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Restrictive and stimulative impacts of COVID-19 policies on activity trends: A case study of Kyoto

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A R T I C L E I N F O

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A B S T R A C T

This paper employs regression with ARIMA errors (RegARIMA) to quantify the impacts of multiple non-pharmaceutical interventions, daily new cases, seasonal and calendar effects, and other factors on activity trends across the timeline of the ongoing COVID-19 pandemic in Japan. The discussion focuses on two controversial policy sets imposed by the Japanese government that aim to contain the pandemic and to stimulate the recovery of the economy. The containing effect was achieved by stay-at-home requests and declaring a "State of Emergency" in the combat against the first waves of infectious cases. After observing reduced cases, Go-to-travel and Go-to-eat campaigns were launched in July 2020 to encourage recreational travel and to revive the economy. To better understand the impact of the policies we utilize "Google trends" which measure how much these policies are looked up online. We suggest this reflects how much they are part of the public discussion. A case study is conducted in Kyoto, a city famous for tourism. The proposed RegARIMA model is compared with linear regression and time series models. The outperformances in measuring the magnitude of intervention impacts and forecasting the future trends are confirmed by using a total of twelve activity and mobility indices as the dependent variable. Nine indices are released by Google and Apple and three are obtained from local Wi-Fi packet sensors. The effect of the State of Emergency declaration is found to erode at the second implementation, and the second stage of the Go-to-travel campaign successfully stimulated travel demand in the autumn sighting season of 2020.

1. Introduction

In the combat against the globally-spreading COVID-19 pandemic, more than a hundred countries have taken actions to restrict human mobility and activities by the end of March 2020 (Parady et al. 2020). Hale et al. (2020) provide a list of countries that have implemented a wide range of containing policies such as school closure, workplace closure, public transportation closure, stay-at-home requests, restrictions on public gatherings and events, and so forth. In this paper, we focus on the COVID-19 timeline of Japan. Japan initially experienced containing stages against the first wave of infectious cases from March 2020 to May 2020, a restriction-free period with policies to encourage mobility and activities during July 2020 and December 2020 regardless of a second wave, and has been under changing restrictions for a long period since January 2021 due to the third and fourth waves as well as Tokyo Olympic Games. Table 1 summarizes the key events and the interventions implemented in the COVID-19 timeline of two Japanese cities, Tokyo and Kyoto. For some policies we can observe a small lag of Kyoto compared to Tokyo.

Among the policies implemented in Japan, there are four types of non-pharmaceutical interventions: school closures, stay-at-home requests, declarations of a "State of Emergency", and "Quasi-Emergency Measures". All of these have the goal to contain the pandemic by imposing restrictions on human mobility and activities. The distinctions between the latter two policies are mainly as follows: Firstly, venues allow up to 50% of the capacity or 5000 people to attend a public gathering under State of Emergency, while Quasi-Emergency Measures allow 100% of the capacity to be used if the audience does neither cheer nor interacts directly in other ways. Secondly, in a State of Emergency all the recreational venues providing alcoholic beverages and karaoke services are closed. Other recreational venues, such as restaurants and cafes, are requested to shorten business hours and close no later than 8 pm. These requirements on closure and business hour shortening are loosened to some degree under Quasi-Emergency Measures. Note that

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Table 1
Key interventions and dates in the COVID-19 timeline of Tokyo and Kyoto.

Interventions	Date – Tokyo	Date – Kyoto
School closure	2 March 2020 – 31 May 2020	5 March 2020 – 31 May 2020
Stay-at-home request	28 March 2020 – 31 May 2020	10 April 2020 – 31 May 2020
State of Emergency (1)	7 Apr 2020 – 25 May 2020	16 Apr 2020 – 21 May 2020
Go-to-travel Campaign (1)	N/A	22 Jul 2020 – 30 Sep 2020
Go-to-travel Campaign (2)	1 Oct 2020 – 28 Dec 2020	1 Oct 2020 – 28 Dec 2020
State of Emergency (2)	8 Jan 2021 – 21 Mar 2021	14 Jan 2021 – 28 Feb 2021
Vaccination	12 April 2021 – present	12 April 2021 – present
Quasi-Emergency Measures (1)	12 April 2021 – 24 April 2021	12 April 2021 – 24 April 2021
State of Emergency (3)	25 Apr 2021 – 11 May 2021	25 Apr 2021 – 11 May 2021
Quasi-Emergency Measures (2)	12 May 2021 – 11 July 2021	12 May 2021 – 11 July 2021
Quasi-Emergency Measures (3)	N/A	2 August 2021 – 19 August 2021
State of Emergency (4)	12 Jul 2021 – 30 September 2021	20 August 2021 – 30 September 2021

the State of Emergency was only imposed on Tokyo and Okinawa during 12 Jul 2021 and 22 August 2021 in response to high infection cases and the Tokyo 2020 Olympic Games, and then extended to 12 September 2021 as well as to several other regions including Kyoto since 20 August 2021 due to the fierce fifth wave. Later a nationwide extension to the end of September was issued. Accordingly, we can observe in Table 1 that the restrictions in 2021 frequently switch between a full State of Emergency and Quasi-Emergency Measures. These switches are mainly driven by the desire to balance pandemic containment needs and to avoid economic recession. The desire to "quickly return to normality" is evident in the policies as early as July 2020. The "Go-to-travel Campaign", an intervention to stimulate mobility and activities related to casual travel, is a noteworthy feature of the COVID-19 timeline in Japan.

Not only in Japan but worldwide, governments are struggling to understand the right timing to remove or lessen restrictive non-pharmaceutical interventions and to possibly start promoting certain activities again. Japan is among the first to launch a series of such activity-stimulating interventions. Our objective is neither to cast criticism nor approval on this policy. Given the changing nature of the ongoing COVID-19 pandemic and the multidimensional challenges to the policy makers, it is demanding to require a definitive correct answer to the question of how to contain the pandemic while maintaining the economy. Our goal is to support this discussion by quantifying the effects of the implemented policies and sharing the lessons learned from the combat against COVID-19 in Japan.

In this paper, we develop a regression model with time series errors that follows classical intervention models proposed by Box and Tiao (1975) and Tsay (1984). The contributions to the worldwide community and existing literature are threefold: (1) We suggest this is an approach to produce less biased estimates for the effects of the policies implemented in the COVID-19 timeline than we found in other papers; (2) we show that we can forecast future mobility and activity trends at an acceptable accuracy; (3) We extract some lessons learned from the unique timeline of Japan characterized by the aforementioned local and interregional travel demand stimulating policies. These methodological and practical findings are believed to benefit policy makers.

Cities holding tourism as an important economic driver are anticipated to be more sensitive to the aforementioned two diverging policy sets and mobility patterns in such cities are more fluctuating (Schmöcker, 2021). This is motivating our choice for Kyoto as our case study. We select 15 February 2020 to 2 April 2021 as the observational period in order to exclude the effect of pharmaceutical interventions such as vaccination. By 2 April 2021, less than 1% of the Japanese population in Japan was vaccinated and this rate was close to zero for Kyoto as the vaccination in Kyoto officially started on 12 April 2021 (Government CIO portal, 2021).

The remainder of this paper is organized as follows. Section 2 reviews the studies concerning the impacts of the ongoing COVID-19 pandemic on human mobility and activity patterns and travel behavior. Section 3 discusses intervention models with time series data and explains the suitability of regression models with time series errors for the studied problem. Section 4 provides details on the selection and data processing of the dependent and independent variables. A focus of this section is the implementation of Google trends data to better reflect exogenous policy variables. We show that the consideration of trending is useful for a range of policies. Section 5 reports the estimated magnitude and significance of the exogenous variables, discusses policy implications, and presents the forecasted future trends of higher accuracy than benchmark models. The conclusion and suggestions for future research directions given the limitations of this paper and the concerns on the current pandemic situation in Japan can be found in Section 6.

2. Literature review

This unprecedented pandemic has been globally shaking the status quo of human society in a variety of aspects. Narrowing the focus on human mobility and travel behavior, intervention implementation to contain the spread of the coronavirus has been decreasing travel demand and reshaping travel behavior. Human mobility is known to be a critical driver for the spread of this infectious disease (Merler and Ajelli, 2010; Kraemer et al. 2019; Wei et al. 2020). Non-pharmaceutical interventions therefore mainly restrict human mobility and activity. Flaxman et al. (2020) and Lai et al. (2020) illustrate the effects of non-pharmaceutical interventions on reducing cases and deaths by comparing actual and virtual scenarios of different interventions and timings. Interventions falling into this category can be soft policies such as stay-at-home requests relying on self-regulation. They can be upgraded to harder ones such as a declaration of an emergency state shortening business hours, closures of recreational places, or even full-scale "lockdowns" of areas. To note is that in Japan COVID restricting policies were never as stringent as in other countries, for example, there were never penalties imposed on private gatherings. The government mainly relied on the collaboration of the population.

