devices and allow "location history" recording. The data is widely used to study the relationship between mobility and COVID-19 incidence.

This study uses mobility data of "retail and recreation" and "transit station" areas as proxies for mobility in crowded areas. Section 5.1 presents detailed explanations of Google Mobility data used in this study.

1.3 Objectives of this study

The COVID-19 pandemic has lasted for over three years in Japan. As previous studies suggested, when a pandemic outbreak lasts for a long time, people's vigilance gradually slackens and their willingness to take protective measures decreases, which is known as pandemic fatigue. From this perspective, this study investigates how people adjust their mobility according to COVID-19 cases and policy influences throughout the seven waves of the pandemic and reveal whether there was pandemic fatigue in Japan's case. As the specific objectives, firstly, this study aims to reveal the variations in the degree of influences COVID-19 cases have on mobility. Secondly, to reveal how the ESD, "Pre-emergency measures", and the "Go To Travel" Campaign affect mobility. Thirdly, to verify how the vaccination rate affect mobility.

2 Previous studies

Many previous studies evaluated the connection between human mobility and the COVID-19 pandemic. Jung et al. (2021) combined human mobility data, temperature, and risk awareness to predict the reproduction number of COVID-19 in Japan. Kraemer et al. (2020) analyzed the correlation between real-time mobility data from Wuhan and COVID-19 cases. Their result shows that travel restrictions implemented in China were effective, particularly in the early stage of an outbreak. In another highly influential study, Badr et al. (2020) show that mobility patterns strongly correlate with COVID-19 case growth rates for the most affected counties in the United States. Specifically, decreased mobility has a significant positive relationship with reduced case growth. Kurita et al. (2020) applied Apple mobility data to estimate the increase in COVID-19 cases. They concluded that mobility data could explain Japan's pandemic outbreak trend. Therefore, monitoring mobility data is a helpful way to adjust measures to control the pandemic.

Based on the verified fact that human mobility plays a decisive role in the COVID-19 case growth, measures implemented to restrict mobility, such as lockdowns and stay-at-home orders, were also effective in previous studies. Tian et al. (2020) found that measures including suspending intracity public transport, closing entertainment venues, and banning public gatherings were associated with COVID-19 case reductions. The national emergency statement appears to have delayed the growth and limited the influence of the COVID-19 pandemic in China.

Regarding the case of Japan, Inoue and Okimoto (2022) evaluated the relationship between mobility, vaccination, and the number of new infections. Their results show that mobility control measures and the ESD have effectively lower the growth rate of new infections.

Moreover, they found that vaccination suppressed the increase of new infections, but encouraged increases in mobility. Masuhara and Hosoya (2022) investigated how mobility and vaccination affect the trends of COVID-19 Infections in Canada, Germany, Italy, and Japan. Their results also indicated that vaccination increases mobility.

As introduced above, most previous studies used mobility to monitor or forecast COVID-19 cases reproduction. In these studies, the number of COVID-19 cases is used as the dependent variable. However, there was little discussion about how the pandemic affect mobility, in other words, how people adjust their behavior according to the pandemic. Except for Watanabe & Yabu (2020), they used mobility data to examine how government's policies led to mobility changes. Their analysis found that the declaration of the state of emergency significantly reduced the number of people leaving their homes by 8.5%. Second, a 1% increase in new infections reduces people's outings by 0.027%. Their findings offer pivotal insights into behavioral adaptations during the pandemic. Nevertheless, their analysis is confined to data ranging from January 6 to June 28, 2020. The dynamic nature of the impact relationship throughout the seven waves of the pandemic remains unexplored. Moreover, the author extends this investigation by incorporating the effects of vaccination, a critical determinant influencing both the actual risk of infection and public perception thereof.

3 Hypotheses

The author set up the following hypotheses to investigate the aforementioned questions. Firstly, Hypothesis 1 assumes that COVID-19 cases' influence on mobility was gradually weakening with the long-lasting pandemic.

H1: COVID-19 cases' influence on mobility was gradually weakening.

Secondly, since vaccination can effectively reduce the risk of infection, hypothesis 2 assumes that vaccination rate has a positive influence on mobility.

H2: The vaccination rate has a positive influence on mobility.

Thirdly, policies implemented during the pandemic significantly influence people's behavior. Hypothesis 3.1 assumes that the ESD and "Pre-emergency measures" restricted mobility in "retail and recreation" and "transit station" areas, while hypothesis 3.2 assumes that the "Go To Travel" campaign stimulates mobility in these areas.

H 3.1: The ESD and "Pre-emergency measures" has a negative influence on mobility.

H 3.2: The "Go To Travel" campaign has a positive influence on mobility.

4 Model specification and variables

The model presented below is constructed to verify the hypotheses. Table 1 shows explanations of each variable and corresponding data sources. In the model, GM_{it} represents mobility in "retail and recreation" areas and "transit station" areas in prefecture i at time t. $C_{i(t\text{-}n)}$ represents daily reported Covid-19 positive cases in each prefecture i at time $t\text{-}n$. In the analysis,the author applied different lags for this variable to examine positive cases' incluence on mobility. Since the number of newly confirmed positive cases is reported one day later, $C_{i(t\text{-}1)}$ indicates the newly confirmed positive cases that reported one day before (which is actually the confirmed cases of two day before). K_dum_{it} is the dummy variable of the ESD period, M_dum_{it} is the dummy variable of the “Pre-emergency measures” period. The specific start and end dates of each ESD and “Pre-emergency measures” period varies from prefecture to prefecture. Values of this two variables is is set according to “The period of the COVID-19 emergency declaration state” published by Ministry of Justice (2022). G_dum_{it} is the dummy variable of the “Go To Travel” campaign period. H_dum_t represents the dummy variable of holidays, including statutory holidays, and consecutive holidays such as the New year, Golden Week, and Obon Festival. W_dum_t represents the dummy variable of the seven waves of the COVID_19 pandemic.The specific start and end dates of each wave are set according to the National Institute of Infectious Diseases (2022)’s research (Table 2)[(1)]. $V_{i(t-1)}$ represents vaccination rate in prefecture i at time $t-1$.