Policy impacts are worth attention not only for their immediate effects but also for possibly profound, longer-term impacts leading to a different "new normal" in post-COVID periods. The changes may be twofold: model preference and trip purpose. Beck and Hensher (2020a, 2020b) investigate the effect of restricting interventions carried out in Australia on travel behavior, using longitudinal surveys in the days under and right after the restrictions. They confirm the reduction in travel demand and the change in mode preference driven by the restrictions and the pandemic itself. Their latter work finds that the trips by private car rebounded much more significantly than by public transport in the days when the restrictions were eased. Jenelius and Cebecauer (2020) provide evidence on the drop of public transport ridership using the data of passenger counts and fare collection in Stockholm, Sweden. Eisenmann et al. (2021) report travel survey results in Germany and quantify the preference of people to travel by private car in the lockdown period. Luan et al. (2021) mention that the ride-hailing industry in China was heavily hit by the pandemic. Note that these studies show the changes in model preference triggered by the pandemic but that the definite form in post-COVID times remains vague and dependent on, among others, what actions are taken by stakeholders such as transport service providers.

Parady et al. (2020), Abdullah et al. (2020), and Shakibaei et al. (2021) emphasize the short-run changes in travel purpose before and during the COVID-19 pandemic using surveys. Parady et al. (2020) find that in the early stage of COVID-19 non-essential grocery shopping and eating-out demand in the Kanto region of Japan was effectively restricted by self-regulation and soft governmental requests. Abdullah et al. (2020) receive survey results from various countries via social media, and their data show that 56.6% of the 1203 respondents never go to office or college due to COVID-19. Instead, the respondents' primary trip purpose shifts from working to shopping. Shakibaei et al. (2021) confirm a sharp reduction in commuting, social/recreational/leisure, and shopping demand in Istanbul. The pattern that the commuting and recreational travel demand recover in the long term is considered to rely on future policies, such as whether teleworking and online education will be encouraged in post-COVID, whether policies will be implemented to increase leisure trips. Therefore, tracking behavior changes over a longer-term is required to provide better predictions.

The above literature informs policy makers of the current situation and the future trend of travel demand and mode preferences. Yet, the causality interpretation on the relationship between policies and mobility changes remains insufficient. Other researchers attempt to estimate the effect of COVID-19 policies and forecast future mobility trends using a range of passive data in line with the approach taken in this paper. Multiple open datasets ease the difficulties in tracking policy implementations and mobility changes in time series. The Oxford COVID-19 Government Response Tracker (OxCGRT) provides an open dataset that contains a time series of stringency indices for a variety of countries (Hale et al. 2021). These indices include the anticipated strength of each policy and the overall stringency level of a country. Activity and mobility indices are publicly released by Google and Apple, which will be elaborated in Section 4. As an overview of the relationship between governmental COVID-19 policy and human mobility, we refer to McKenzie and Adams (2020) who calculate the similarity between national stringency and mobility indices for 108 countries. They further illustrate how the pattern of human response to containing policies varies from country to country by a cluster analysis. Chan et al. (2021) also use OxCGRT and mobility indices to uncover the interactions among policy, mobility, and infectious cases in Hong Kong by a Granger causality analysis.

To further understand human response to a specific policy and to allow for inter-policy comparison, our subsequently proposed model distinguishes the effect of individual policies by employing policy-specific exogenous variables. Regression with time series errors is used to address the model misspecification incurred due to serially correlated observations and therefore to provide less biased policy effects. A related research is conducted by Hu et al. (2021). Their work measures the effect of multiple stay-at-home orders imposed in the United States by a generalized additive mixed model. They apply the model with spatial errors to the whole country while our paper focuses on a single city considering the lag of local policies coming into force compared to national announcements. In addition to policies, we consider that the number of infected cases itself has a certain restrictive power on daily mobility as also proposed in Suzuki and Utsumi (2021). As the population in Japan and other countries is frequently exposed to the latest local and national infection records broadcasted via TV news, website headlines, and social media trends, their behavior will to some degree respond to the potential infection risk according to the virus spread.

3. Models

In this section, we discuss models to quantify the effects of interventions on a dependent time-series variable in general. Let Y_t denote the dependent variable at time t, $\boldsymbol{X}_t$ denote the set of exogenous variables at time t, and $\boldsymbol{\beta}$ be a vector to represent the marginal effect of each variable in $\boldsymbol{X}_t$. We suppose that $\dots, Y_{t-1}, Y_t, Y_{t+1}, \dots$ are time series observations with identical time intervals. A general form of intervention models can be obtained as in Eq. (1) to capture the relationship between the dependent time-series process and exogenous time-series processes, where Z_t is the noise. Eq. (1) allows for either linear or nonlinear assumptions on the relationship and various assumptions on the noise term. The general form is first proposed in a seminal study on intervention models by Box and Tiao (1975) and can also be found in Tsay (1984).

$$Y_t = f(\boldsymbol{X}_t, \boldsymbol{\beta}) + Z_t \tag{1}$$

One can assume Z_t to be white noise and therefore to be independent and identically distributed random variables. However, Box and Tiao (1975) point out that the successive observations in a time series are usually serially correlated. This results in a dependent structure of noise which may violate this basic assumption. They instead model the noise with a mixed autoregressive moving average (ARMA) process. Tsay (1984) extends this discussion on ARMA errors by considering Z_t as an unobservable time series process and allowing it to be nonstationary. A procedure to determine the order of the ARMA model for Z_t is also provided in Tsay (1984).

Given the time series observations after the interventions come into force, it is difficult to explicitly distinguish the isolated impacts of interventions and to distinguish the influence of the prior days on a certain observation. We consider the collection of regression models specifying a time series process for the errors suitable to answer our research questions. In this paper, we attempt to illustrate the usefulness of regression models with ARIMA errors (RegARIMA) in measuring the impact of the afore-mentioned interventions. We assume a linear relationship for the dependent and exogenous time-series processes. For comparison purposes, we introduce linear regression (LR) models and autoregressive integrated moving average models with exogenous variables (ARIMAX) as benchmark methods. The model specification for the RegARIMA and LR models can be found in Eq. (2). For the LR model, Z_t is simplified to be white noise ε_t which follows a normal distribution having mean zero and variance $(\sigma_\varepsilon)^2$.

$$Y_t = \sum_{i=1}^{k} \beta_i X_{i,t} + Z_t \tag{2}$$

We select an ARIMA (1,0,0) order for the time series errors of the RegARIMA model according to the results of the residuals analysis. The model specification of the error term therefore becomes Eq. (3) with an ARIMA (1,0,0) process specified for the errors Z_t, where B is the backshift operator (also often referred to as lag operator L), φ_1 is the autoregessive coefficient of this (1,0,0) process and can be written as AR(1). White noise ε_t remains after the original noise Z_t is explained by a first-order autoregressive process. A comprehensive discussion on the ARIMA process and its general forms can be found in Box et al. (2015).

$$(1 - \varphi_1 B) Z_t = \varepsilon_t \tag{3}$$

The same ARIMA order is applied to an ARIMAX model whose specification is shown in Eq. (4). The nuances between LR, RegARIMA, and ARIMAX can be further clarified by comparing the specification of the three models. The difference between LR and RegARIMA mainly is due to the assumption specified for the noise, while ARIMAX differs from RegARIMA by imposing the backshift operation on the dependent variable instead of the noise. This subtle distinction between RegARIMA and ARIMAX explains why the coefficients estimated by RegARIMA are considered more interpretable than ARIMAX.

$$(1 - \varphi_1 B) Y_t = \sum_{i=1}^{k} \beta_i X_{i,t} + \varepsilon_t \tag{4}$$

4. Data analysis and variable selection

This section provides detailed descriptions of the variables we use in the models. The reasons and data support for variable selection are also discussed.