$$GM_{it} = \beta_0 + \beta_1 C_{i(t-n)} + \beta_2 K\_dum_{it} + \beta_3 M\_dum_{it} + \beta_4 G\_dum_{it} + \beta_5 H\_dum_t + \beta_6 W\_dum_t + \beta_7 C_{i(t-n)} {}^* W\_dum_t + \beta_8 V_{i(t-1)} + \varepsilon$$

$i = 1,\ldots,47$ Japanese prefectures. $t = Daily$

In sum, mobility changes are influenced by COVID-19 cases, two policies aimed at restricting mobility (the ESD and pre-emergency status), the “Go To Travel” campaine, holidays, and vaccination rates. Furthermore, the interaction term between $C_{i(t-n)}$ and W_dum_t is applied to elucidate how the relationship between COVID-19 cases and mobility varies across the seven waves of the pandemic.As shown in the column “data frequency” in Table 1, Google Mobility data, COVID-19 case data, and vaccination rate data is daily based data by prefecture. The collected dataset contains data of 47 prefectures in 942 days.

Regarding the estimation method, as well known, the advantage of panel data is that it includes information in both time-series and cross-section dimensions. However, panel regression models also tend to have problems such as autocorrelation and heteroskedasticity in the error terms. The issues of autocorrelation (where error terms are correlated over time) and heteroskedasticity (where the variance of error terms differs across observations) violate the

Table 1 Variables and their meanings

Notation	Variable Meaning	Data frequency
GM	Location history data published by Google Mobility	Daily
C	The number of daily new confirmed COVID-19 positive cases	Daily
K_dum	Emergency State Declaration	Dummy
M_dum	Pre-emergency measures	Dummy
G_dum	“Go To Travel campaign”	Dummy
H_dum	Holidays	Dummy
W_dum	The seven waves of the pandemic.	Dummy
V	Vaccination rate	Daily

Table 2 The start and end date of the seven waves

Waves	Start and end date
1st	2020.3.23~2020.5.17
2nd	2020.6.22~2020.9.27
3rd	2020.10.26~2021.2.28
4th	2021.3.1~2021.6.20
5th	2021.7.12~2021.9.26
6th	2022.12.20~2022.6.19
7th	2022.7.1~2022.10.15

fundamental assumption of Ordinary Least Squares (OLS) estimation, leading to biased and inconsistent estimation results.

To confirm heteroskedasticity and autocorrelation in this panel dataset, the author conducted the Modified Wald test (for groupwise heteroskedasticity) and the Wooldridge test (for autocorrelation). The results show that there is groupwise heteroskedasticity and first-order autocorrelation. Therefore, the author estimates the model by the feasible generalized least squares (FGLS) estimator since it addresses these problems and produces a consistent and more robust estimate.

The fundamental concept of FGLS involves constructing a weighted variance-covariance matrix of error terms based on the heteroscedasticity and autocorrelation characteristics present in the data. This construction aims to ensure that the weighted matrix exhibits homoscedasticity and no autocorrelation, therefore enables parameter estimation using Ordinary Least Squares (OLS) while mitigating the biases mentioned earlier. Its advantages include providing more efficient and consistent estimates that accommodate complex data structures, thereby enhancing the reliability of statistical inference in empirical research. In addition, the FGLS estimator is particularly suitable for the long panel data used in this analysis, which has a greater number of periods (T) and a much smaller number of cross-sections (N).

5 Data visualization

5.1 Mobility

The dependent variable GM_{it} represents the mobility in prefecture i at time t. Google "Community Mobility Reports" provides data that reflect the mobility changes in six categories of areas: retail and recreation, grocery stores and pharmacies, parks, public transport, workplaces, and residences. This data is derived from users who have opted into Location History and accessed Google's service. It reflect mobility's relative percentage change compared to baseline period (2020.1.3-2020.2.6), not the absolute number of visitors. Specifically, the daily percentage changes were calculated relative to the median for each corresponding weekday or weekend during the baseline period. Since mobility patterns will be different on weekdays and weekends, data on a Monday are compared to corresponding data from the baseline series for a Monday. Baseline day figures are calculated for each day of the week and as the median value (Google 2020). For example, a decrease of 50% in retail and recreation mobility indicates that mobility in that area reduced to half of the baseline level. The mobility data of Japan was downloaded on 10 December 2022.

Figures 1 and 2 illustrate the mobility trends in "retail and recreation" and "transit station" areas across Aichi, Kanagawa, Osaka, and Tokyo. The left y-axes on of Figures 1-3 represents the percentage change in mobility compared to the baseline period. The right y-axes represent the values of the ESD dummy variable. The figures are marked with light orange zones representing the ESD periods (i.e., with a value of 1), which varied among the prefectures. For Tokyo, the specific ESD periods were from April 7 to May 25, 2020; January 8 to March 21, 2021; April 25 to June 20, 2021; and July 12 to September 30, 2021. Mobility in both categories of areas experienced the most significant decline during the first ESD period, which was announced at the beginning of the pandemic. Subsequent ESD periods also show notable reductions in mobility. Notably, the "transit station" areas saw a more pronounced decrease compared to "retail and recreation" areas. This disparity could be attributed to the substantial reduction in public transport usage as remote work became more prevalent.