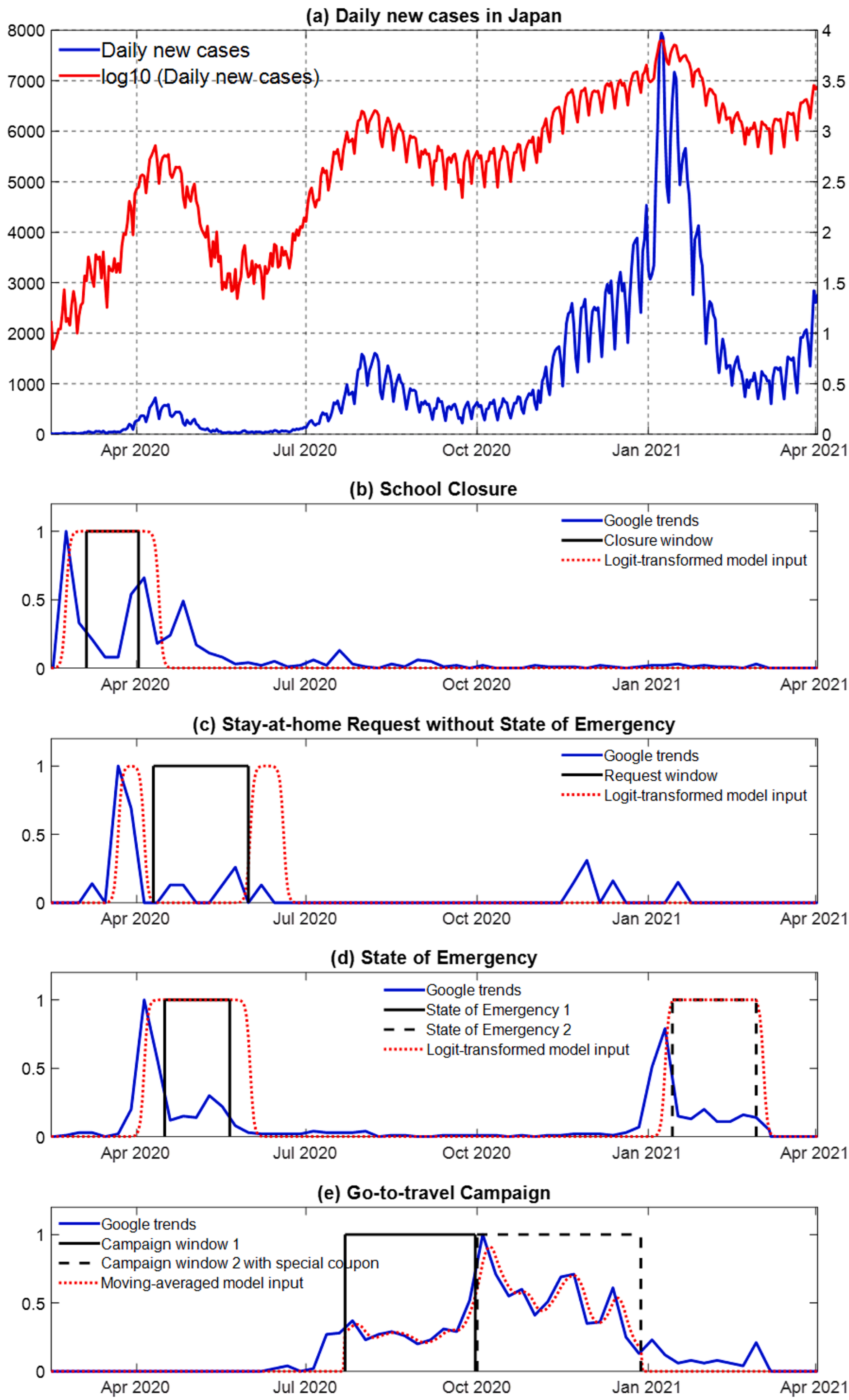

Fig. 1. Daily new cases of COVID-19 in Japan and non-pharmaceutical interventions.

4.1. Dependent variables

4.1.1. Google mobility indices

In response to the public health challenges of this unprecedented pandemic, Google released COVID-19 Community Mobility Reports for various countries since February 2020 and updates them regularly to assist the policy makers to contain the spread (Google, 2020a). According to Google, this data are generated by using the same raw data that are used for Google's "Popular times" service, and the raw data are based on the users who have opted in to Google Location History (Google, 2020b). These reports have been used by a number of studies for an overview regarding the impacts of COVID on human activities in the studied country or region (Beck and Hensher, 2020a, 2020b; Jenelius and Cebecauer, 2020; Parady et al., 2020). A few studies use the data to analyze the behavioral changes during the COVID-19 timeline (Cot et al. 2021; Chan et al. 2021). In this paper, we refer to this data as "Google Mobility Indices". For each day since middle February 2020, a percentage change of the visits to a specific category of places is provided by this data, and the percentage change is compared with a baseline shortly before the outbreak of the pandemic. More specifically, the published percentage change for a specific date is the difference of visits between this day and the average visits on the corresponding day of the week during the five weeks between 3 January and 6 February 2020. As the baseline is the visits in a fixed month, one has to control the effects of season and temperature in the analysis. These Google Mobility Indices are available for six activity/mobility categories: Retail & recreation, Grocery & pharmacy, Parks, Transit station, Workplace, and Residential. For many countries, the index per category is further divided into regions and sub-regions. For Japan, the six indices per category are available at prefecture-level, including Kyoto prefecture, since 15 February 2020.

4.1.2. Apple mobility indices

For similar purposes, Apple started publishing COVID-19 Mobility Trends Reports (Apple, 2020). In this paper we refer to them as "Apple Mobility Indices". They are based on the searches via Apple Maps. Apple re-scales the searches by taking the searches on 13 January 2020 as 100 and the baseline. Apple Mobility Indices are broken down into three categories in line with the transportation modes available on Apple Maps: Driving, Transit, and Walking. We note that these search data may be different from the number of real trips. The data are also available for Kyoto prefecture and per transport mode. To make the data comparable with Google Mobility Indices, the data are processed into percentage changes from the corresponding day of the week by using the mean value in January as the baseline.

4.1.3. Wi-Fi mobility indices

To obtain more detailed information regarding mobility changes at specific, important places in Kyoto we furthermore use information from Wi-Fi packet sensors. The raw data are the probe requests sent by portable electronic devices for Wi-Fi access captured by the sensors installed at specific places. The number of received probe requests therefore can be considered to reflect the busyness of a place. Twelve sensors in total are installed throughout Kyoto City, ten of which have complete data availability in the studied COVID-19 timeline of this paper. The sensors are located at the main tourist attractions, the central business district, and Kyoto Station which is the most important railway station in the city. More details regarding the sensor locations and the data collection mechanism can be found in Gao (2021). We select the data of three sensors as the dependent variables: Kiyomizu Temple which is one of the most famous and frequently visited tourist attractions in the city, Nishiki Market which is located in the central business area of the city and has a collection of restaurants, and Kyoto Station. Kyoto station is the portal for most visitors coming to Kyoto except for those from the surrounding cities, in particular Osaka.

In summary, six Google Mobility Indices, three Apple Mobility Indices, and three Wi-Fi Mobility Indices are employed as the dependent variables. All of them are processed into percentage changes from the baseline in January 2020. Twelve models are therefore respectively fitted for LR, RegARIMA, and ARIMAX.

4.2. Independent variables

4.2.1. Daily new cases

It can be seen in Fig. 1(d) that both times the declaration of a State of Emergency in Japan lagged behind the peak of the first and third waves of domestic daily new cases. We note that a correlation between independent variables is introduced if both daily new cases and interventions are taken into the set of exogenous variables, as the soaring cases usually persuade the intervention implementation. Regardless of this, we include daily new cases into the set of independent variables $\mathbf{X}$. Another concern is that the impact of daily new cases on human mobility may not be linear. Therefore, we first take a common logarithm for daily new cases and then take the moving average of the past seven days. A noteworthy fact is that the daily new cases in Japan, Kyoto, Tokyo, and Osaka are statistically correlated, independent as to whether the original or processed values are used. The pair-wise correlation coefficient is always > 0.8. We therefore only keep the cases in Japan in the set of independent variables and drop the other three, although the pandemic situations in Kyoto and other major cities with a strong connection to Kyoto are supposed to be influential on the activity trends in Kyoto.

4.2.2. Temperature and precipitation

The mobility demand tends to be influenced by weather conditions, in particular in Kyoto with its distinctive seasons. Here we use temperature and precipitation as two weather indicators. To make them comparable with the dependent mobility indices which all have a January 2020 baseline, the weather indicators in January 2020 are taken as the baseline and the baseline means are calculated by day of the week. The changes in temperature and precipitation from the baseline are used as independent variables in the models.

4.2.3. Seasonal and calendar effects

To account for other seasonal and calendar effects during the studied period, weekends, holidays, and two conventional sightseeing seasons are converted to dummy variables. Kyoto City is globally and domestically known for its tourism. The harmonious combinations of natural scenery and historical architecture characterize the unique and impressive sightseeing experience in Kyoto City, attracting explosive numbers of tourists especially in spring and autumn. The two sightseeing dummies are in line with the period for viewing cherry blossom and maple leaves in spring from 16 March to 15 April and in autumn from 16 November to 15 December.

4.2.4. Intervention policies and Google trends

It is common to interpret an intervention as a dummy variable by using one to represent its presence if time t is within the time window of the intervention and zero to denote the absence if it is out of the time

Table 2
Model fit of the proposed RegARIMA and three benchmark models.

	AIC				RMSE			
	LR1	LR2	ARIMAX	RegARIMA	LR1	LR2	ARIMAX	RegARIMA
Retail & recreation	2265.18	2252.33	2189.70	**2152.46**	6.16	**6.05**	6.22	6.07
Grocery & pharmacy	2123.52	2130.55	2099.65	**2073.82**	**5.03**	5.08	5.14	5.04
Parks	2828.11	2832.19	2795.76	**2794.32**	13.84	13.92	**13.82**	**13.82**
Transit station	2253.60	2193.74	2105.70	**2047.21**	6.06	**5.56**	5.68	5.67
Workplace	2321.76	2329.91	**2240.48**	2254.73	6.69	6.76	**6.40**	6.71
Residential	1459.40	1462.41	**1388.33**	1400.59	1.94	1.95	**1.86**	1.92
Driving	3010.83	2975.19	**2706.90**	2723.65	17.99	**17.10**	19.19	17.85
Transit	3268.59	3228.42	**2870.91**	2900.33	26.06	**24.60**	27.48	25.93
Walking	3009.97	2942.88	**2588.21**	2623.11	17.97	**16.32**	17.29	16.81
Kiyomizu Temple	3164.89	3090.51	**2788.56**	2801.28	22.45	20.18	**19.80**	28.13
Nishiki Market	2800.42	2736.69	**2472.15**	2496.35	13.30	**12.14**	12.69	13.10
Kyoto Station	2524.32	2437.39	2271.81	**2244.97**	8.94	**7.89**	7.97	7.90

window. In this paper we attempt to demonstrate that the consideration of people's adaptation process to the interventions can measure the effects more properly. Given a pandemic situation and the request type policies without much enforcement we suppose that the population gradually adjusts its behavior around the time in which the containing policy comes into effect. To capture the emergence of behavior changes in mobility as well as the date of the emergence, Google trends data relevant to the intervention policies are employed. The numbers of searches for a specific keyword in a time period are rescaled within 0 and 100 by Google trends (Google, 2020c). The data are on a weekly basis and are thus linearly interpolated to a daily basis in this paper. It is found in Fig. 1 that the searches of a keyword always reach the peak several days prior to the starting day of the pandemic containing policies. The exogenous variable of a specific containing intervention is therefore synthesized by combining the search data and the policy window. For a containing intervention, we apply a piecewise function as in Eq. (5) to synthesize the exogenous variable, where "→" is an operator to compute the days from the left term to the right term. Logit functions are used to model the process of gradual adaptation and dropout. We therefore have ones for time t within the policy window and values from zero to one for the days before and after the intervention. The policy strength is assumed to keep the maximum level of 100% during the policy window and a single policy window is not divided into phases. We assume that the effect of the policy would be 50% of the full effect at the time point when the relevant searches reach the peak. The parameter m controlling the 0.5 point of the logit functions in Eq. (5) is hence obtained by differencing the date of the intervention start and the date of the searched peak. Stay-at-home requests and declarations of a State of Emergency are taken as three exogenous variables. The two times of the State of Emergency are used as separate variables, in order to investigate whether there is a potential "tiring" or "fade-out" effect of this containing policy. The converted exogenous variables are illustrated by dotted lines in Fig. 1(c) and 1(d). As the State of Emergency is considered an upgrade of the Stay-at-home request, we use the difference between the logit curves of these two policies for the variable of the Stay-at-home request during its overlapping days with the State of Emergency. As a result, the variable of the Stay-at-home request values zero during the overlapping days as shown in Fig. 1(c) and the impacts on mobility changes during that period are attributed to the declaration of the State of Emergency.

$$x_{i,t,i\in S} = \begin{cases} \dfrac{1}{1+\exp((d_{start}\rightarrow t) - m)}, & \text{if } t < d_{start} \\ 1, & \text{if } d_{start} \le t \le d_{end} \\ \dfrac{1}{1+\exp((t\rightarrow d_{end}) - m)}, & \text{if } t > d_{end} \end{cases} \tag{5}$$

Another set of interventions introduced in Japan are the policies to stimulate mobility and associated consuming activities to promote the recovery of the economy. The first stage of this policy provides 35% discount on the total travel expense for those who make domestic leisure travels. Fig. 1(e) shows the search trend of "Go-to-travel Campaign" which is the major policy of this category. Different from the containing policies, this policy never received as much attention neither prior to the starting date nor during its first stage. People's attention drastically increased at the start of its second stage where special coupons that allow for a further 15% discount to the travel expense. Another difference is that during this second stage the visits to the neighboring prefecture also qualified one to apply for the discount. The adaptation process considered for containing policies and Eq. (5) are not suitable for this stimulating policy. The differences are manifold. Firstly, a behavioral response to the policy is not mandatory for anyone. Secondly, the action of making a journey motivated by this policy is more likely to lag compared to the search trend. Thirdly, mobility indices receive no influence of this policy before or after the campaign window since no discount or gift is released. Therefore a moving average search trend of the past seven days of time t is computed and divided by 100 to represent this policy as the associated exogenous variable to the model.

In the following case study, two LR models are used to illustrate the improvement by considering the adaptation processes for the containing policies. LR1 uses dummy policy variables and LR2 uses the synthesized policy variables. With the improvement confirmed, the synthesized policy variables are applied to RegARIMA and ARIMAX models. We conclude this section by noting that we do not include any intercept for the models since we assume no independent constant percentage change from the baseline.

5. Results and interpretation

As is mentioned in Section 1, the studied timeline is from 15 February 2020 to 2 April 2021. The starting date is due to the data availability of the dependent mobility indices. The data during 15 February 2020 and 28 January 2021 are used as the sample data, and the data after 28 January 2021 are used as the test data for forecasting. The model estimation of LR1, LR2, ARIMAX, and RegARIMA is conducted by Matlab R2021a. The latter two models are estimated by the Econometric Modeler of Matlab R2021a. All the mobility indices in the studied time series pass the augmented Dickey-Fuller test (Dickey and Fuller, 1979) at a significance level of 0.05 except for Nishiki Market whose p-value is 0.057. As this is still close to the required significance level, we regard all the dependent time series processes as stationary or trend-stationary.

5.1. Model fit

Four indicators are selected to evaluate the model fit: Akaike information criterion (AIC), Bayesian information criterion (BIC), Root Mean Square Error (RMSE), and R-squared. The former two indicators are commonly used to evaluate the model fit for models incorporating time series processes and are estimated using the maximum likelihood mea-

Table 3
Estimation results of RegARIMA, significance codes: p-Value ≤ 0.01***, 0.05**, 0.1*

	Google Mobility Index (%)						Apple Mobility Index (%)			WiFi Mobility Index (%)		
	Retail & recreation	Grocery & pharmacy	Parks	Transit station	Workplace	Residential	Driving	Transit	Walking	Kiyomizu Temple	Nishiki Market	Kyoto Station
Daily new cases	−4.28***	−0.37	−7.21***	−9.77***	−5.40***	2.61***	−2.58	−8.08*	−7.04**	−19.36***	−9.94***	−4.97***
Weather												
Temperature (°C)	0.11	0.24***	0.87***	−0.02	−0.05	−0.02	0.05	−0.46	−0.08	0.54**	−0.13	0.19*
Precipitation (mm)	−0.18***	−0.21***	−0.71***	−0.11***	−0.07*	0.06***	−0.03	−0.04	−0.05	−0.27***	−0.02	−0.01
Seasonal and calendar effects												
Weekend	−2.44***	0.73	−6.59***	−8.80***	−0.02	−0.92***	−1.87	−0.35	−0.52	3.26**	−0.40	−6.20***
Holiday	10.52***	0.28	26.57***	−14.87***	−39.58***	9.95***	−1.19	−2.68	−1.72	6.29***	−4.06***	−4.84***
Spring	7.78***	4.23**	27.58***	6.93***	6.53*	−2.93***	16.79*	29.78***	15.28*	16.36	10.44	11.23***
Autumn	2.85	1.69	10.79**	2.70	4.04	−1.51	2.77	8.30	1.11	14.08	−1.30	−5.75**
Policies												
Stay-at-home	−9.35***	−1.59	−5.54	−12.46***	−2.82	2.70**	−15.69	−15.57	−17.64*	−24.27*	−25.46***	−12.52***
State of Emergency (1)	−26.35***	−4.64***	−8.13**	−26.25***	−11.65***	7.02***	−38.52***	−45.08**	−45.90***	−53.97*	−43.34***	−40.39***
State of Emergency (2)	−8.22**	−4.96	−2.51	−1.15	6.23	−2.07*	−13.57	−15.10	−13.69	−13.08	−16.63	−16.18**
Go-to-travel(1)	1.69	−7.27	−3.13	14.12*	10.04	−5.19*	62.76***	57.74*	65.87***	7.86	11.94	16.05
Go-to-travel(2)	7.40**	0.69	22.20***	19.15***	11.44**	−5.45***	43.50**	65.06**	59.09***	25.21	18.75**	13.50**
Time series errors												
AR(1)φ_1	0.53***	0.42***	0.36***	0.64***	0.47***	0.42***	0.76***	0.81***	0.80***	0.88***	0.77***	0.68***
Variance $(\sigma_\varepsilon)^2$	26.23***	20.92***	165.89***	19.38***	35.19***	3.02***	135.40***	224.96***	101.43***	169.24***	70.46***	34.22***
Model fit												
AIC	2152.46	2073.82	2794.32	2047.21	2254.73	1400.59	2723.65	2900.33	2623.11	2801.28	2496.35	2244.97
BIC	2206.40	2127.75	2848.25	2101.14	2308.66	1454.52	2777.58	2954.26	2677.04	2855.21	2550.28	2298.90
RMSE	6.07	5.04	13.82	5.67	6.71	1.92	17.85	25.93	16.81	28.13	13.10	7.90
R-squared	0.75	0.29	0.59	0.83	0.78	0.82	0.60	0.58	0.72	0.46	0.66	0.83

Table 4
Forecast performance of LR, ARIMAX, and RegARIMA.