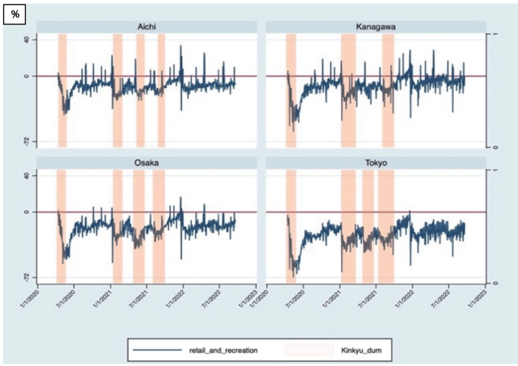

Figure 1 Mobility in retail and recreation areas

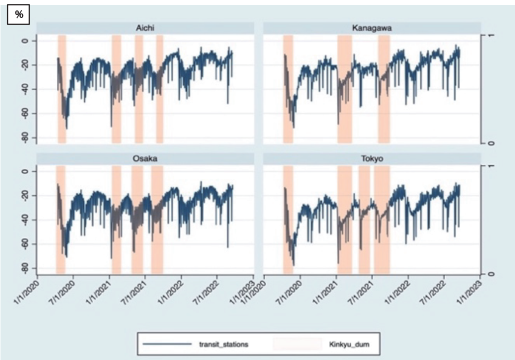

Figure 2 Mobility in transit stations areas

Figure 3 shows the mobility trend in Tokyo, with the light green zone indicating the period of the "Go To Travel" campaign. Following a marked decrease during the first ESD period, mobility in these areas rebounded to a level approximately 30% lower than the baseline, subsequently exhibiting a slow but upward trend with sporadic downturns.

By July 2020, a notable recovery in mobility was observed. The implementation of the "Go To Travel" campaign on the 22nd of July 2020 contributed to a further increase in mobility. This campaign was suspended in 27th December 2020 in response to a new wave of severe COVID-19 cases growth.

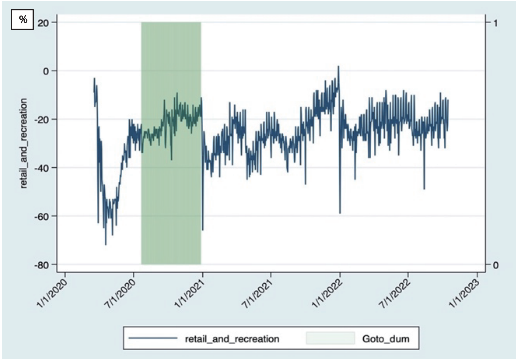

Figure 3 Mobility in retail and recreation areas - Tokyo

5.2 The number of COVID-19 Cases

The author uses daily reported COVID-19 positive cases as explanatory variable to assess the pandemic's impact on mobility changes. Data were retrieved from the NHK website dedicated to Coronavirus updates (NHK 2022). Figures 4 presents the COVID-19 positive cases for the same four prefectures, illustrating the evolving trend of the pandemic. All prefectures demonstrate a similar trend with seven waves of increasing positive cases. The first and second peaks (occurring around April 2020 and August 2020, respectively) are barely discernible due to their relatively smaller magnitude compared to the latter two peaks (around July to August 2022), which marked the most severe outbreaks in all the prefectures. The light orange zones in the figures, indicating the ESD periods, coincide with the periodic surges in positive cases.

5.3 Vaccination rate

In the initial phase of the pandemic, mobility

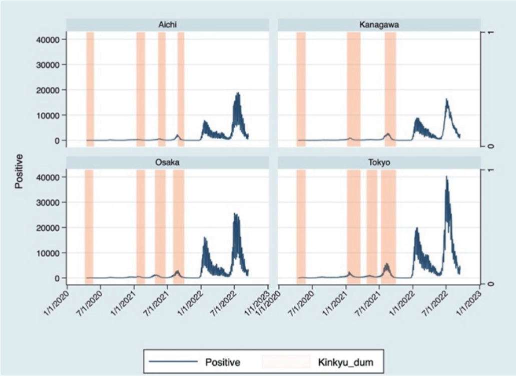

Figure 4 Daily reported COVID-19 positive cases

restrictions served as the primary means to mitigate the spread of the virus. With the efficacy of vaccines against infection established through clinical trials, vaccination became the principal strategy to reduce infection risks. In Japan, the first round of vaccinations started from April 2021. According to Idogawa, et al. (2020), by December 2021, over 70% of the population in most prefectures had received their second vaccine dose, indicating complete vaccination. This study analyzes the completed vaccination rate to determine its impact on individuals' decisions to engage in outdoor activities, thereby influencing mobility patterns.

6 Results

This chapter presents the estimation results. Subsequent interpretations and discussions are based on the results of the FGLS model. The author applied three different time lags (4 days, 8 days, and 12 days) to the variable of COVID-19 cases to reveal the delayed effects of its influence on mobility.

6.1 Retail and recreation mobility

Table 3 presents the results with GM (retail and recreation) as the dependent variable. All variables show statistically significant estimated coefficients across all three models, except for *W_dum* (7).