	RMSE				R-squared			
	LR1	LR2	ARIMAX	RegARIMA	LR1	LR2	ARIMAX	RegARIMA
Retail & recreation	7.82	5.15	5.16	**4.65**	0.60	0.73	0.72	**0.76**
Grocery & pharmacy	4.03	4.31	4.40	**3.99**	0.43	0.41	0.38	**0.47**
Parks	14.17	14.16	14.08	**13.85**	0.66	0.66	0.65	**0.67**
Transit station	8.80	**4.00**	4.15	4.02	0.28	0.80	0.78	**0.81**
Workplace	3.97	3.94	4.31	**3.76**	0.78	0.79	0.75	**0.80**
Residential	2.78	**1.57**	1.60	1.64	0.32	**0.70**	0.69	0.68
Driving	31.13	**22.94**	24.48	23.95	0.66	0.78	0.76	**0.82**
Transit	42.39	**33.26**	39.36	36.54	0.65	0.74	**0.75**	**0.75**
Walking	31.57	**21.11**	25.54	22.64	0.64	0.80	0.80	**0.81**
Kiyomizu Temple	54.53	**44.38**	47.91	52.94	0.64	0.76	**0.85**	0.83
Nishiki Market	28.13	19.34	21.07	**17.25**	0.26	0.81	0.83	**0.86**
Kyoto Station	23.51	**17.30**	18.20	17.85	0.81	0.82	0.79	**0.83**

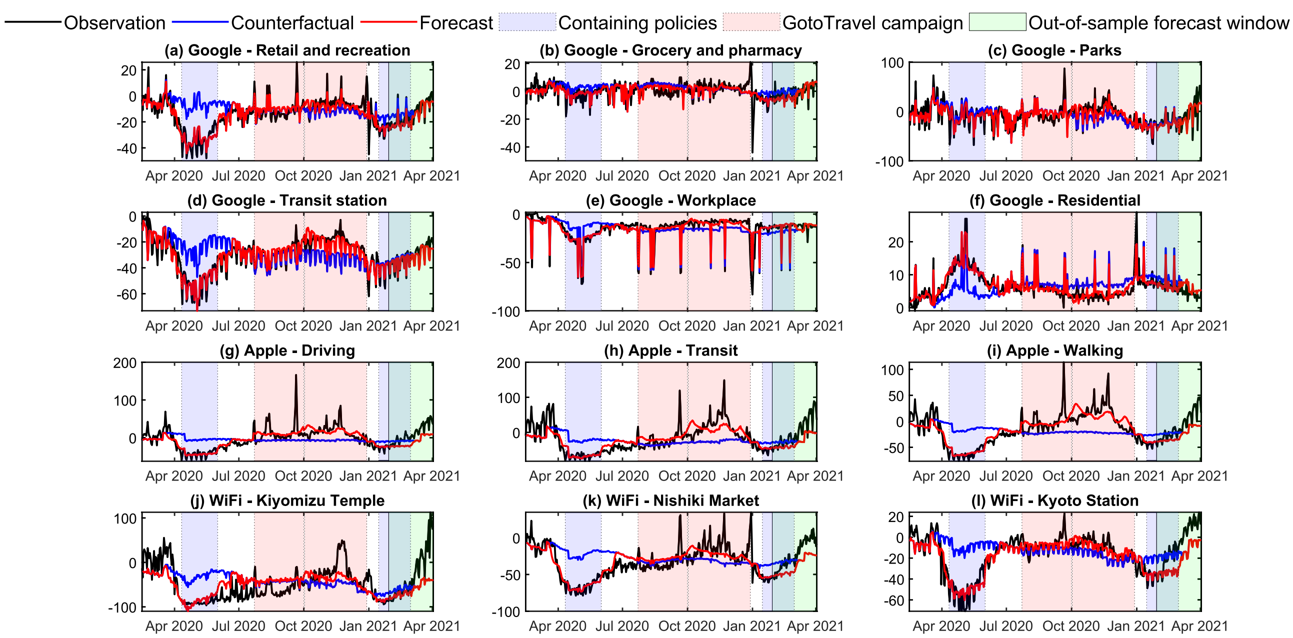

Fig. 2. Forecast results of RegARIMA model.

sure. Let $\widehat{L}$ be the maximum value of the likelihood function, n be the sample size, k be the number of parameters including variable coefficients, intercept, and error variance. With these definitions we obtain Eqs. (6) and (7) to compute AIC and BIC respectively. Lower values of AIC and BIC are favorable. Both AIC and BIC add a penalty for the number of parameters to adjust the model fit. RMSE and R-squared here are based on the difference between in-sample forecast values and observations.

$$AIC = 2k - 2\ln(\widehat{L}) \tag{6}$$

$$BIC = k\ln(n) - 2\ln(\widehat{L}) \tag{7}$$

Table 2 compares the model fit of the RegARIMA model with the other three models. Only AICs are listed since AIC and BIC show the same tendency in this comparison. RMSEs are provided to show the in-sample forecast errors of the models. For most categories AIC and RMSE are decreased from LR1 to LR2, showing the effectiveness of using Google trends data to synthesize the policy variables. Moreover, significant improvement is achieved by the two models more capable of describing time series data. We can observe a pronounced drop in AIC from LR2 to ARIMAX and RegARIMA for each mobility category. Considering the time-series nature of the data can account for this improvement in model soundness. It can be found in Appendix B that the significant autocorrelation in the residuals of LR2 is addressed by these two models incorporating an ARIMA process. Among these two models, each is superior in half of the categories with respect to AIC. We judge the RegARIMA model as preferred because the contributions of the exogenous variables to the dependent variable are considered to be "diluted" in the ARIMAX model by the time series term φ_1 shown in Eq. (4). To illustrate this, comparing the estimation results of LR2 and ARIMAX in Appendix C with the results of RegARIMA in Table 3, one can find that the magnitude of the coefficients estimated by LR2 are similar to those obtained by RegARIMA while ARIMAX estimates much smaller coefficients than RegARIMA. Therefore, we report the estimation result of our preferred RegARIMA model in Table 3, including the estimated coefficient and significance of each variable as well as the indicators of model fit. The results of other models can be found in Appendix C. For the variables related to time series errors, we report the coefficient of the autoregressive term and the variance of white noise ε_t.

5.2. Measured impacts of policies and other factors

The impacts of the five implementations or stages of three policies are measured by the model and reported in Table 3. The unit of the estimated coefficients is percentage as the dependent variable of the models is always the percentage change from a baseline in January 2020. Among the policies, State of Emergency was used twice in the studied timeline, and we use the number in brackets to distinguish the first time and second time of this policy implementation. Also for the two Go-to-travel campaigns, the number in brackets is used to distinguish the different stages.

Among the three implementations of restrictive policies, the first State of Emergency in general imposed the most significant impact in reducing mobility and activity demand. It reduced the activity at retail & recreational places by 26.35% and it reduced the visits of transit stations by 26.25%. Furthermore, it decreased workplace visits only by 11.65%, indicating that the working-from-home strategy had not been widely adopted by the companies during the initial waves of the pandemic. The impact of the first State of Emergency was not obvious for places categorized as grocery & pharmacy or parks. As these places mainly serve for daily minor shopping and leisure demand and are mostly less crowded, it is in line with our expectations that the associated visits were not strongly restricted by the State of Emergency. We also notice that for all categories the impact of the first implementation of the State of Emergency was much more pronounced than the effect of the Stay-at-home request.

For all activity categories, except for residential, the impact of the State of Emergency on restricting activities eroded significantly at the second implementation, such as from 26.35% to 8.22% for retail & recreation and from 26.25% sharply to 1.15% for transit station. This fading-away effect due to repeated implementations can be also observed in the results estimated from all the Apple indices. The measured effect magnitude on driving, transit usage, and walking compared to the baseline were all significantly less in the second stage. The coefficients for our models with the Wi-Fi mobility indices also confirm these trends. On average, the impact of the second implementation was one-third of the first one.

We then turn our focus to the policies to stimulate travel demand. As noted before the second stage of Go-to-travel Campaign provided a more attractive discount therefore larger effects are explainable. For example, our model suggests that the second stage increased activities at transit stations by a significant 19.15%, whereas the effect of the first campaign is found to be only weakly significant at 14.12%. For the places considered to be likely target destinations of tourists, the second stage increased the visits by 7.4% at retail & recreation, 22.2% at parks, and 25.21% at Kiyomizu Temple, which is a famous tourist attraction. The significance and magnitude for the variables of the second stage are in general much larger.

Finally, the following observations on other influential factors appear also important: First, the increases in temperature and precipitation imposed opposite effects on mobility. We note that the baseline is in January which is the coldest season of the year in Kyoto. Favorable weather with higher temperature and less precipitation significantly motivated the trips to open spaces such as parks and sightseeing places such as Kiyomizu Temple. The visits to parks were increased by 0.87% if the temperature was higher than that in January by 1 °C and decreased by 0.71% per 1 mm rainfall more than that in January. Second, as the baseline distinguishes workdays and weekends, the effect of weekend shows the difference of a weekend during COVID-19 from a weekend before COVID-19. It can be seen that the mobility generated on weekends was generally decreased during COVID-19. On the contrary, the baseline does not treat holidays differently so that the effect of holiday is amplified by comparing a holiday with a normal day; in particular the model estimates that holidays reduced the visits to a workplace by 39.58%. Third, we can observe significantly positive effects of the two sightseeing seasons. The effect is found more pronounced in spring than in autumn.

5.3. Forecast performance

We now focus on the out-of-sample forecast performance of the models. RMSE and R-squared are used as performance indicators. Table 4 reports the indicators of each model and each mobility category. The unit of RMSE is percentage in this analysis as the dependent variable is the percentage change. The improvement from LR1 to LR2 shows the advantages of using the logit-transformed policy variables over the traditional dummy variable approach. It can be seen that the LR2 model produces more accurate predictions than LR1 for all categories except for grocery & pharmacy. Notably, the error is reduced by half for transit stations and residential locations, and the R-squared is improved by 0.1 for the three Apple indices and 0.55 for Nishiki Market. The differences between LR2, ARIMAX, and RegARIMA then emphasize the various considerations of time series errors in the models. Different from the performance of in-sample forecast, RegARIMA produces the best performance in terms of RMSE for four out of six Google mobility categories. For the other two Google indices, Apple indices, and WiFi indices, it usually produces the second-best performance. Furthermore, RegARIMA outperforms other models in terms of R-squared for ten out of twelve categories. For the two categories where it does not perform best, the gap is merely 0.02. We therefore conclude that RegARIMA is more suitable for forecasting future mobility trends under COVID-19 interventions.

We do note, however, that the differences in many cases are not very large. Among LR2, ARIMAX, and RegARIMA, the difference between the best and the worst model per category is usually within 3 units for RMSE and 0.1 for R-squared. The forecast capability of LR2 and ARIMAX is acceptable, even though, we remind our previous discussion that the former one fails to address the serial correlation and the policy magnitude obtained from the latter may be diluted and difficult to interpret.

A closer look at the forecast performance of RegARIMA is given in Fig. 2 which illustrates the forecasted mobility trends. The policy windows of containing and stimulating interventions are shaded by different colors, in-sample and out-of-sample windows are distinguished, and counterfactual estimates are introduced. The counterfactuals create the curves using the fitted models but assuming no policy is forced in the COVID-19 timeline.

We observe that our model captures the drops due to the restrictive interventions and the rebounds provoked by the stimulating ones as well as the sightseeing seasons during the in-sample window. More importantly, it successfully forecasts the trends in the out-of-sample window. The out-of-sample window contains several weeks during the second State of Emergency from 28 January 2021 to 28 February 2021. The initial days in the spring sightseeing season of 2021 are also included in this window. The acceptable forecast results for Google indices indicate that the effects of the second State of Emergency and the spring sightseeing season are properly measured. However, some concerns of underestimation of general spring effects arise given the downward deviation of the forecasts from the observations at the end of the timeline for the three Wi-Fi indices located at important attractions in Kyoto City. This underestimation is not surprising in that the spring effect is estimated from the spring of 2020 in the sample data. In the spring of 2020 the sightseeing desire was reduced by the emerging risks of the pandemic and the mobility was partially restricted by soft interventions such as the Stay-at-home request. However, the spring of 2021 overlaps with a restriction-free period and is embraced by the rebounding travel desire. Accordingly, the forecast gap is more significant for the popular recreation places.

6. Conclusion and further research

In this paper, we shed light on the estimation of non-pharmaceutical intervention effects and the forecast of future mobility and activity trends for the ongoing COVID-19 pandemic with a regression model incorporating time series errors. We specify an ARIMA process of (1,0,0) for the errors and obtain interpretable estimates on the effects, in light of the classical intervention models proposed by Box and Tiao (1975) and Tsay (1984). Our model also succeeds to forecast future trends at an acceptable accuracy. The model is tested by twelve activity and mobility indices including nine of them published by Google and Apple at prefecture level based on the usage of their digital map services. Google's indices are broken down into activity categories while Apple's are specific to transport modes. The remaining three are processed by our own data at critical places in the city. We are therefore presenting overviews on the policy effects at city level and closer looks at some specific places.

We confirm the restriction effects of containing policies on mobility trends and show that the effects of the recurrence of an intervention or an event may be substantially different. We demonstrate the fading-away effect by comparing the estimated effects of the first and second State of Emergency. One may expect the effect to be further declining for the third and fourth times so that reduced coefficients might be used to forecast the future trends. However, the decay is not likely to be linear so that the reduced policy effect is ambiguous. Moreover, the concurrence with other unexperienced events and the upgrade of the policy itself may make the effect on mobility trends more unpredictable. This is more of concern for out-of-sample forecasting than for in-sample estimation. Similar issues exist for the seasonal effects. As a lesson learned from the estimation on the spring effect, the rebounding effect caused by containing interventions should be considered. This can be resolved to some extent by taking the data from previous normal years into account, though Google and Apple mobility reports are unfortunately not available for times before January 2020.

We demonstrate people's reactions to the implemented interventions by using Google trends data that help to enrich the exogenous variables. This improves the forecast accuracy of the model. The online searches for a policy indicate people's attention, though, their attitudes and behavioral connections to it are not clear. For future work we suggest that search frequency and a "population sentiment analysis" based on, for example, Twitter data could be used to further improve the modelling of the population adaptation process.

Japan was among the first countries to implement "reverse interventions" to stimulate domestic travel demand. These interventions have the potential to help the recovery of the economy, however, at the risk of accelerating the virus spread. We confirm their motivating effects on mobility, especially for the stage with a more favorable discount to travel expenses. For further work, we recommend investigations into the interactions among pandemic cases, mobility trends, and economic indicators in terms of correlation and causation.

The effect of vaccination is excluded in this paper by cutting the studied timeline before the national and regional vaccination rates exceed 1% of the associated population. After the studied timeline in this paper, Japan entered the third State of Emergency from 25 April 2021 to 11 May 2021, which involves four prefectures as Tokyo, Kyoto, Osaka, and Hyogo. Tokyo and Okinawa entered the fourth one initially scheduled from 12 July to 22 August, partly in response to the Summer Olympic Games. The fourth one was extended to 30 September 2021 and expanded to several other prefectures including Kyoto. Meanwhile, the vaccination rate was increasing fast and had reached 65.10% (55.50% fully vaccinated) by the end of September in Kyoto (Government CIO portal, 2021). It then gradually increased to 72.99% (72.42% fully vaccinated) in the middle of January 2022. Given such a mixture of interventions, we hope that extensions of this work, including a longer timeline, could help to also clarify the effect of vaccinations on the population's mobility and activity. Given "COVID tiredness" and less risk perception among the vaccinated population we suspect that the effect of policy interventions is declining compared to our model estimates.

CRediT authorship contribution statement

Wenzhe Sun: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **Jan-Dirk Schmöcker:** Conceptualization, Methodology, Writing – review & editing, Supervision, Funding acquisition. **Satoshi Nakao:** Conceptualization, Methodology.