First, *W_dum* is used to represent the seven waves of the pandemic. Since the first wave is designated as the base period, subsequent waves are compared to the first wave. Thus, a significant coefficient for *W_dum(2)* indicates that the mean mobility during the second wave differs significantly from that during the first wave. The same interpretation applies to the third through sixth waves, except for the seventh wave. *W_dum(0)* represents periods that do not belong to any wave (as shown in Table 4, there are empty days between waves). The coefficient for *W_dum(0)* signifies that the mean mobility during these periods differs significantly from that during the first wave.

Secondly, concerning the impact of COVID-19 positive cases, the lagged effects (4-days, 8-days, 12-days) of *C(positive)* all show a negative influence on mobility. Moreover, the coefficients of the interaction terms C_{t-n}*W_dum are all statistically significant, indicating that the influence of COVID-19 positive cases on mobility differs significantly across subsequent waves compared to the first wave. Using the result of model C_{t-8}, the author computed the marginal effects[(2)] of positive cases on mobility. As shown in Table 5 and Figure 5, during the first wave, an increase in positive cases correlates with a mobility decrease of 0.036 in "retail and recreation" areas. During the second wave, this decrease is 0.020. The effect slightly strengthens in the fourth wave compared to the third, before gradually diminishing until the seventh wave of

Table 3 Results of Retail and recreation Mobility (Made by the author)

Dependent	GM (retail and recreation)		
	C_{t-4}	C_{t-8}	C_{t-12}
C_{t-n}	-0.028***	-0.036***	-0.023***
	(0.006)	(0.006)	(0.005)
W_dum (2)	4.836***	6.573***	7.284***
	(1.017)	(1.012)	(1.043)
W_dum (3)	3.253***	4.986***	5.956***
	(0.940)	(0.938)	(0.970)
W_dum (4)	6.135***	7.984***	8.642***
	(0.905)	(0.903)	(0.936)
W_dum (5)	2.597**	4.483***	5.366***
	(1.030)	(1.028)	(1.055)
W_dum (6)	0.827	3.070***	3.629***
	(1.057)	(1.055)	(1.079)
W_dum (7)	-0.340	1.624	2.430**
	(1.110)	(1.106)	(1.130)
W_dum (0)	3.841***	5.806***	6.589***
	(0.894)	(0.906)	(0.936)
C_{t-n}*W_dum (2)	0.012*	0.016**	0.012**
	(0.006)	(0.007)	(0.006)
C_{t-n}*W_dum (3)	0.026***	0.031***	0.020***
	(0.006)	(0.006)	(0.005)
C_{t-n}*W_dum (4)	0.024***	0.029***	0.018***
	(0.006)	(0.006)	(0.005)
C_{t-n}*W_dum (5)	0.028***	0.035***	0.023***
	(0.006)	(0.006)	(0.005)
C_{t-n}*W_dum (6)	0.028***	0.035***	0.023***
	(0.006)	(0.006)	(0.005)
C_{t-n}*W_dum (7)	0.028***	0.036***	0.023***
	(0.006)	(0.006)	(0.005)
C_{t-n}*W_dum (0)	0.026***	0.032***	0.021***
	(0.006)	(0.006)	(0.005)
K_dum	-5.335***	-5.082***	-5.050***
	(0.147)	(0.143)	(0.140)
M_dum	-2.833***	-2.768***	-2.775***
	(0.103)	(0.101)	(0.100)
G_dum	3.843***	3.792***	3.806***
	(0.637)	(0.623)	(0.629)
H_dum	5.006***	5.077***	5.261***
	(0.401)	(0.393)	(0.393)
V_{t-1}	0.134***	0.127***	0.129***
	(0.009)	(0.009)	(0.009)
Constant	-15.660***	-17.250***	-18.060***
	(0.736)	(0.743)	(0.780)
Observations	44,086	43,898	43,710

Notes: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4 Results of Transit stations Mobility (Made by the author)

Dependent	GM (transit stations)		
	C_{t-4}	C_{t-8}	C_{t-12}
C_{t-n}	-0.016***	-0.017***	-0.019***
	(0.005)	(0.005)	(0.005)
W_dum (2)	9.997***	10.990***	12.360***
	(1.145)	(1.143)	(1.165)
W_dum (3)	7.250***	8.522***	10.030***
	(1.060)	(1.060)	(1.083)
W_dum (4)	12.440***	13.550***	14.930***
	(1.031)	(1.032)	(1.055)
W_dum (5)	5.989***	7.081***	8.614***
	(1.178)	(1.179)	(1.197)
W_dum (6)	5.472***	6.763***	8.090***
	(1.286)	(1.298)	(1.314)
W_dum (7)	9.459***	10.640***	12.340***
	(1.348)	(1.356)	(1.372)
W_dum (0)	9.754***	10.700***	12.180***
	(1.013)	(1.041)	(1.064)
C_{t-n}*W_dum (2)	1.50E-05	-0.003	0.004
	(0.005)	(0.006)	(0.005)
C_{t-n}*W_dum (3)	0.013***	0.014***	0.016***
	(0.005)	(0.005)	(0.005)
C_{t-n}*W_dum (4)	0.011**	0.011**	0.015***
	(0.005)	(0.005)	(0.005)
C_{t-n}*W_dum (5)	0.015***	0.016***	0.017***
	(0.005)	(0.005)	(0.005)
C_{t-n}*W_dum (6)	0.016***	0.017***	0.018***
	(0.005)	(0.005)	(0.005)
C_{t-n}*W_dum (7)	0.016***	0.017***	0.018***
	(0.005)	(0.005)	(0.005)
C_{t-n}*W_dum (0)	0.013***	0.014***	0.017***
	(0.005)	(0.005)	(0.005)
K_dum	-4.032***	-3.908***	-3.923***
	(0.193)	(0.191)	(0.190)
M_dum	-2.115***	-2.139***	-2.155***
	(0.143)	(0.143)	(0.142)
G_dum	7.970***	8.024***	7.943***
	(0.723)	(0.707)	(0.707)
H_dum	-3.709***	-3.773***	-3.894***
	(0.369)	(0.362)	(0.367)
V_{t-1}	0.178***	0.178***	0.176***
	(0.012)	(0.012)	(0.012)
Constant	-33.990***	-35.100***	-36.490***
	(0.835)	(0.845)	(0.876)
Observations	44,086	43,898	43,710