Declaration of Competing Interest

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

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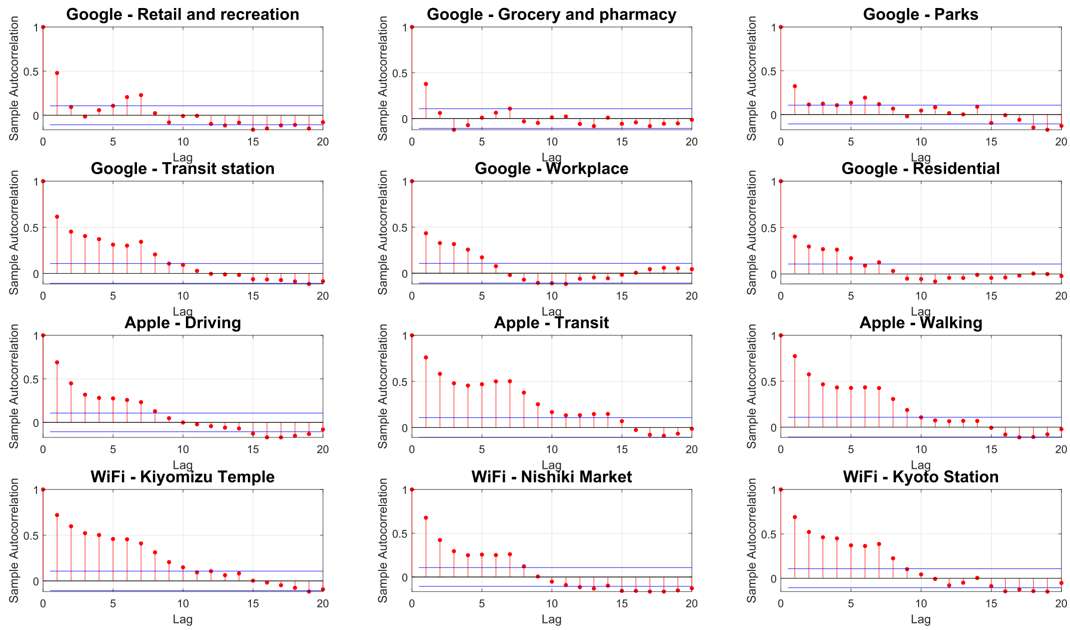
Appendix A. Supplementary data

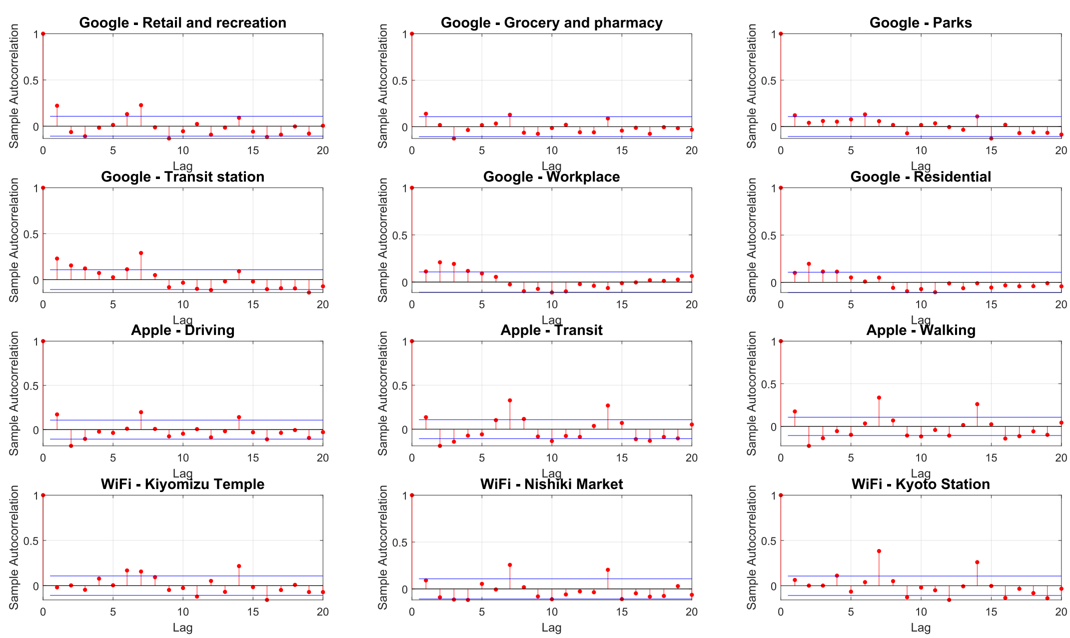
Supplementary data to this article can be found online at https://doi.org/10.1016/j.trip.2022.100551.

Appendix B. Autocorrelation in the residuals of the models

Fig. 3

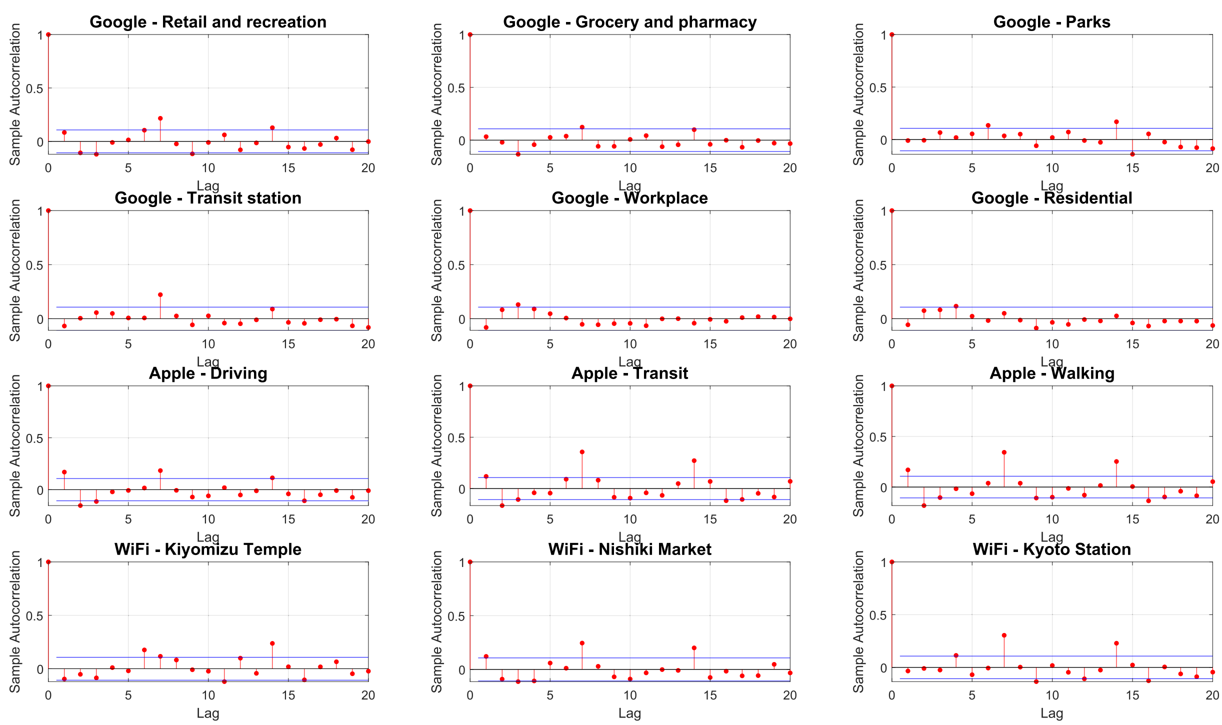


(a) LR2



(b) ARIMAX

Fig. 3. Autocorrelation in the residuals of LR2, ARIMAX, and RegARIMA.



(c) RegARIMA

Fig. 3. (*continued*).