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5 The marginal effect of COVID-19 cases at each wave of the pandemic (Made by the author)

$C_{t\text{-}8}$ *at*	Retail and recreation	Std. Err.	Transit stations	Std. Err.
W_dum (1)	-0.036***	(0.006)	-0.017***	(0.005)
W_dum (2)	-0.020***	(0.003)	-0.020***	(0.002)
W_dum (3)	-0.005***	(0.001)	-0.004***	(0.001)
W_dum (4)	-0.007***	(0.001)	-0.006***	(0.001)
W_dum (5)	-0.001***	(0.000)	-0.001***	(0.000)
W_dum (6)	-0.000***	(0.000)	-0.000***	(0.000)
W_dum (7)	-0.000***	(0.000)	-0.000***	(0.000)

Notes: *** p<0.01, ** p<0.05, * p<0.1

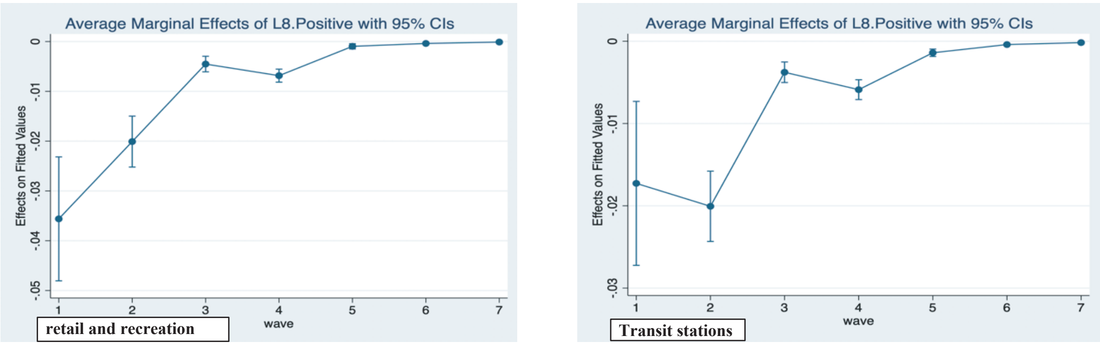

Figure 5 The marginal effect of COVID-19 cases at each wave of the pandemic (Made by the author based on the second and fourth columns values in Table-5)

the pandemic.

Thirdly, regarding the impact of the ESD and "Pre-emergency measures", the significant coefficients of both *K_dum* and *M_dum* indicate that they effectively restricted mobility in "retail and recreation"areas, with the ESD exerting a stronger influence. Fourthly, the coefficients of *G_dum* indicate that the "Go To Travel" campaign promoted mobility in "retail and recreation"areas, resulting in an increase of approximately 3.8. Fifthly, the coefficient of *H_dum* suggests that mobility in"retail and recreation"areas significantly increases during holidays. Lastly, the one-day lag of the vaccination rate contributes positively to increases in mobility.

6.2 Transit stations mobility

Table 4 presents the results with GM (transit stations) as the dependent variable. The estimated coefficients for all variables are statistically significant in all three models, except for the coefficient of the interaction term between $C_{t\text{-}n}$*W_dum (2). *W_dum* is defined as explained in Section 6.1.

COVID-19 positive cases have a significantly negative effect on mobility in "transit station" areas. Concerning the interaction terms, most coefficients are significant, indicating that the impact of positive cases on mobility during the third to seventh waves differs significantly from that during the first wave. However, the coefficients of $C_{t\text{-}n}$*W_dum(2) are not significant, suggesting no significant difference in the impact of positive cases on mobility between the second wave and the first wave. The marginal effects are presented in the fourth column of Table 5. An increase in positive cases is associated with a decrease of 0.017 in mobility in "transit stations" areas during the first wave. This impact not only did not diminish compared to the first wave but rather intensified during the second wave (In Table 5, the coefficient of *W_dum (2)* in the fourth column shows a significant result, indicating that during the second wave, the impact of positive case numbers on mobility is significantly −0.020. This is not contradictory to the insignificant coefficient of the interaction term $C_{t\text{-}n}$*W_dum (2) in Table 4, which indicates that the difference between the second and first waves is not significant). During the third wave, an increase in positive cases is associated with a decrease of 0.0038 in mobility, which is significantly weaker compared to the first two waves. In the fourth wave, this effect strengthened slightly compared to the third wave, and the trend of weakening has persisted since the fourth wave until the seventh wave of the pandemic.

The significant coefficients of both *K_dum* and *M_dum* reveal that they effectively restricted mobility in "transit stations" areas. Specifically, the ESD had a greater impact than"Pre-emergency measures". The coefficients of *G_dum* show that the "Go To Travel" campaign significantly encouraged mobility in these areas, with an increase of about 8.0, which is much greater compared to its impact on mobility in "retail and recreation" areas (approximately 3.8). Regarding coefficients of *H_dum*, there was a significant decrease in mobility in "transit stations" areas during holiday periods. Lastly, the vaccination rate also contributes positively to mobility increases in "transit stations" areas.

6.3 Summary

Drawing from the above results, all hypotheses are strongly supported. In summary, the COVID-19 pandemic had a negative impact on mobility in both "retail and recreation" as well as "transit stations" areas. As illustrated in Figure 5, the negative impact of positive cases on mobility was most pronounced at the initial stage of the pandemic and gradually approached zero as the pandemic persisted. The results from three different time lags (4-days, 8-days, and 12-days) for COVID-19 cases are consistent, indicating the stability of the estimated effects. They also suggest a persistent influence of positive cases on mobility with a time lag. Specifically, the number of positive cases reported on a given day significantly affected people's decision to go out four, eight, and twelve days later. Furthermore, the efficacy of both policy measures is confirmed. The ESD and the "Pre-emergency measures" effectively restricted mobility, whereas the "Go To Travel" campaign encouraged mobility increase. Finally, increases in the vaccination rate significantly promoted an upturn in mobility.

Additionally, the author included *H_dum* to examine the impact of holidays on mobility. The results indicate a significant increase in mobility in "retail and recreation" areas during holidays, while mobility in "transit stations" areas significantly decreases. This difference may stem from two reasons. Mobility in "transit stations" areas encompasses commuting, tourism, and other purposes. Firstly, commuting is unnecessary during holidays, resulting in a significant reduction in mobility. Secondly, considering the impact of the pandemic, there is a corresponding decrease in long-distance travel that requires the use of public transportation, which may also contribute to the reduction in mobility.

7 Discussions

This study endeavors to attain a more nuanced comprehension of mobility changes during the COVID-19 pandemic, with a particular focuses on the pandemic fatigue in the context of the prolonged health crisis. In this section, the author further discusses insights that may be gain from the results.

7.1 COVID-19 cases and mobility

This analysis found that the number of COVID-19 cases negatively affects mobility patterns. The results indicate that individuals adjust their decisions regarding visits to crowded areas based on the number of newly reported cases. While extant literature predominantly provides evidence of how human mobility influences the spread of the COVID-19 pandemic, this study offers a contrary perspective, demonstrating that the pandemic's severity significantly impacts mobility trends. In other words, the interplay between the pandemic and human mobility should be conceptualized as a dynamic, interactive process. This reconceptualization is critically important, as previous studies has extensively investigated the necessity of restricting human mobility to mitigate the pandemic's proliferation. Nonetheless, there is a paucity of research on the factors that influence mobility and the strategies to modulate it effectively. The current study reveals that the reporting of new COVID-19 cases can lead to changes in actual behavior. Echoing Chan et al. (2020), it is posited that perceived risk, rather than actual risk, predominantly dictates behavioral responses.

It is noteworthy that the impact of the pandemic on mobility, though pronounced initially, has diminished across the seven waves. As shown in Figure 5, during the first wave, an increase in reported cases was correlated with a 0.036 decrease in mobility in "retail and recreation" areas, and a 0.017 decrease in mobility in "transit stations" areas. Contrastingly, during the sixth and seventh waves—despite a substantial rise in COVID-19 cases—the public's responsiveness to the pandemic waned considerably. By the seventh wave, the correlations between the rise in positive cases and mobility changes are as minimal as approximately zero.

7.2 The effect of the ESD and "Pre-emergency measures"

Regarding the effect of the ESD, the results indicate that the ESD have led to mobility decreases in both "retail and recreation" areas and "transit station" areas. These findings are in alignment with previous studies that have confirmed the influence of restrictive measures on mobility, as evidenced in studies by Badr et al. (2020) and Kurita et al. (2020). The results verified that the ESD has effectively contributed to mobility decreases in crowded areas.

Furthermore, the "Pre-emergency measures" also effectively reduced mobility in these two areas. As introduced in Section 1.1, the "Pre-emergency measures" were implemented before the ESD to prevent the rapid spread of the pandemic. In terms of intensity, the requirements of the “Pre-emergency measures” are weaker than those of the ESD. This is also reflected in the results of this analysis, where the effect of the ESD on mobility reduction (approximately −5 in “retail and recreation” areas and −4 in “transit station” areas) is greater than that of the “Pre-emergency measures” (approximately −2.8 in “retail and recreation” areas and −2.1 in “transit station” areas).

As indicated by previous study (National Institute of Infectious Diseases 2021), the reduction in mobility resulting from these two preventive policies is attributed, on one hand, to direct factors such as closures or shortened operating hours of commercial and dining facilities, and event cancellations. On the other hand, the implementation of these policies inherently communicates the severity of the pandemic, raising public awareness and indirectly influencing individuals’ decisions to go out. In other words, the rigorous mobility restriction measures heightened the public’s sense of urgency and awareness of the infection risk, subsequently leading to significant mobility decreases.

7.3 The effect of the “Go To Travel” campaign

With respect to the impact of the “Go To Travel” campaign, this analysis revealed that it has fostered increased mobility in both “transit station” and “retail and recreation” areas. Moreover, since the “Go To Travel” campaign encouraged people to travel by offering discounts on travel expenses, it resulted in an 8.0 increase in mobility in “transit stations” areas, which was much greater than that observed in “retail and recreation” areas.