Appendix C. Estimation results of benchmark models

Tables 5–7

Table 5
Estimation results of LR1, significance codes: p-Value ≤ 0.01***, 0.05**, 0.1*

	Google Mobility Index (%)						Apple Mobility Index (%)			WiFi Mobility Index (%)		
	Retail & recreation	Grocery & pharmacy	Parks	Transit station	Workplace	Residential	Driving	Transit	Walking	Kiyomizu Temple	Nishiki Market	Kyoto Station
Daily new cases	−4.80***	−0.48*	−7.73***	−10.39***	−5.75***	2.76***	−6.60***	−11.75***	−11.17***	−19.25***	−11.88***	−6.79***
Weather												
Temperature (°C)	−0.11**	0.19***	0.78***	−0.28***	−0.07	0.02*	0.08	−0.69***	−0.07	−1.22***	−0.77***	0.19***
Precipitation (mm)	−0.16***	−0.18***	−0.74***	−0.10***	−0.05*	0.05***	−0.14*	−0.25**	−0.09	−0.44***	−0.07	0.07*
Seasonal and calendar effects												
Weekend	−2.66***	0.43	−6.37***	−8.52***	0.21	−0.76***	0.85	3.28	1.34	9.45***	2.54	−5.61***
Holiday	12.79***	0.59	30.32***	−10.76***	−42.23***	9.99***	19.81***	22.03***	15.43***	25.26***	9.85***	−0.20
Spring	1.11	3.52***	28.26***	0.50	4.46***	−1.06***	14.84***	33.67***	10.97***	31.28***	−1.57	2.47
Autumn	2.10	0.81	10.81***	4.61***	3.10**	−0.98**	8.17**	20.31***	8.12**	36.28***	1.90	−1.90
Policies												
Stay-at-home	−15.81***	−3.27**	−13.78***	−18.84***	−8.80***	4.95***	−30.77***	−44.48***	−36.49***	−46.45***	−26.42***	−27.93***
State of Emergency (1)	−25.52***	−4.11***	−4.01	−23.99***	−11.52***	6.70***	−33.75***	−36.29***	−41.93***	−38.67***	−35.64***	−41.10***
State of Emergency (2)	−7.19***	−4.92***	−0.80	0.00	6.90***	−2.47***	−2.02	−7.21	−2.33	−17.21**	−12.32***	−11.28***
Go-to-travel(1)	5.30***	−1.43	0.68	10.26***	4.42***	−2.85***	29.77***	25.34***	31.32***	18.86***	17.22***	9.33***
Go-to-travel(2)	8.63***	2.14**	15.17***	14.40***	8.57***	−4.25***	32.14***	46.8***	42.09***	27.74***	22.72***	11.47***
Model fit												
AIC	2265.18	2123.52	2828.11	2253.60	2321.76	1459.40	3010.83	3268.59	3009.97	3164.89	2800.42	2524.32
BIC	2311.41	2169.74	2874.34	2299.82	2367.99	1505.63	3057.05	3314.81	3056.20	3211.12	2846.65	2570.55
RMSE	6.16	5.03	13.84	6.06	6.69	1.94	17.99	26.06	17.97	22.45	13.30	8.94
R-squared	0.75	0.31	0.60	0.81	0.78	0.83	0.60	0.58	0.68	0.66	0.66	0.78

Table 6
Estimation results of LR2, significance codes: p-Value ≤ 0.01***, 0.05**, 0.1*

	Google Mobility Index (%)						Apple Mobility Index (%)			WiFi Mobility Index (%)		
	Retail & recreation	Grocery & pharmacy	Parks	Transit station	Workplace	Residential	Driving	Transit	Walking	Kiyomizu Temple	Nishiki Market	Kyoto Station
Daily new cases	−3.80***	−0.08	−6.82***	−9.57***	−5.42***	2.56***	−3.98***	−7.66***	−8.29***	−16.28***	−9.38***	−5.73***
Weather												
Temperature (°C)	−0.04	0.15***	0.68***	−0.16***	−0.03	−0.01	0.27*	−0.61***	0.11	−1.04***	−0.61***	0.36***
Precipitation (mm)	−0.18***	−0.19***	−0.75***	−0.13***	−0.07**	0.06***	−0.21***	−0.34***	−0.17**	−0.51***	−0.12**	0.04
Seasonal and calendar effects												
Weekend	−2.80***	0.40	−6.48***	−8.64***	0.18	−0.74***	0.57	2.86	1.10	8.92***	2.29	−5.85***
Holiday	11.31***	0.25	30.00***	−12.15***	−43.15***	10.48***	17.98***	20.26***	12.98***	24.65***	7.69***	−2.02
Spring	8.09***	4.00***	28.48***	8.54***	7.57***	−3.09***	25.14***	43.54***	24.12***	43.48***	10.30***	15.18***
Autumn	3.21**	1.27	11.60***	5.94***	4.69***	−1.58***	9.89**	22.06***	10.13***	35.41***	3.31	−1.31
Policies												
Stay-at-home	−8.03***	−0.74	−3.97	−11.60***	−3.75**	2.66***	−18.23***	−21.91***	−21.99***	−22.76***	−19.66***	−14.92***
State of Emergency (1)	−26.01***	−4.16***	−7.20***	−25.87***	−11.88***	6.96***	−42.61***	−51.43***	−50.66***	−53.05***	−41.77***	−42.53***
State of Emergency (2)	−10.42***	−6.17***	−4.40	−2.25	6.61***	−1.90***	−12.25**	−24.12***	−13.35**	−29.88***	−22.50***	−14.44***
Go-to-travel(1)	4.71	−4.70	3.71	19.58***	9.38**	−5.93***	61.95***	43.49**	66.69***	24.09*	24.12***	11.23**
Go-to-travel(2)	7.39***	1.02	22.51***	18.55***	10.75***	−5.38***	39.41***	59.04***	56.18***	34.00***	23.16***	12.48***
Model fit												
AIC	2252.33	2130.55	2832.19	2193.74	2329.91	1462.41	2975.19	3228.42	2942.88	3090.51	2736.69	2437.39
BIC	2298.55	2176.78	2878.41	2239.97	2376.14	1508.64	3021.42	3274.64	2989.11	3136.74	2782.91	2483.61
RMSE	6.05	5.08	13.92	5.56	6.76	1.95	17.10	24.60	16.32	20.18	12.14	7.89
R-squared	0.76	0.30	0.60	0.84	0.78	0.82	0.64	0.63	0.74	0.73	0.72	0.83

Table 7
Estimation results of ARIMAX, significance codes: p-Value ≤ 0.01***, 0.05**, 0.1*

	Google Mobility Index (%)						Apple Mobility Index (%)			WiFi Mobility Index (%)		
	Retail & recreation	Grocery & pharmacy	Parks	Transit station	Workplace	Residential	Driving	Transit	Walking	Kiyomizu Temple	Nishiki Market	Kyoto Station
Daily new cases	−2.58***	−0.12	−5.41***	−6.02***	−3.76***	1.85***	−0.65	−1.36	−1.32*	−5.11***	−2.04***	−2.33***
<u>Weather</u>												
Temperature (°C)	0.02	0.14***	0.63***	−0.07	−0.03	−0.01	0.07	−0.11	0.05	−0.11	−0.05	0.21***
Precipitation (mm)	−0.17***	−0.18***	−0.71***	−0.11***	−0.06	0.06***	−0.01	0.03	−0.04	−0.29***	−0.01	0.01
<u>Seasonal and calendar effects</u>												
Weekend	−1.75**	0.73	−5.32***	−7.46***	0.45	−1.01***	2.41*	6.35***	4.44***	5.40***	−0.32	−4.44***
Holiday	8.75***	−0.57	27.16***	−11.65***	−39.03***	9.66***	−10.59***	−12.76***	−10.56***	11.05***	−7.17***	−2.98**
Spring	5.32***	3.11**	22.80***	5.49***	5.09***	−2.15***	3.87	4.30	1.71	10.79***	1.82	6.25***
Autumn	1.97	0.89	8.34**	3.59***	3.34	−1.11*	0.67	0.77	−0.27	8.36***	−0.57	−0.90
<u>Policies</u>												
Stay-at-home	−5.49***	−0.82	−3.99	−7.75***	−2.71	1.99***	−5.27	−5.66	−4.61	−8.21**	−5.97**	−6.87***
State of Emergency(1)	−17.03***	−3.31***	−6.84***	−16.69***	−8.22***	5.00***	−7.49**	−6.24	−6.40**	−15.50***	−8.46***	−17.74***
State of Emergency(2)	−6.19***	−4.33**	−2.54	−1.36	4.44**	−1.38**	−2.40	−2.88	−1.53	−6.13	−4.01	−5.61**
Go-to-travel(1)	1.05	−4.66	−3.20	11.71***	8.43	−4.57**	11.02	9.85	8.88	−0.46	3.28	2.41
Go-to-travel(2)	4.89***	0.60	17.17***	11.79***	7.26***	−3.75***	6.49	8.93	7.30	10.56**	5.93**	5.31**
<u>Time series terms</u>												
AR(1)φ_1	0.36***	0.26***	0.23***	0.35***	0.27***	0.27***	0.82***	0.87***	0.87***	0.74***	0.79***	0.58***
Variance $(\sigma_\varepsilon)^2$	29.72***	22.93***	170.44***	23.33***	34.40***	2.95***	131.93***	211.65***	93.71***	166.94***	67.07***	37.65***
<u>Model fit</u>												
AIC	2189.70	2099.65	2795.76	2105.70	2240.48	1388.33	2706.90	2870.91	2588.21	2788.56	2472.15	2271.81
BIC	2243.59	2153.54	2849.65	2159.59	2294.37	1442.22	2760.79	2924.80	2642.10	2842.45	2526.04	2325.70
RMSE	6.22	5.14	13.82	5.68	6.40	1.86	19.19	27.48	17.29	19.80	12.69	7.97
R-squared	0.73	0.26	0.59	0.83	0.79	0.83	0.54	0.52	0.70	0.74	0.68	0.82

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