Delgado (2023) stated that the campaign significantly bolstered tourism. During the protracted periods of quarantine, tourism demand had been considerably suppressed. Within this context, the launch of the “Go To Travel” campaign emerged as a pivotal stimulus for travel by conveying to the public that the pandemic has subsided and that travel was once again safe. The implementation of the “Go To Travel” campaign met the repressed demand for tourism, effectively contributed to tourism recovery. However, from the perspective of pandemic control, it has led to significant increases in mobility, resulting in crowded gatherings and increased infection risks. Consequently, it faced widespread criticism and was suspended in late December 2020.

7.4 Vaccination rate and mobility

Vaccination is the key factor in controlling the spread of the virus, subsequently alleviating the public’s fear of infection and contributing to increases in mobility. This analysis investigated the impact of vaccination rates on mobility, concluding that higher rates of completed vaccinations correlate with mobility increases. This finding aligns with previous studies (Fukao and Shioji 2022, Masuhara and Hosoya 2022), which have also confirmed the positive effects of vaccinations on mobility. As the vaccinated population grows, the resumption of events and social gatherings becomes more probable. At the mean time, as more people get vaccinated, it could restore confidence in attending avents, participating in outline activities, and visiting crowded areas, which all contributes to the boost of mobility.

8 Conclusions

This study examines factors influencing

human mobility across the seven waves of the COVID-19 pandemic in Japan. Using a Feasible Generalized Least Squares (FGLS) model with panel data from 18 March 2020 to 15 October 2022, the author arrives at several key conclusions. First, the number of COVID-19 cases negatively affects mobility, reflecting behavioral adaptations in response to the evolving pandemic situation. Notably, while the pandemic's initial impact on mobility was profound, this influence has steadily waned, becoming negligible by the seventh wave. This trend illustrates the behavioral adaptations during a prolonged public health emergency, the so-called "pandemic fatigue". Second, the study examines the role of the ESD and the "Pre-emergency measures" in reducing mobility. Conversely, the "Go To Travel" campaign, led to significant mobility increases, especially in "transit stations" areas. Lastly, the findings show that the vaccination rate exerts a considerable positive effect on mobility increases.

Factors affecting personal movement decisions are complex and interrelated. During the global transmission of the COVID-19 pandemic, the more complex and continually changing situation makes it much more difficult to cope with. This study aims to enhance the comprehension of behavioral responses during such public health emergencies and assist corresponding policymaking. As a major contribution, this study has quantitatively evaluated the relationship among the pandemic, policy interventions, vaccination, and mobility, specifically through the lens of pandemic fatigue. Diverging from most prior research that discusses the influence of human behavior on the spread of COVID-19, the present study focuses on how individuals adapt their behavior in response to the severity of the pandemic and the impact of related policies. It adds a discussion to the existing literature on risk perception and determinants of human mobility amidst public health crises. Additionally, this study offers insights into the efficacy of the ESD and the "Pre-emergency measures" in limiting mobility and underscores the critical role of vaccination as a prerequisite for economic recovery.

This study subject to certain limitations. First, the mobility data provided by Google are derived from users who utilize Google's services or applications and consent to sharing their location history. Consequently, this data may not comprehensively represent the mobility patterns of the entire population. Nevertheless, this data source has been widely employed in prior research to evaluate mobility chenges during the pandemic. Second, the analysis is predicated on observational data that exclusively encapsulate mobility changes and does not encompass other behavioral responses to the pandemic, such as mask-wearing, hand hygiene, or social distancing. Future studies are necessary to uncover additional behavioral and psychological changes, particularly concerning pandemic fatigue, using surveys or in-depth interviews.

Acknowledgement

This paper was initially presented at the SSI (Society of Socio-Informatics) 12th Annual Conference in 2023 on September 16th, and revised based on the discussant's advice. The author thanks the discussant and participants at the conference for their valuable advice and comments.

Note

(1) According to National Institute of Infectious Diseases (2022),the period of epidemic waves is

defined based on the pandemic curve by diagnostic week. Each wave is defined as follows: the start week is characterized by "an increase over three weeks with a peak increase of 10% or more compared to the previous week, or two consecutive weeks with a week-over-week increase of 1.5 or more." The end week is defined as "a decrease over three weeks with a peak decrease of 10% or less (until the start of the next wave)".

(2) The marginal effects of interaction terms refer to how changes in the independent variables impact the predicted outcome variable when these variables interact with each other. Specifically, it quantifies the additional change in the predicted outcome variable due to the interaction between two independent variables, holding all other variables constant. This helps to understand how the relationship between variables changes depending on the values of the interacting variables, providing insights into complex relationships and conditional effects within the regression model.

Reference

1) Anzai, Asami and Hiroshi Nishiura. 2021. "Go to Travel Campaign and Travel-Associated Coronavirus Disease 2019 Cases: A Descriptive Analysis, July-August 2020." *Journal of Clinical Medicine* 10(3) (21 January,): 398. doi:10.3390/jcm10030398.

2) Badr, Hamada S., Hongru Du, Maximilian Marshall, Ensheng Dong, Marietta M. Squire, and Lauren M. Gardner. 2020. "Association between mobility patterns and COVID-19 transmission in the USA: a mathematical modelling study." *The Lancet Infectious Diseases* 20.11: 1247-1254.

3) Bonaccorsi, Giovanni, Francesco Pierri, Matteo Cinelli, Andrea Flori, Alessandro Galeazzi, Francesco Porcelli, Ana Lucia Schmidt, et al.2020. "Economic and social consequences of human mobility restrictions under COVID-19." *Proceedings of the National Academy of Sciences* 117.27: 15530-15535.

4) Chan, Ho Fai, Ahmed Skali, David A. Savage, David Stadelmann, and Benno Torgler. 2020. "Risk Attitudes and Human Mobility during the COVID-19 Pandemic". *Scientific reports* 10.1: 19931.

5) Delgado, Augusto. 2023. "COVID-19 with Stigma: New Evidence from Mobility Data and "Go to Travel" Campaign." *Heliyon* 9(5): e15704-e15704.

6) Elshendy, Mohammed, Andrea Fronzetti Colladon, Elisa Battistoni, and Peter A. Gloor. 2018. "Using Four Different Online Media Sources to Forecast the Crude Oil Price." *Journal of Information Science* 44(3) (Jun): 408-421. doi:10.1177/0165551517698298.

7) Fukao, Mitsuhiro, and Etsuro Shioji.2022. "Is there a trade-off between COVID-19 control and economic activity? Implications from the Phillips curve debate." *Asian Economic Policy Review* 17.1: 66-85.

8) Google. 2020. COVID-19 Community Mobility Report. https://www.google.com/covid19/mobility?hl=en.

9) Inoue, Tomoo, and Okomioto Tatsuyoshi. 2022. "Exploring the Dynamic Relationship between Mobility and the Spread of COVID-19, and the Role of Vaccines" *RIETI Discussion Paper Series* 22-E-011.

10) Jung, Sung-mok, Akira Endo, Andrei R. Akhmetzhanov, and Hiroshi Nishiura. 2021. "Predicting the effective reproduction number of COVID-19: inference using human mobility, temperature, and risk awareness." *International Journal of Infectious Diseases* 113 (2021): 47-54.

11) Johns Hopkins University (JHU), 2020 COVID-19

Dashboard by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University.

12) Kimura, Aya Ida, Rina Fukushima, Naoko Oyabo-Mathis, and James Mathis. "Jishuku, altruism, and expatriate emotion." *Contexts* 14, no. 2 (2015): 28-33.

13) Kurita, Junko, Tamie Sugawara, and Yasushi Ohkusa. 2020. "Mobility data can explain the entire COVID-19 outbreak course in Japan." *medRxiv*.

14) Kurita, Junko, Tamie Sugawara, and Yasushi Ohkusa. 2020. "First Peak of COVID-19 Outbreak in Japan might Pass as of 26 April, 2020". *medRxiv*. doi:10.1101/2020.04.26.20081315.

15) Kurita, Kenichi, Yuya Katafuchi, and Shunsuke Managi. 2023. "COVID-19, Stigma, and Habituation: Evidence from Mobility Data." *BMC Public Health* 23(1): 98-17.

16) Masuhara, Hiroaki, and Hosoya Kei. 2022. "What Impacts Do Human Mobility and Vaccination Have on Trends in COVID-19 Infections? Evidence from four developed countries" *RIETI Discussion Paper Series* 22-E-087.

17) Ministry of Justice.2022. The period of the COVID-19 state of emergency declaration. https://hakusyo1.moj.go.jp/jp/69/nfm/n69_2_7_2_0_3.html

18) National Institute of Infectious Diseases. 2021. Quantitative evaluation of the effects of the Priority Measures to Prevent Spread and the State of Emergency on the dynamics of COVID-19 infection. https://chatgpt.com/c/8933475f-6a66-49f5-b348-92b667bbf9e8

19) National Institute of Infectious Diseases. 2022. Epidemiological study of gender and age characteristics during each wave of COVID-19 outbreaks in Japan. (IASR Vol.43 p273-275:2022.12) https://www.niid.go.jp/niid/ja/typhi-m/iasr-reference/2605-related-articles/related-articles-514/11696-514r01.html

20) NHK. 2022. The infection data by prefecture. https://www3.nhk.or.jp/news/special/coronavirus/data/

21) Pavlicek, Jaroslav and Ladislav Kristoufek. 2015. "Nowcasting Unemployment Rates with Google Searches: Evidence from the Visegrad Group Countries." *PloS One* 10(5): e0127084.doi:10.1371/journal.pone.0127084.

22) Smith, Richard D. 2006. "Responding to Global Infectious Disease Outbreaks: Lessons from SARS on the Role of Risk Perception, Communication and Management." *Social Science & Medicine (1982)* 63(12): 3113-3123.doi:10.1016/j.socscimed.2006.08.004.

23) Idogawa, Masashi, Shoichiro Tange, Hiroshi Nakase, and Takashi Tokino. 2020. "Interactive Web-based Graphs of Coronavirus Disease 2019 Cases and Deaths per Population by Country". *Clinical Infectious Disease*s ; 71:902-903. https://dx.doi.org/10.1093/cid/ciaa500

24) Sulyok, M. and M. Walker. 2020. "Community Movement and COVID-19: A Global Study using Google's Community Mobility Reports." *Epidemiology and Infection* 148 (Nov 13,): e284. doi:10.1017/S0950268820002757. https://dx.doi.org/10.1017/S0950268820002757.

25) Watanabe, Tsutomu and Tomoyoshi Yabu. 2021. "Japan's Voluntary Lockdown." *PloS One* 16(6): e0252468-e0252468.

26) Wu, Lynn and Erik Brynjolfsson. "The Future of Prediction: How Google Searches Foreshadow Housing Prices and Sales." *SSRN Electronic Journal*. doi:10.2139/ssrn.2022293.